Hochschule Düsseldorf
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Online Negotiations

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An Analysis of the Importance and Impact of Different Negotiation Competencies

Bachelor's Thesis

BNCOW

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Hochschule Düsseldorf
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Fachbereich Elektro- & Informationstechnik
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Bachelor-Thesis

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Simulating Hybrid Negotiations:

Behavioral Insights from Remote and In-Person Scenario Using Eye Tracking and Facial Analysis – Developing and Evaluating a Custom Analysis Tool

Submitted by [redacted]
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List of Abbreviations

AOI – Area of Interest

AU – Action Unit

BEACON - Behavioral Analysis of Communication and Negotiation

CNN - Convolutional Neural Network

CPU - Central Processing Unit

ERA - Emotion Recognition Accuracy

ET – Eye Tracking

FA – Facial Analysis

GDPR - General Data Protection Regulation

GPU - Graphics Processing Unit

PoV – Point of View

PANAS - Positive and Negative Affect Schedule

RAF - Real-world Affective Faces

RBF - Radial Basis Function

RDC – Remote Data Collection

SVM – Support Vektor Machine

TSL - Technical Sales Lab

Abstract

In today's digitalized and globalized world, hybrid negotiations where some participants meet in person while others join remotely have become standard practice. However, these settings present challenges, particularly regarding visual attention and emotional expressions among negotiation participants.

This study explores the application of Eye-Tracking (ET) and Facial Analysis (FA) in hybrid negotiations. In particular, it examines differences in gaze distribution and emotional responses between in-person and remote participants. Furthermore, a custom open-source FA tool is developed and benchmarked against the commercial software Affectiva to evaluate its accuracy and practical applicability.

The research is based on experimental negotiation simulation with students and an industry expert. ET data reveals significant differences in attention distribution: In-person participants primarily focus on facial expressions, whereas remote participants direct their gaze mainly toward written materials. FA results indicate that emotional expressions vary throughout the negotiation process and may correlate with negotiation outcomes.

A comparison of the open-source FA tool and Affectiva demonstrates that the commercial software exhibits higher accuracy, particularly in detecting emotions like surprise and fear. However, this study highlights the potential of cost-effective, open-source alternatives for research and practical applications.

By leveraging ET and FA, this research provides valuable insights into hybrid negotiation dynamics and contributes to the development of accessible analytical tools.

Introduction

The increasing digitalization and globalization of business and diplomacy have transformed traditional negotiation settings. Hybrid negotiations are now commonplace. This shift introduces new complexities, particularly regarding visual attention and emotional expressions, two key factors that influence negotiation dynamics and outcomes.

ET and FA are potent technologies for studying these aspects. While ET provides detailed insights into gaze distribution, FA enables the analysis of emotional responses through facial expressions. Despite the growing adoption of these technologies, there is limited publicly available research on their application in hybrid negotiations. Many companies already utilize such methods, often behind closed doors, restricting broader scientific access. This study aims to offer insights into hybrid negotiations and systematically explore the role of ET and FA in this context.

Objectives of the Study

This research is conducted at the Technical Sales Lab (TSL) of Hochschule Düsseldorf as part of the Behavioral Analysis of Communication and Negotiation (BEACON) project, which focuses on optimizing technical sales processes through data-driven analyses. The project explores how modern technologies can enhance negotiation strategies by providing deeper insight into human behavior and decision-making processes.

Within this framework, this study pursues two key objectives. First, it examines the differences in gaze distribution and emotional expressions between in-person and remote negotiation participants to understand better how hybrid settings influence visual attention and emotional engagement. Second, it focuses on developing a custom open-source FA tool for emotion recognition. The performance of this tool is systematically evaluated and compared with the commercial software Affectiva, assessing its validity, reliability, and potential as a cost-effective alternative for academic and professional applications.

To achieve these objectives, this study investigates three key research questions:

- **How does the distribution of attention to Areas of Interest (AOIs) differ between the in-person participants and the remote participant in a hybrid negotiation?**

- **To what extent can negotiation outcomes be predicted based on eye-tracking data and facial expression analysis?**
- **How valid and reliable is the facial expression analysis performed by the developed Python tool compared to a commercial state-of-the-art tool such as Affectiva?**

By addressing these questions, this study contributes to a deeper understanding of hybrid negotiation dynamics and demonstrates how ET and FA technologies can be leveraged to optimize negotiation processes. Furthermore, developing an open-source FA tool presents a potentially cost-effective alternative to commercial solutions, particularly benefiting academic and business applications.

Structure of the Thesis

This thesis is structured into several sections to address the research objectives systematically.

After the introduction, the “Literature Review” provides an overview of existing research on hybrid negotiations, the role of ET and FA, and a comparison between commercial and open-source analysis tools. It highlights current research gaps and serves as the theoretical foundation for the study.

The “Methodology” chapter outlines the research design and methodological approach. First, it introduces the fundamental concepts related to the applied technologies and methods. Then, it presents two case studies: The first case study focuses on analyzing visual attention and emotional expressions in negotiation scenarios using ET and FA. The second case study describes the development of a custom FA tool.

The “Field Tests” chapter applies the previously introduced methodologies and is divided into two main sections. The first section focuses on analyzing negotiations using ET and FA. It covers the study setup, participant surveys, and the analysis of AOIs to compare visual attention between in-person and remote participants. Additionally, FA is used to assess emotional expressions during negotiations.

The second section centers on the development of a custom FA tool. It details the implementation of face recognition, the selection of datasets, and the evaluation of machine learning models for emotion detection. Finally, the tool’s performance is compared to the commercial Affectiva software to assess its accuracy and effectiveness.

The “Limitations” chapter reflects on methodological and technical constraints, such as sample size, challenges in data collection, and potential biases that may affect the validity of the results.

Finally, the “Discussion” chapter synthesizes the key findings and evaluates their implications for hybrid negotiations. It compares visual attention patterns, explores the potential of ET and FA in predicting negotiation outcomes, and assesses the performance of the self-developed FA tool against Affectiva. Additionally, it discusses practical applications of ET and FA in negotiation training and decision-making. The last part of this chapter outlines future research directions, focusing on improving dataset quality, refining FA models, and further investigating the relationship between visual attention, emotional expressions, and negotiation success.

Literature Review

Understanding the dynamics of hybrid negotiations requires insights from multiple disciplines, including behavioral economics, psychology, and data science. Two key technological approaches have emerged as particularly useful in this context: ET and FA. While ET provides objective data on visual attention and gaze patterns, FA enables the automated detection of emotional expressions, offering valuable insights into non-verbal communication.

Despite their growing adoption in various fields, research on the combined application of ET and FA in hybrid negotiations remains scarce. Existing studies typically focus on either visual attention or emotional recognition separately, without integrating both perspectives to analyze negotiation behavior. Furthermore, many commercially available FA tools are proprietary, making it difficult to assess their reliability and validity in different contexts.

This literature review is divided into two main sections. The first part examines how ET and FA have been used to analyze negotiation dynamics, focusing on key findings from prior research. The second part provides a comparative analysis of open-source and commercial FA tools, discussing their strengths, limitations, and applicability for research and business settings. By synthesizing these insights, this review highlights existing research gaps and establishes the foundation for this study's methodological approach.

Analyzing Negotiations Using ET and FA

ET and Emotion Recognition Accuracy (ERA) have become pivotal tools in understanding the complex dynamics of negotiation processes. They enable researchers to assess how visual and emotional cues influence both the behavior of individuals and the outcomes of interactions. This section synthesizes insights from several key studies, which collectively demonstrate how ET and ERA contribute to more effective and insightful negotiation practices.

Stitzlein et al. (2006) conducted foundational research on the role of interface design in visual attention during hybrid negotiations. Their study categorized AOIs into text sections, close-up participant views, and wide-angle group perspectives. They discovered that close-up views of participants drew the most attention, suggesting that focusing on individual faces during negotiations is a primary visual behavior.

The study emphasized the importance of designing interfaces that prioritize textual AOIs to ensure that crucial information remains accessible and enhances decision-making. This research highlights how ET can inform the development of interfaces that optimize attention distribution and promote smoother negotiation processes. [1]

Building on the connection between visual and emotional factors, Elfenbein et al. (2007) explored the role of ERA in shaping negotiation success. Their work focused on how accurately recognizing and interpreting emotions impacts performance in mixed-motive scenarios, which require both cooperation and competition. The findings revealed that participants with higher ERA were better able to collaborate effectively and claim value competitively. This underlines the importance of emotional intelligence in negotiations, as it fosters better social interaction, improves communication, and ultimately leads to more favorable outcomes. [2]

In a similar vein, Li et al. (2015) examined the synchronization of facial expressions during video conferencing and its implications for negotiation outcomes. Using advanced probabilistic models such as coupled Hidden Markov Models, the study demonstrated that synchronized nonverbal communication, such as mutual smiles or shared neutral expressions, strongly predicted negotiation success. This finding highlights the power of interactional synchrony in fostering rapport and creating an environment conducive to effective negotiations, particularly in remote settings where nonverbal cues play a critical role. [3]

Sharma et al. (2020) expanded the discussion by conducting a meta-analysis of 64 studies examining emotional expressions in negotiation contexts. Their work synthesized three decades of research and identified key mechanisms through which emotions influence negotiation dynamics. Applying the emotions as social information theory, the authors demonstrated that emotional expressions have both immediate and long-term effects. These include influencing immediate negotiation outcomes and building trust and cooperation over time. Power dynamics emerged

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[1] Stitzlein, C., & Li, J. (2006). *Gaze analysis in a remote collaborative setting*.
[2] Elfenbein, H. A., Foo, M. D., White, J., Tan, H. H., & Aik, V. C. (2007). *Reading your Counterpart: The Benefit of Emotion Recognition Accuracy for Effectiveness in Negotiation*.
[3] Li, R., Curhan, J., & Hoque, M. E. (2015). *Predicting video-conferencing conversation outcomes based on modeling facial expression synchronization.*

as a critical factor moderating the effectiveness of emotional expressions, with high-power individuals reacting differently to emotional cues than those in lower-power positions. [4]

Finally, Vrzakova et al. (2020) explored social visual attention patterns in mixed-media video conferencing during negotiations. Their research revealed three distinct gaze patterns: mutual gaze, joint attention, and gaze aversion. Joint attention, where participants focus on the same element, was found to positively correlate with collaborative outcomes, while gaze aversion was linked to faster agreements but poorer overall joint scores. Surprisingly, mutual gaze occurred infrequently and did not significantly impact outcomes. These findings underline the nuanced relationship between visual attention and negotiation dynamics, illustrating that specific patterns of social visual behavior can enhance or hinder collaborative efforts. [5]

Together, these studies paint a comprehensive picture of the interplay between visual and emotional factors in negotiations. They highlight how leveraging tools like ET and ERA can provide actionable insights for improving negotiation strategies. Practical applications include designing interfaces that prioritize critical AOIs, training negotiators in emotional intelligence, and fostering nonverbal synchrony to improve rapport. These findings also open avenues for further research into optimizing digital platforms for remote negotiations, where technology often mediates visual and emotional cues.

This synthesis illustrates the multidimensional nature of negotiation research and reinforces the importance of integrating insights from ET and ERA to create more effective negotiation frameworks. By combining advanced technologies with a deeper understanding of emotional and visual behavior, researchers and practitioners can develop more nuanced strategies for negotiation success.

[4] Sharma, S., Elfenbein, H. A., Sinha, R., & Bottom, W. P. (2020). *The Effects of Emotional Expressions in Negotiation: A Meta-Analysis and Future Directions for Research.*
[5] Vrzakova, H., Amon, M. J., Rees, M., Faber, M., & D'Mello, S. (2020). *Looking for a Deal?: Visual Social Attention during Negotiations via Mixed Media Videoconferencing*.

Comparison of Open-Source and Commercial Tools for Facial Expression Analysis

Facial expression analysis has significantly advanced due to developments in machine learning and computer vision, enabling a wide range of applications in both academia and industry. Tools such as AFFDEX 2.0 (commercial), open-source solutions like Py-Feat, LibreFace, implementations based on Convolutional Neural Networks (CNNs) and OpenCV, as well as comparative studies of commercial tools, each have unique strengths and limitations tailored to different user groups and application areas.

AFFDEX 2.0, a commercial tool developed by Affectiva, stands out for its real-time analysis of facial expressions and its ability to detect basic emotions and Action Units (AUs). It is optimized for use under real-world conditions ("in the wild") and has shown improved performance across diverse demographic groups. These features make AFFDEX 2.0 a preferred choice for industrial applications such as marketing, driver monitoring, and healthcare. However, its proprietary nature can limit reproducibility and scientific validity, as access to internal algorithms and data is restricted, posing challenges for independent evaluation. [6]

The comparative study by Dupré et al. (2018) evaluates the performance of three commercial systems—Affectiva, Kairos, and Microsoft Azure—on dynamic and spontaneous facial expressions. The study highlights significant differences between these systems using metrics such as True Positive, False Positive, True Negative, and False Negative rates. Affectiva and Microsoft Azure performed relatively well in avoiding false detections, while Kairos exhibited higher misclassification rates. Furthermore, the study underlines the challenge of analyzing natural, spontaneous facial expressions due to their variability and complexity. This research provides a critical benchmark for assessing the accuracy and reliability of facial expression analysis tools, emphasizing the need for context-specific evaluation. [7]

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[6] Bishay, M., Preston, K., Strafuss, M., Page, G., Turcot, J., & Mavadati, M. (2022). *Comparison of Open-Source and Commercial Tools for Facial Expression Analysis*.
[7] Dupré, D., Andelic, N., Morrison, G., & McKeown, G. (2018). *Accuracy of three commercial automatic emotion recognition systems across different individuals and their facial expressions*.

Another example of advancements in facial expression analysis is the combination of CNNs and OpenCV, as presented in a study from 2022. This approach leverages the power of CNNs to analyze facial expressions in both live video and stored images. With an accuracy of 98.65% for stored images, this method offers a scalable and efficient solution for real-time analysis. Its seamless integration into existing systems is particularly noteworthy. However, potential challenges include limited generalizability to more complex datasets and scenarios, which might restrict its usability in highly variable environments. [8]

A further open-source alternative is LibreFace, introduced in 2023. LibreFace integrates cutting-edge deep learning models such as ResNet and Swin-Transformer to accurately analyze facial expressions, action units, and other features. The toolkit is flexible and supports both CPUs Central Processing Units (CPUs) and Graphics Processing Units (GPUs), making it efficient across various environments. Unlike commercial tools like AFFDEX 2.0, LibreFace emphasizes transparency and extensibility. However, it is better suited for experienced users due to its lower user-friendliness and limited beginner documentation. [9]

Also released in 2023, Py-Feat is another open-source toolkit designed specifically for academic research. Py-Feat is distinguished by its user-friendliness, extensive documentation, and tutorials that enable even beginners to apply advanced facial analysis methods. It offers comprehensive support for detecting facial features, emotions, and AUs. Py-Feat demonstrates high robustness, as confirmed by benchmark tests under challenging conditions such as poor lighting or occlusion. Moreover, its modular structure allows for easy integration of new models and functionalities, making it particularly adaptable for future developments. [10]

In summary, each of these tools and studies offers specific advantages. While AFFDEX 2.0 excels in industrial applications with its user-friendly and real-time capabilities, open-source tools like Py-Feat and LibreFace stand out for their

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[8] Giri, S., Singh, G., Kumar, B., Singh, M., Vashisht, D., Sharma, S., & Jain, P. (2022). *Emotion Detection with Facial Feature Recognition Using CNN & OpenCV.*

[9] Chang, D., Yin, Y., Li, Z., Tran, M., & Soleymani, M. (2023). *LibreFace: An Open-Source Toolkit for Deep Facial Expression Analysis*.

[10] Cheong, J. H., Xie, T., Byrne, S., Kenney, M., & Chang, L. J. (2023). *Py-Feat: Python Facial Expression Analysis Toolbox*.

scientific openness, extensibility, and high accuracy. The comparative study by Dupré et al. provides valuable insights into the varying accuracy and reliability of commercial tools under real-world conditions, offering an essential benchmark for comparison. The combination of CNNs and OpenCV presents another promising option, particularly suited for specialized applications. A systematic comparative study examining the validity and reliability of these tools could provide valuable insights for their future development and application.

Methodology

Understanding

AOIs are crucial for analyzing eye-tracking data. They refer to specific regions within a visual stimulus the researcher defines and serve as targets for detailed investigation. One of the most important metrics associated with AOIs are fixations and gaze points. Fixations measure the duration for which the eyes remain focused on a specific point, providing insights into where visual attention is concentrated. Gaze points, on the other hand, indicate where the eyes are directed during a given period. These metrics form the foundation for further analyses within an AOI. In this study, the following metrics are used:

Gaze based metrics: [11]

- Dwell Count: Average of how often the gaze of the respondents entered the AOI (i.e., how often they visited the AOI on average).
- Revisit Count: Average of how often the respondents looked back at the AOI after the first dwell.
- Dwell time (ms): Average of how long the respondents gazed at the AOI.

Fixation based metrics:

- Revisit count - Average of how often the respondents looked back and fixated on the AOI after the first dwell.
- Fixation count - Average amount of fixations detected inside the AOI.
- Dwell time (ms): Average of how long the respondents fixated at the AOI.

The Remote Data Collection (RDC) is a module developed by iMotions that enables data collection, FA data, voice analyses, respiratory data, and survey responses directly through a web browser. By eliminating the need for physical lab setups, the RDC allows researchers to conduct studies with participants located across diverse geographical regions, thereby increasing accessibility and scalability. This study uses the module to collect ET and FA data from remote participants. [12]

[11] iMotions. (n.d.). AOI Metrics Documentation. https://help.imotions.com/docs/aoi-metrics
[12] iMotions. (n.d.). iMotions Cloud Module. https://imotions.com/products/imotions-lab/modules/cloud/

Libraries play a crucial role in Python programming, as they provide collections of modules and packages with pre-written code designed to efficiently perform various tasks. This study specifically utilizes the following libraries to develop a FA tool:

- **OpenCV**, short for “Open Source Computer Vision Library,” is an open-source library for computer vision, machine learning, and image processing. This study uses OpenCV to read video files and process them to prepare the data for further analysis. [13]
- **NumPy** is an open-source library designed to efficiently handle multidimensional arrays and matrices and perform a wide range of mathematical operations on these data structures. In this study, NumPy is utilized to split data from a CSV file into two components, the image data and the corresponding emotion labels, and to store them in arrays for subsequent processing. [14]
- **Scikit-learn** is an open-source library for machine learning, offering a wide range of tools for data preprocessing, model selection, and algorithm implementation. This study uses Scikit-learn to classify emotion data, enabling the development and evaluation of machine learning models for emotion recognition. [15]
- **Seaborn** is an open-source library based on Matplotlib that is designed for statistical data visualization. It provides a wide range of customizable plots and facilitates the representation of complex relationships within datasets. In this study, Seaborn generates the confusion matrix, offering a visual interpretation of the model's predictions and enhancing the evaluation of emotion recognition performance. [16]
- **TensorFlow** is an open-source machine learning platform known for its flexible architecture, enabling the development and deployment of neural networks. This study uses TensorFlow to implement a CNN for emotion recognition. The model is trained to classify emotions from facial images.

[13] OpenCV. (n.d.). OpenCV: Open Source Computer Vision Library. https://opencv.org/
[14] Harris, C. R., Millman, K. J., van der Walt, S. J., Gommers, R., Virtanen, P., Cournapeau, D., ... & Oliphant, T. E. (2020). Array programming with NumPy. *Nature*, *585*(7825), 357–362. https://doi.org/10.1038/s41586-020-2649-2
[15] Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., ... & Duchesnay, É. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research, 12*, 2825–2830. http://jmlr.org/papers/v12/pedregosa11a.html
[16] Waskom, M. L. (2021). Seaborn: Statistical data visualization. *Journal of Open Source Software, 6*(60), 3021. https://doi.org/10.21105/joss.03021

Additionally, TensorFlow is utilized for model optimization and performance evaluation. [17]

Also, the following two datasets are used to train and test the FA tool:

- **FER2013** is a publicly available dataset widely used for facial expression recognition tasks. It contains 35,887 grayscale images of faces, each with a resolution of 48x48 pixels. These images are categorized into seven distinct emotions: anger, disgust, fear, happiness, neutral, sadness, and surprise. In this study, the FER2013 dataset is utilized to train the custom FA tool. [18]
- **RAF**, short for "Real-world Affective Faces," is a dataset for facial expressions. It contains 15.000 images tagged by 40 independent taggers. The images are categorized into the same emotion classes as FER2013. In this study, RAF is utilized to train the custom FA tool. [19]

Data classification is a fundamental task in data analysis and machine learning. This study examines Logistic Regression, Support Vector Machines (SVMs), and CNNs, which represent essential methods for addressing classification problems.

Logistic Regression is a statistical model used to predict a categorical dependent variable, often binary-coded (0 or 1). It is based on a linear combination of input variables, with predictions transformed using the logistic sigmoid function to produce a probability distribution in the range [0,1]. This ensures a probabilistic estimation of a data point's membership in each class.

The SVM is a supervised learning algorithm for classification and regression tasks. Its goal is to determine an optimal separating hyperplane in a high-dimensional feature space. It maximizes the margin, which is the distance between the decision boundary and the nearest data points, known as support vectors. The SVM employs the kernel trick to handle non-linearly separable data, which projects the data into a higher-dimensional space where a linear separation becomes possible.

A CNN is a specialized artificial neural network architecture designed for processing images and spatial data. CNNs utilize convolutional layers, which extract local

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[17] Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., ... & Zheng, X. (2016). TensorFlow: A system for large-scale machine learning. *12th USENIX Symposium on Operating Systems Design and Implementation (OSDI 16), 265-283*. https://www.usenix.org/system/files/conference/osdi16/osdi16-abadi.pdf

[18] Sambare, M. (n.d.). FER2013 [Dataset]. Kaggle. https://www.kaggle.com/datasets/msambare/fer2013/data

[19] Alok, S. (n.d.). RAF-DB Dataset [Dataset]. Kaggle. https://www.kaggle.com/datasets/shuvoalok/raf-db-dataset

features and capture hierarchical structures within the data. This ability to automatically learn and extract relevant features makes CNNs particularly effective in image processing, object recognition, and speech recognition applications.

The comparison with Affectiva was conducted because, as part of the Technical Sales Lab at Hochschule Düsseldorf, the ET and FA software, along with the corresponding hardware from iMotions, was acquired, and Affectiva is used for emotion recognition within this system.

Case Design: Analyzing attention and emotional expressions using ET and FA.

Objective:

The study aims to analyze variations in attention allocated to specific AOIs by participants during in-person and remote negotiations. Additionally, it investigates whether the collected data can predict negotiation outcomes.

Methodological Approach:

A mixed-methods approach was employed, combining empiric data (e.g., ET and Fa) with qualitative insights (e.g., pre- and post-negotiation surveys) to comprehensively understand negotiation dynamics.

- **Empirical Data:**
    - ET: Monitoring participant's gaze behavior
    - FA: Monitoring emotional expressions during the negotiation.
    - RDC: Using a web application for integrated data gathering.
- **Qualitative Data:**
    - Self-assessment surveys conducted before and after the negotiation, including:
        - PANAS for pre-negotiation emotional state.
        - Post-negotiation self-assessments on perceived strengths and weaknesses.

Participants:

The study involved 10 students with varying negotiation expertise and one industrial expert.

Materials and Tools:

- Data Collection Tools:
    - ET: Neon Glasses by Pupil Labs.
    - FA: High-definition camera.
    - RDC: iMotions web application.
    - Survey: Administered pre- and post-simulation.
- Data Analysis:
    - Conducted using the iMotions software

- Additional Materials:
  - Case materials for negotiation participants.
  - Microsoft Teams for remote simulations.
  - Camera and microphone for recording the Teams call.

Procedure:

- Before the Simulation:
  1. Participants received the case materials and instructions one week in advance.
  2. The technical setup was prepared and tested for functionality.
  3. Data protection guidelines were communicated, and participants provided written consent.
  4. Participants completed pre-simulation surveys.
- During the Simulation
  1. Teams call was initiated for remote participants.
  2. The setup was adjusted to meet participants' needs.
  3. Negotiations lasting approximately 10 minutes were conducted.
  4. ET, FA, and audio recordings were captured.
- After the simulation
  1. All collected data was securely stored.
  2. Participants completed the post-simulation survey.

Data Collection:

The data collection process was conducted using the iMotions software.

- Empirical Data:
  - ET
    - Analysis of AOIs: The analysis focuses on specific AOIs during the negotiation process. These include the counterpart's face, the own camera feed displayed on the screen, the presented offer, and the participant's notes.
    - **Objective:** To examine attention distribution differences between in-person and remote settings and identify patterns that might predict negotiation outcomes.
  - FA

        - Evaluation of participants' emotional expressions during negotiation.
        - **Objective:** To identify patterns that predict negotiation outcomes.
    - RDC
        - Integration of ET and FA data for a comprehensive analysis of remote participant behavior.

- Qualitative Data:
    - Surveys (Pre- and Post-Simulation):
        - Pre-simulation: Assessed emotional states using PANAS.
        - Post-simulation: Reflecting on participants' perceived strengths and weaknesses during the negotiation.

Case Design: Developing a custom FA tool

Objective:
This study aims to evaluate the validity and reliability of a custom Python-based FA tool for emotion detection by comparing its accuracy against Affectiva.

Procedure:
1. Relevant libraries were selected to facilitate video processing, face recognition, emotion detection, model training, and other minor tasks. These included OpenCV, NumPy, scikit-learn, TensorFlow, Seaborn, and Matplotlib.
2. A tool was developed to detect faces in video footage from the negotiation. The detected faces were extracted, converted into grayscale images, and stored in a CSV file.
3. A dataset containing labeled images was identified and artificially expanded through geometric transformations, such as rotation and scaling, and the addition of Gaussian noise. The datasets FER and RAF were used.
4. Different models for face recognition, including machine learning approaches and Convolutional Neural Networks (CNNs), were tested to compare their validity in emotion detection.
5. A custom tool was developed to classify emotions and trained using the dataset. Slight adjustments were made to optimize its performance.

6. The FA tool was applied to the preprocessed video frames, detecting and storing the emotions.
7. The detected emotions were compared with Affectiva-generated data to validate the model's performance in comparison.

Field Tests

In this section, the methodologies outlined in the previous chapter are applied in two experimental studies.

The first study, “Analyzing Negotiations with ET and FA,” simulates a hybrid negotiation scenario. Ten students, grouped into pairs with different skill levels, negotiate for ten minutes with an industry expert. ET and FA data are recorded during these sessions to examine differences in visual attention and emotional expressions between in-person and remote participants.

The second study, “Developing a custom analysis tool,” focuses on creating a Python-based emotion recognition tool. This tool was tested against the commercial software Affectiva to evaluate its accuracy and process efficiency in recognizing emotions from facial expressions. The comparison aimed to assess the potential of an open-source alternative for emotion analysis in negotiation research.

Analyzing negotiations with ET and FA

Case and Setup

As part of the negotiation simulation, the students and the industry expert were assigned a specific case. The students represented the car dealership CarNova Motors and were tasked with selling a fleet of ten vehicles to the industry expert, who represented ABC Distribution GmbH on behalf of their company. They had to consider the buyer's requirements, including specific equipment features such as parking assistance, infotainment systems, and potentially hybrid gear while adhering to a predefined budget range of €180,000 to €200,000.

The buyer's objective was to negotiate a cost-efficient solution that met the requirements of ABC Distribution GmbH's various sales divisions. The buyer aimed to secure the best possible deal at the lowest price while maintaining a consistent negotiation approach across the different student groups. Meanwhile, the students had to present compelling offers through strategic argumentation while keeping their profit margins in mind.

Detailed case descriptions can be found in the appendix.

To ensure a standardized and controlled environment for the negotiations, the setup was structured as follows in the TSL of the Hochschule Düsseldorf:

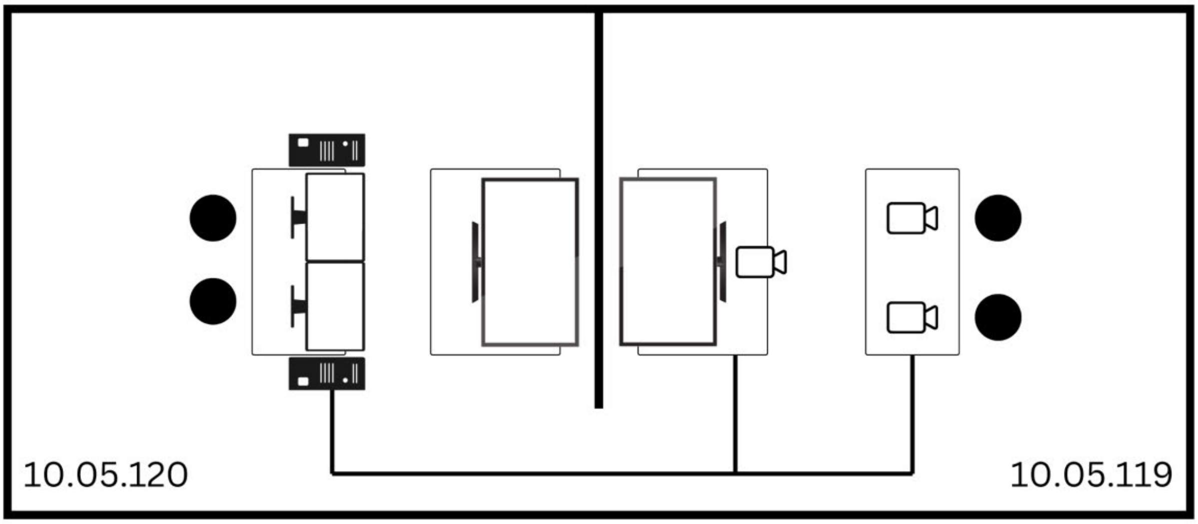

Figure 1: Simulation Setup

The control room (10.05.120) housed the observers and technical equipment. This room was used to monitor and record the negotiation without interfering with the participants' interactions.

The recording room (10.05.119) was where the two students conducted their negotiation. This space was equipped with the necessary audiovisual recording devices to capture their conversation and interactions.

The industrial expert participated remotely and only required a laptop to join the negotiation.

Student Surveys

Before the Negotiation

The PANAS was administered before the negotiation to assess the participant's emotional baseline. This self-assessment helps determine their initial emotional state and its potential influence on their subsequent negotiation performance. In this study, the PANAS was used to measure Positive Affect and Negative Affect. Participants rated each emotion-related adjective (e.g., afraid, nervous) on a 5-point Likert scale, ranging from 1 (very slightly or not at all) to 5 (extremely), indicating their emotional state at the given moment.

Participants		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Average**
Positive Affects	Alert	2	2	3	4	4	4	4	4	4	3	3,4
	Inspired	1	3	2	3	1	3	2	2	3	3	2,3
	Determined	3	3	4	2	3	3	4	4	2	2	3
	Attentive	1	3	4	3	5	5	2	5	1	2	3,1
	Active	3	4	4	4	3	3	5	4	4	4	3,8
Average		2	3	3,4	3,2	3,2	3,6	3,4	3,8	2,8	2,8	
Negative Affects	Hostile	1	2	1	1	2	1	3	1	1	3	1,6
	Upset	1	1	1	1	3	2	1	4	1	1	1,6
	Ashamed	1	1	1	1	4	1	2	1	2	2	1,6
	Nervous	3	3	2	3	5	2	1	3	3	4	2,9
	Afraid	1	2	1	2	3	1	2	2	4	2	2
Average		1,4	1,8	1,2	1,6	3,4	1,4	1,8	2,2	2,2	2,4	

Table 1: Student's results of the PANAS test

Since the PANAS survey was only completed by the in-person participants, no direct comparison can be made between on-site and remote negotiators. However, these results provide insight into the general emotional state of the in-person participants before the negotiation. Higher levels of Alertness and Determination suggest an active and engaged mindset, which could positively impact negotiation performance. At the same time, elevated Nervousness scores indicate that some participants may have experienced pre-negotiation stress, which could potentially influence their negotiation strategies. The PANAS results, therefore, provide valuable insights into how the participants' initial emotional states may have shaped their negotiation dynamics.

After the Negotiation

The post-negotiation self-assessment survey provides insights into participants' reflections on their performance, strategies, and areas for improvement. Most

participants felt partially prepared for the negotiation, with some indicating that more detailed information on financing, services, and product specifications could have enhanced their preparation. While a majority had a partial strategy, only a few had a fully defined approach, and most reported implementing their strategy consistently. Regarding communication, participants rated their position as clear, but some acknowledged room for improvement in areas such as asking more questions, speaking more clearly, and managing pauses effectively. The arguments that worked well included price justifications, product superiority, and flexibility in configurations. In terms of adaptability, most participants considered themselves flexible or very flexible when faced with unexpected situations. However, not all participants fully reached their negotiation goals, with reasons such as price disagreements, unachieved contract closures, or limited profit margins being cited.
Overall, the majority were satisfied with their negotiation performance, but some identified areas for improvement, including better preparation, more practice, and a stronger initial stance in pricing negotiations. The survey highlights key takeaways, such as the importance of not conceding too quickly, refining argumentation skills, and maintaining adaptability in high-stakes discussions. To further improve their skills, participants planned to practice negotiations more frequently, enhance preparation methods, and integrate negotiation techniques into daily life.
Detailed surveys can be found in the appendix.

Analyzing AOIs of In-person and remote participants

The analysis of the ET data was conducted using AOIs. The AOIs *"Own Camera"* and *"Opponent's Camera"* were divided into two phases: before and during the presentation of the offer. The AOI *"Notes"* remained visible throughout the entire negotiation, while the AOI *"Offer"* was only displayed during the offer presentation. Additionally, the analysis distinguished between students and the industry expert.
The following figure illustrates the student’s Point of View (PoV) along with the AOIs as defined in this study:

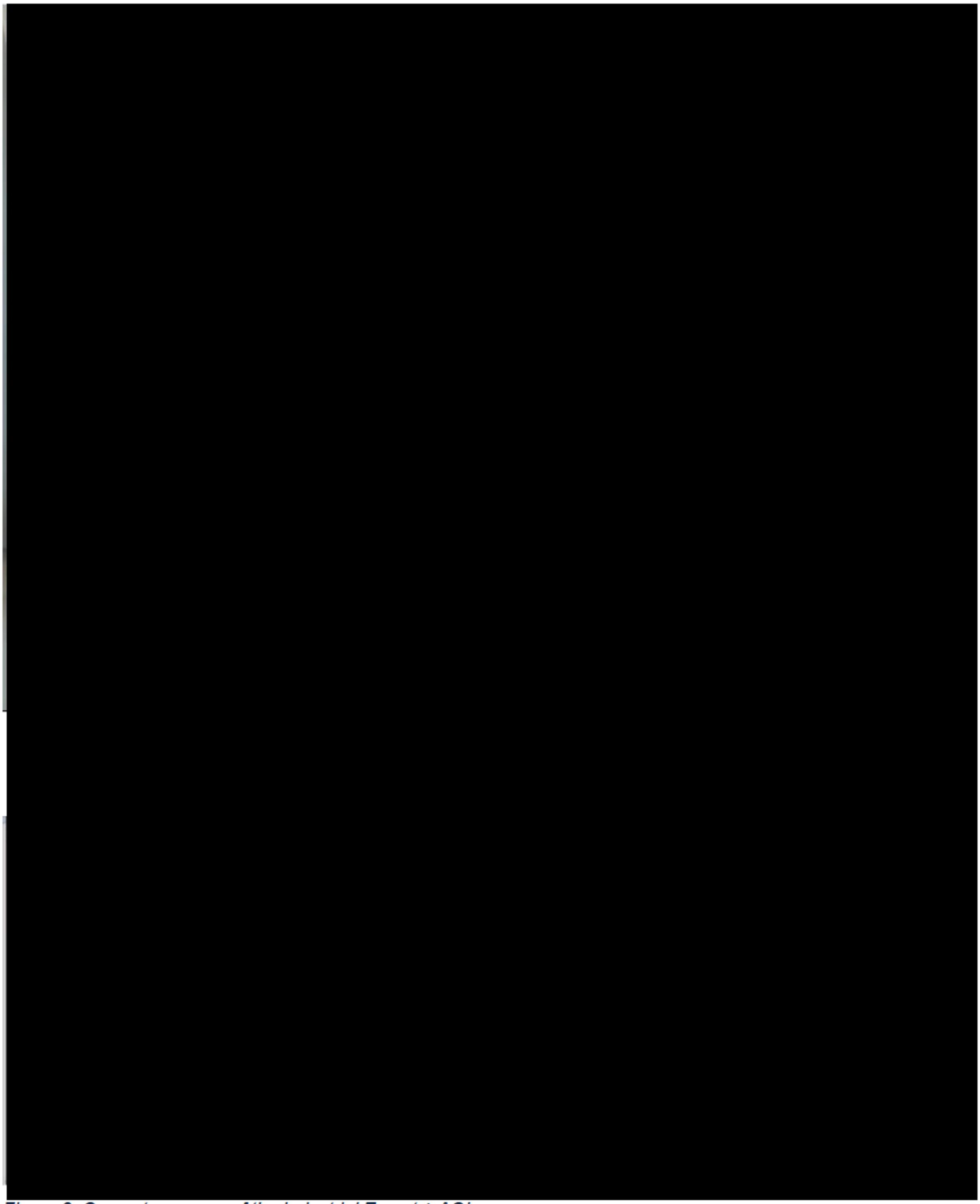

Figure 3: Computer screen of the Industrial Expert + AOIs

In the conducted simulation, all recordings from the students were included in the analysis, whereas only three out of five datasets from the industry expert were usable. This resulted in a slight discrepancy in the *AOI Duration* times.

The following table presents the results of the analysis, differentiated by various metrics. For each metric, the mean value was calculated.

		Students (10 recordings)			Industrial Expert (3 recordings)		
		Own Camera	Opponent/ Expert Camera	Notes	Own Camera	Opponent/ Student Camera	Notes
Information	AOI duration (min)	1,8	1,8	1,8	2,41	2,41	2,41
Gaze based metrics	Dwell count	6,25	20,875	13,25	6,33	0,67	25,67
	Revisit count	5,375	19,875	12,25	5,33	0,33	24,67
	Dwell time (min)	0,07	0,66	0,54	0,08	0,00	0,96
Fixation based metrics	Revisit count	3,25	11,625	6,875	4,33	0,33	15,33
	Fixation count	12,125	**142,125**	98,75	7,33	0,67	**101,33**
	Dwell time (min)	0,03	**0,32**	0,2	1	0,00	**1,39**

Table 2: AOI-Data from the students and the industrial expert before the offer

The analysis of the eye-tracking data reveals significant differences in the distribution of visual attention between the in-person participants (students) and the remotely connected industry expert.

Before the presentation of the offer, the students primarily focused on the expert's camera. With an average of 142,125 fixations and a dwell time of approximately 0.32 minutes, they dedicated significantly more attention to the industry expert's face compared to other visually relevant areas.

In contrast, the industry expert exhibited a distinctly different gaze pattern. His visual attention was primarily directed toward his notes, with 101,33 fixations and a dwell time of 1.39 minutes. The students' camera, on the other hand, was barely fixated upon, with an average of only 0.67 fixations and a dwell time of 0 minutes.

Once the offer was presented, the student's gaze behavior shifted significantly. The results are shown in the following table:

		Own Camera	Opponent/ Expert Camera	Notes	Offer
Information	AOI duration (min)	10,15	10,15	10,15	10,15
Gaze based metrics	Dwell count	63,2	84,8	38,7	145,4
	Revisit count	62,2	83,8	37,7	144,4
	Dwell time (min)	0,47	0,98	1,33	5,11
Fixation based metrics	Revisit count	39,7	59,5	21	94,1
	Fixation count	115,5	228,8	180,7	892,4
	Dwell time (min)	0,34	0,74	0,33	1,93

Table 3: AOI-Data of the students during the offer

While their focus had previously been directed primarily at the industry expert's camera, their visual attention now concentrated predominantly on the offer. This is particularly evident in the number of fixations: with 892 fixations, the offer was by far the most frequently viewed element. The average dwell time (fixation) for the offer was 1.93 minutes, indicating that the students engaged intensively with the document.

The industry expert's camera remained a relevant focal point (228,8 fixations, 0.74 minutes dwell time), but it was a lower priority than the offer. Additionally, the students' notes continued to receive attention, with 180,7 fixations and a dwell time of 0.33 minutes.

During the presentation of the offer, the industry expert's gaze behavior changed significantly compared to the previous phase of the negotiation. This is illustrated in the following table:

		Own Camera	Opponents/ Students Camera	Notes	Offer
Information	AOI duration (min)	11,51	11,51	11,51	11,51
Gaze based metrics	Dwell count	0	22,33	107,00	153,67
	Revisit count	0	22,00	106,00	152,67
	Dwell time (min)	0	0,13	2,34	2,32
Fixation based metrics	Revisit count	0	15,67	86,33	113,67
	Fixation count	0	18,33	260,67	240,00
	Dwell time (min)	0	0,37	2,04	2,51

Table 4: AOI-Data of the Industrial expert during the offer

Instead of primarily focusing on his notes, the industry expert now focused more on the offer. This is particularly evident in the high number of fixations on the offer (240 fixations) and an extended dwell time of approximately 2.51 minutes. As a result, the offer was examined with nearly the same intensity as the expert's own notes (260,67 fixations, 2.04 minutes dwell time).

When examining the individual AOI values of the industry expert, the "Offer" AOI stands out significantly. The results are presented in the following table:

Industrial Expert		Simulation/ Group 2	Simulation/ Group 3	Simulation/ Group 4
Information	AOI duration (min)	15,13	10,33	9,08
Gaze based metrics	Dwell count	148	203	110
	Revisit count	147	202	109
	Dwell time (min)	1,17	4,32	1,47
Fixation based metrics	Revisit count	122	128	91
	Fixation count	175	391	154
	Dwell time (min)	1,41	4,62	1,51

Table 5: Offer-AOI-Data of the industrial expert in the different simulations

The analysis indicates that the industry expert's attention allocation varied considerably. In particular, the third simulation demonstrated a substantial increase in visual engagement with the offer. The expert recorded more than twice as many fixations on the offer compared to other simulations, and the dwell time was extended to three times the duration observed in prior cases.

The analysis highlights distinct differences in gaze behavior between students and the industry expert. While students initially focused more on their counterpart's face, their attention shifted significantly to the offer once it was presented. The industry expert, on the other hand, demonstrated a more stable gaze pattern, emphasizing his notes before the offer and then engaging more deeply with the offer during its presentation. Notably, the third simulation stood out due to a pronounced increase in fixations on the offer, indicating a potentially stronger interest or engagement in that particular negotiation scenario.

These findings suggest that screen layout and the way information is displayed can heavily influence visual attention distribution. Before the offer presentation, the prominence of video feeds led to higher fixation rates on faces. Once the offer became the focal point, the reduction in video feed size shifted the participants' attention accordingly. This emphasizes the importance of optimizing visual setups in hybrid negotiations to ensure effective communication and engagement with key information.

FA-Analysis

For the analysis, the seven basic emotions—*Anger, Disgust, Fear, Happiness, Sadness, Surprise,* and *Neutral*—were considered. Since a clear distinction between certain emotions is not always possible, the sum of values may exceed 100% in some cases. Frames in which no face was detected were excluded from the analysis.

The following table presents the emotions recorded for the five student groups, with values representing the meaning of individual results.

(%)	Group 1	Group 2	Group 3	Group 4	Group 5
Anger	2,475	0,905	0,36	0,745	0,455
Disgust	0,555	0,375	0,255	0,365	0,29
Fear	5,86	1,01	0,655	1,415	1,98
Happy	1,545	0,21	4,37	1,28	0,735
Sad	4,845	1,01	4,04	2,525	0,88
Surprise	2,325	0,165	0,86	0,8	3,585
Neutral	89,16	96,64	90,58	93,525	93,62

Table 6: Emotions of the Different Groups

The results show that Neutral was by far the most prevalent emotion across all groups. The values range from 89.16% in Group 1 to 96.64% in Group 2, indicating that neutral emotions dominated in most cases.

There is a strong variation among negative emotions across the groups. Fear was most frequently observed in Group 1 at 5.86%, while other groups exhibited significantly lower values (ranging between 0.65% and 1.98%). A similar pattern is seen with Sadness, which reached a relatively high value of 4.85% in Group 1 but fluctuated considerably in other groups.

The emotion Happiness also displayed notable variation: it was highest in Group 3 at 4.37%, whereas it was the lowest in Group 2 at just 0.21%. This suggests that the occurrence of positive emotions varies significantly between groups.

A particularly striking observation is the distribution of Surprise. While this emotion was relatively frequent in Group 5, at 3.58%, it was almost absent in Group 2, appearing in only 0.16% of cases. This indicates that Surprise played a more significant role in some groups than in others.

In comparison to the student groups, the industry expert exhibited the following emotional distribution. As mentioned earlier, only 3 out of 5 simulations were successfully completed for the industry expert.

	Simulation/ Group 2	Simulation/ Group 3	Simulation/ Gruppe 4
Anger	0,58	0,37	0,5
Disgust	0,22	0,19	0,23
Fear	10,94	14,46	14,51
Happy	8,87	19,18	9,53
Sad	5,61	3,93	5,92
Surprise	15,14	23,09	19,77
Neutral	74,56	69,59	71,17

Table 7: Emotions of the Industrial Expert

A particularly striking observation is the emotion *Surprise*, which appeared most frequently in Group 3 at 23.09%, while it was slightly lower but still strongly present in Group 2 (15.14%) and Group 4 (19.77%). This suggests that *Surprise* played a significantly different role depending on the group.

Similarly, *Fear* exhibited substantial variation. It was most prominent in Group 3 at 14.46%, followed closely by Group 4 (14.51%) and Group 2 (10.94%). This indicates that this emotion was more prevalent in certain groups than in others.

The emotion *Happiness* reached its highest value in Group 3 at 19.18%, while it was considerably lower in Group 2 (8.87%) and Group 4 (9.53%). This suggests potential differences in the emotional responses among the groups.

Negative emotions such as *Sadness* and *Anger* were generally less frequent. *Sadness* was most pronounced in Group 4 at 5.92%, while *Anger* remained below 1% in all groups.

Developing a custom analysis tool

This section focuses on the development and evaluation of a custom-programmed, Python-based emotion recognition tool, which is compared to the established software Affectiva. The objective is to assess the performance of the custom tool in analyzing emotions from video data.

Seven fundamental emotions (Anger, Disgust, Fear, Happy, Sad, Surprise, Neutral) were considered in the analysis. To ensure a comprehensive evaluation, various machine-learning approaches were tested, including Logistic Regression, SVM, and CNN. The results provide insights into the custom tool's strengths and areas that require further optimization, particularly in comparison to Affectiva.

Face Recognition

To recognize emotions, the face must first be detected, extracted, and stored in a CSV file. In the initial step, the Haar Cascade Detector from OpenCV is used to identify the face within the video. Subsequently, the detected face is resized to 48x48 pixels, converted to grayscale, and saved in a CSV file for further processing.

Dataset

The dataset serves as the foundation for training and evaluating the models. To enhance the diversity of emotions and expand the training base, two publicly available datasets, *FER2013* and *RAF*, were merged. This resulted in a combined dataset consisting of 51,226 data points. However, certain emotions, particularly *Disgust* and *Fear*, were significantly underrepresented, leading to class imbalance. To mitigate this issue and improve model performance, data augmentation techniques were applied. Initially, geometric transformations such as horizontal flipping, rotation, and shifting were employed to increase data diversity. This step expanded the dataset to 204,904 samples. To further enhance generalization and robustness, Gaussian noise was introduced, ultimately increasing the dataset size to 256,130 samples.

The following table provides a detailed breakdown of the dataset, showing the number of images per emotion before and after augmentation:

	Total Emotions	Anger	Disgust	Fear	Happy	Sad	Surprise	Neutral
FER 2013	35887	4953	547	5121	8989	6077	4002	6198
RAF	15339	867	877	355	5957	2460	1619	3204
Total	51226	5820	1424	5476	14946	8537	5621	9402
+ geo. Trans.	204904	23280	5696	21904	59784	34148	22484	37608
+Gauß	256130	29100	7120	27380	74730	42685	28105	47010

Table 8: Size of the Dataset

Additionally, the following figure provides a visual representation of the applied transformations. The original image is shown on the left, followed by its augmented variations: horizontally flipped, rotated by 45°, shifted, and altered with Gaussian noise. These transformations were applied primarily to increase the dataset size and address class imbalances by generating additional training samples.

Figure 4: Dataset Transformations (Original, Horizontally Flipped, 45° Rotated, Shifted, and with Gaussian Noise)

For logistic regression and the Support Vector Machine (SVM), the dataset was converted into a binary classification structure. In this process, the target emotion was encoded as *1*, while all other emotions were grouped together and labeled as *0*.

Evaluation of Machine Learning Models for Emotion Detection

In this section, different models are tested using the enhanced dataset from the previous chapter. First, logistic regression and an SVM are trained on the binary dataset. In the next step, a multiclass SVM and a CNN with the unchanged dataset are trained and evaluated. The test results of each model are presented in the following chapters.

Logistics Regression

The application of the model yielded the following results:

	Accuracy Total	Precision		Recall		F1-Score		Support	
		0	1	0	1	0	1	0	1
Anger	0,88	0,89	0,49	1	0,01	0,94	0,01	36345	4636
Disgust	0,97	0,97	0,36	1	0	0,99	0,01	39858	1123
Fear	0,89	0,89	0,29	1	0	0,94	0	36621	4360
Happy	0,74	0,76	0,65	0,93	0,3	0,84	0,41	28934	12047
Sad	0,83	0,83	0,33	1	0,01	0,91	0,01	34157	6824
Surprise	0,89	0,9	0,62	0,99	0,12	0,94	0,2	36448	4533
Neutral	0,82	0,82	0,48	0,99	0,07	0,9	0,07	33523	7458

Table 9: Emotion Recognition Performance of a Logistic Regression Model

Notably, the overall accuracy is very high in most cases, suggesting that the model performs well in making predictions. However, a closer examination of other key metrics—particularly *precision, recall,* and *F1-score*—reveals a significant discrepancy between the model's performance for the two classes. For *Class 0* (absence of a specific emotion), the model consistently achieves high scores across all metrics, indicating that it reliably detects when an emotion is not present.

In contrast, for *Class 1* (emotion present), the model performs significantly worse, especially in terms of *recall*. For instance, emotions such as *Anger, Disgust,* or *Sad* are rarely correctly identified, with recall values ranging between only 0.01 and a maximum of 0.12.

These results suggest that the model is heavily influenced by the class distribution within the dataset, as *Class 0* consistently has much higher *support* (i.e., more training samples). This imbalance particularly affects the recognition of underrepresented emotions like *Disgust* and *Surprise*, leading to a model that excels at making negative predictions (*Class 0*) but struggles with identifying positive instances (*Class 1*).

SVM

In the next step, an SVM with the *RBF* (Radial Basis Function) kernel was initialized and tested using both a binary dataset and a multiclass dataset. The results for the binary dataset were as follows:

	Accuracy Total	Precision		Recall		F1-Score		Support	
		0	1	0	1	0	1	0	1
Anger	0,88	0,89	0,94	1,0	0,01	0,94	0,02	36345	4636
Disgust	0,97	0,97	1	1	0	0,99	0,01	39858	1123
Fear	0,9	0,89	0,07	1	0,01	0,94	0,03	36621	4360
Happy	0,83	0,83	0,84	0,96	0,52	0,89	0,64	28934	12047
Sad	0,83	0,83	1	1	0	0,91	0,01	34157	6824
Surprise	0,91	0,91	0,9	1	0,21	0,95	0,35	36448	4533
Neutral	0,82	0,82	0,88	1	0,02	0,9	0,03	33523	7458

Table 10: Emotion Recognition Performance of an SVM

The SVM exhibits similar tendencies to logistic regression. The overall accuracy remains high across all emotions, suggesting the model is generally effective.
However, a closer metrics analysis reveals significant differences between the two classes. Class 0 consistently achieves very high precision and recall values, whereas the results for Class 1 are more inconsistent. This issue is particularly evident for emotions such as Anger, Fear, and Sad, where recall for Class 1 remains at just 0.01. This indicates that the model struggles to identify instances where these emotions are actually present correctly. A similar pattern is observed in the F1-score, which is also very low for Class 1 in these cases.
A more positive result is observed for the emotion *Happy*, where the model achieves a relatively high recall of 0.52 and an F1-score of 0.64. This suggests that the SVM performed better at recognizing the presence of this emotion compared to logistic regression.
Despite these improvements, the overall recognition of *Class 1* remains problematic, particularly for underrepresented emotions such as *Sadness* and *Surprise*. The considerable difference in support between *Class 0* and *Class 1* further underlines how the imbalanced dataset negatively impacts model performance.
In summary, while the SVM provides some improvements over logistic regression for certain emotions, the challenges in detecting underrepresented emotions persist.

Multiclass SVM

In the next step, a multiclass SVM was trained and tested using the multiclass dataset. The results were as follows:

	Precision	Recall	F1-Score	Support
Anger	0,44	0,21	0,28	4636
Disgust	0,9	0,01	0,02	1123
Fear	0,39	0,18	0,25	4360
Happy	0,55	0,81	0,66	12047
Sad	0,38	0,35	0,36	6824
Surprise	0,61	0,46	0,53	4533
Neutral	0,41	0,51	0,46	7458
Total	0,48			

Table 11: Emotion Recognition Performance of a Multiclass SVM

The results indicate that the model's performance varies significantly depending on the emotion. A particularly striking case is the emotion *Disgust*, which, despite having a high precision of 0.90, exhibits an extremely low recall rate of just 0.01. This means that while the model is highly confident when it does classify an instance as *Disgust*, it almost never actually identifies the emotion correctly in practice. As a result, the F1-score is extremely low at only 0.02.

Similarly, *Fear* and *Anger* also show poor results, particularly in terms of recall (0.18 and 0.21, respectively), suggesting that these emotions are often misclassified or not detected at all. This is reflected in their low F1-scores of 0.25 (*Fear*) and 0.28 (*Anger*).

The best results were achieved for the emotion *Happy*, which had a high recall rate of 0.81. With a precision of 0.55, this results in a relatively strong F1-score of 0.66, indicating that this emotion was the most reliably recognized. Similarly, *Surprise* achieved a solid performance with an F1-score of 0.53, while *Neutral* fell within the mid-range at 0.46.

Overall, the model achieved an average precision of 0.48, a recall rate of 0.51, and an F1-score of 0.46. These values suggest a moderate overall performance, but with clear weaknesses in detecting certain emotions, particularly Disgust.

CNN

The final model was used to classify emotions, with an additional focus on analyzing the impact of different dataset sizes from Table 8 on its performance. The following results were obtained:

Dataset Size	50k	200k	250k
Anger	0,33	0,48	0,4
Disgust	0,17	0,18	0,20
Fear	0,21	0,30	0,22
Happy	0,73	0,88	0,87
Sad	0,48	0,63	0,54
Surprise	0,58	0,73	0,72
Neutral	0,69	0,66	0,68
Total	0,55	0,66	0,62

Table 12: Model Performance Across Different Dataset Sizes

The overall accuracy for the smallest dataset, containing 50,000 samples, was 55%. Emotions such as Happy (0.73) and Neutral (0.69) achieved relatively good results, whereas emotions like Anger (0.33), Disgust (0.17), and Fear (0.21) performed significantly worse. This underperformance is likely due to the limited number of training samples available for these emotions.

Expanding the dataset to 200,000 samples increased overall accuracy to 66%. The most notable improvements were observed in Sad (from 0.48 to 0.63), Surprise (from 0.58 to 0.73), and Happy (from 0.73 to 0.88). These findings highlight that increasing the data size significantly enhances model performance, particularly for previously underrepresented emotions in smaller datasets.

In the final scenario, the dataset was further expanded to 250,000 samples, and Gaussian noise was added to the images. This resulted in an overall accuracy of 62%, which was slightly lower than that of the 200,000-sample dataset. While emotions like Anger (0.4) and Disgust (0.2) showed minor improvements, the performance for Happy (0.87), Surprise (0.72), and Neutral (0.68) remained relatively stable. The use of noise as a data augmentation technique had only a limited effect on overall accuracy.

In summary, increasing the dataset size through geometric transformations significantly improved model performance, especially for underrepresented classes. However, the additional augmentation using noise did not increase accuracy, suggesting that this method should be more selectively optimized to maximize efficiency.

Performance Comparison Between Custom FA Tool and Affectiva

In the following section, the best performance of the custom tool and the commercial tool is compared. For this comparison, the CNN model trained on 200k images is used. The analysis is divided into two parts: first, the processing speed is examined, followed by an evaluation of accuracy.

As outlined in previous chapters, the first step involves detecting and extracting the face. The custom tool requires approximately ±10% of the total video duration for this process. This step could also be performed in real-time during recording, which would significantly speed up the overall workflow. Once the images are extracted, they are analyzed by the FA tool, which takes an average of 2-3 minutes to process. In contrast, Affectiva requires an average of 10 minutes to determine emotions.

In the next step, the accuracy of the predictions from the best model is compared with those from Affectiva. In this case, CNN was the best-performing model. The following results were obtained:

	Affectiva	Own Tool	Difference
Anger	99,00	199,67	-100,67
Disgust	0,67	0,00	0,67
Fear	1010,67	229,67	781,00
Happy	3635,00	4268,67	-633,67
Sad	1086,67	1563,67	-477,00
Surprise	5107,00	43,67	5063,33
Neutral	18975,00	20735,67	-1760,67

Table 13: Comparison of Emotion Recognition Between Affectiva and the Own Tool

The results reveal significant challenges in the custom tool's ability to recognize certain emotions. One of the most striking issues is *Surprise*, which was misclassified in over 5,000 cases compared to Affectiva, leading to an error rate of 99%. This is particularly noteworthy, as the model had previously achieved an accuracy of 73% for this emotion during training with a dataset of 200k samples.

A smaller but significant discrepancy is observed for the emotion *Happy*, where approximately 600 misclassifications occurred, accounting for about 17% of the cases. In the prior evaluation, the model achieved an accuracy of 88% for this emotion, suggesting a relatively more stable recognition compared to Surprise.

The best performance was achieved in recognizing the emotion Neutral. Here, the number of misclassifications was around 1,800, corresponding to an error rate of 9%. In the previous evaluation, the model had an accuracy of 66% for Neutral, making it relatively reliable compared to other emotions.

Limitations

The evaluation of this study revealed several limitations that may have influenced the overall findings. One major constraint is the sample size, which was limited due to time and resource restrictions. Consequently, the dataset may not adequately reflect the diversity of the broader population, potentially limiting the generalizability of the results. Future research with a larger and more diverse sample could provide deeper insights and enhance the robustness of the findings.

In remote data collection, the laptop camera was used to capture ET and FA data, presenting challenges similar to those discussed in the previous section. However, some factors proved to be even more critical. Participants were required to remain as still as possible throughout the entire simulation to ensure accurate data acquisition. Additionally, the calibration process demanded that participants repeatedly undergo a monotonous procedure in which they had to track a point with their eyes. These conditions often resulted in unusable recordings or significantly reduced data quality. In the present study, two out of five datasets had to be discarded due to insufficient quality.

Another key limitation concerns the technological framework employed in this study. While eye-tracking and facial recognition technologies provide valuable insights, they are subject to inherent constraints. Their precision can be compromised by factors such as lighting conditions, participant movement, and calibration difficulties. For instance, poor lighting or excessive motion can lead to inaccurate measurements, potentially distorting the overall results. Moreover, the study's reliance on these technologies may have led to an overemphasis on quantitative metrics at the expense of more qualitative aspects of negotiation dynamics, such as emotional expressions and contextual nuances.
During the programming phase and the training of the classification model, additional limitations emerged. A significant issue stemmed from the use of open-source datasets, which often contained inconsistencies and labeling errors. Some images were misclassified, while others did not depict any facial expressions at all but instead displayed text or symbols:

Figure 5: Some errors in the FER2013 dataset (Mejia-Escobar et al., 2023, Figure 3) [20]

Furthermore, the class distribution within the dataset was highly imbalanced, with emotions such as Anger, Disgust, Fear, and Surprise being significantly underrepresented, while emotions like Happy and Neutral occurred far more frequently (see Table 6: Size of the Dataset).

These limitations negatively impacted the training process and compromised the model's overall accuracy.

In summary, several limitations were identified that may have influenced the accuracy and generalizability of the results. The small sample size restricted the representativeness of the findings, while challenges in remote data collection and calibration led to data loss and reduced measurement precision. Furthermore, the reliance on eye-tracking and facial recognition technologies introduced sensitivity to environmental conditions such as lighting and movement. Lastly, the use of publicly available datasets resulted in inconsistencies, misclassifications, and an imbalanced class distribution, which negatively affected the performance of the classification model. Addressing these limitations in future research—through larger

[20] Mejia-Escobar, C., Cazorla, M., & Martinez-Martin, E. (2023). Towards a better performance in facial expression recognition: A data-centric approach. *Computational Intelligence and Neuroscience, 2023*, Article ID 1394882.

and more diverse datasets, improved technological frameworks, and refined calibration techniques—could enhance the reliability and applicability of similar studies.

Discussion

Summary of Key Findings and Research Questions

How does the distribution of attention to AOIs differ between the in-person participants and the remote participant in a hybrid negotiation?

The analysis of visual attention reveals significant differences between in-person participants and the remotely connected industrial expert. While in-person participants focused heavily on their counterpart's face, the industrial expert primarily concentrated on his notes and the offer.

A key distinction lies in the physical arrangement of the notes: The students had their notes either on the table or on their laptop screen. Looking at them required turning away from the camera and disrupting eye contact with their negotiation partner. This may explain why they switched between different visual stimuli more frequently. In contrast, the industrial expert had both his notes and the Teams call displayed on a single screen, allowing him to keep his gaze steady without looking away. This setup enabled him to distribute his visual attention more efficiently between relevant information on the same display.

These differences suggest that the technical and spatial setup of a negotiation significantly influences how visual attention is managed. While in-person participants must frequently shift their gaze to access all relevant information, remote participants benefit from a more stable visual focus through an optimized screen layout.

To what extent can negotiation outcomes be predicted based on eye-tracking data and facial expression analysis?

The study suggests that specific gaze patterns and emotional expressions are linked to the course and possibly even the outcome of a negotiation. A particularly striking example is Group 3: The industrial expert exhibited more than twice as many fixations on the offer compared to other groups. This could indicate heightened engagement with the offer or a perception of its particular relevance. Interestingly, the negotiation outcome for this group was also better than for the others, suggesting that increased visual focus on the offer may correlate with a more successful agreement.

On an emotional level, a notable deviation was also observed: The industrial expert's facial expression analysis data showed a 10% higher occurrence of the emotion Happy in Group 3 compared to the other groups. This could indicate greater satisfaction with the negotiation process or suggest that a positive emotional reaction influenced the negotiation dynamics.

These observations highlight the potential of eye-tracking and facial expression data as indicators of negotiation dynamics and possibly even outcomes. Increased fixation on the offer might be associated with a more favorable evaluation and, ultimately, a successful agreement. Similarly, positive emotional expressions could signal a more constructive and cooperative negotiation atmosphere. However, further research with larger sample sizes would be necessary to establish these correlations more robustly.

How valid and reliable is the facial expression analysis performed by the developed Python tool compared to a commercial state-of-the-art tool such as Affectiva?

The comparison between the self-developed FA tool and the commercial software Affectiva reveals significant differences in both processing speed and emotion recognition accuracy.

One major advantage of the self-developed tool is its significantly faster processing time. While Affectiva requires an average of 10 minutes to analyze emotions in a video, the self-developed tool completes the initial face detection and extraction in approximately ±10% of the total video duration. Additionally, this step could be performed live during recording, further accelerating the overall workflow. After extraction, the FA tool processes the images within 2–3 minutes, making it a more time-efficient alternative to Affectiva.

Despite its speed advantage, the self-developed tool struggles with recognizing certain emotions, particularly Surprise and Fear. Notably, Surprise was misclassified in over 5,000 cases, indicating substantial inaccuracies. In contrast, Affectiva provided consistent and reliable results across all emotion categories.

A possible reason for these discrepancies lies in the dataset. The training data was imbalanced, with emotions such as Disgust and Fear being significantly underrepresented. Despite the application of data augmentation techniques such as mirroring, rotation, and noise addition, this imbalance could not be entirely corrected, leading to weaker recognition of certain emotions.

Another potential limitation is the model architecture itself. While Affectiva employs an optimized and extensively trained model using a diverse dataset, the developed tool is based on a custom machine-learning approach with limited training data.

However, the results indicate that the model performs relatively well in recognizing certain emotions, such as Neutral and Happy, particularly after dataset expansion.
Overall, the comparison suggests that while the self-developed FA tool still has room for improvement, it offers a significant advantage in processing speed and could serve as an open-source alternative for specific applications. To enhance accuracy and robustness, improvements in data balancing, further model optimization, and fine-tuned training would be necessary. Despite these limitations, the tool presents an interesting foundation for future research, particularly for applications requiring a transparent, customizable, and fast-processing solution.

Practical Applications

The analysis of ET and FA allows companies to gain deeper insights into what works well or poorly in negotiations. By understanding nonverbal cues and emotional responses, organizations can identify behavioral patterns that influence negotiation outcomes. These insights can be leveraged to train employees more effectively, strengthening their communication skills and improving their ability to handle high-stakes discussions. Furthermore, such data-driven approaches enable businesses to refine negotiation strategies, optimize decision-making processes, and enhance overall performance.
To implement FA-based negotiation analysis effectively, companies and research institutes can benefit from open-source FA tools, which offer both cost efficiency and customization options. These tools allow organizations to tailor the software to their specific needs while maintaining full control over their data, a crucial aspect for ensuring privacy protection and compliance with regulations such as the General Data Protection Regulation (GDPR). Additionally, relying on custom FA solutions reduces dependence on commercial providers, safeguarding against unexpected price changes, feature modifications, or service discontinuations. By integrating open-source FA tools, companies and research institutions can achieve greater flexibility, cost-effectiveness, and long-term adaptability in their negotiation research and training efforts.

Recommendations for Future Research

This study provides valuable insights into hybrid negotiations by analyzing attention distribution, emotional responses, and the performance of a custom facial analysis tool compared to a commercial solution. However, several areas require further exploration to refine these findings and enhance the robustness of behavioral analysis in negotiation settings.

The observed correlation between increased fixation on the offer and more successful negotiation outcomes suggests that ET data, in combination with FA, could serve as a key indicator of engagement and decision-making. Results indicate that a higher number of fixations on the offer was associated with more favorable negotiation outcomes, while a greater occurrence of positive facial expressions, such as happiness, appeared to foster a more constructive negotiation atmosphere. To establish a reliable predictive model, future research should focus on collecting a larger and more diverse dataset to validate these correlations and further explore the interplay between visual attention, emotional expressions, and negotiation success.

While the self-developed facial analysis tool demonstrated superior processing speed compared to Affectiva, its emotion recognition accuracy - particularly for *Disgust*, *Surprise,* and *Fear* - was compromised by an imbalanced training dataset. Future research could enhance its performance by expanding and balancing the dataset with high-quality and diverse samples. Additionally, evaluating the model's effectiveness across different demographic groups could help ensure its generalizability.

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The following AI models and tools were used to enhance the fluency of the text and to create images: ChatGPT, GPT-4, GPT-40, Scholar GPT, Grammarly, Canva, and other advanced language models and tools.

Appendix

Appendix 1: Case

Appendix 1.1: Case for the Students

Verhandlungssimulation: Fahrzeugbeschaffung

Ausgangssituation

In dieser Verhandlungssimulation repräsentiert ihr das fiktive Autohaus "CarNova Motors". Ihr sollt Autos für die Vertriebsflotte des Unternehmens "ABC-Vertrieb GmbH" anbieten. Die ABC-Vertrieb GmbH ist ein mittelständisches Unternehmen, das Fahrzeuge für den eigenen Vertrieb beschafft. Die Verhandlungen werden von [redacted], dem Flottenmanager der ABC-Vertrieb GmbH, geführt. Ziel ist es, eine Fahrzeuglösung zu finden, die den unterschiedlichen Anforderungen der Vertriebler gerecht wird und gleichzeitig kosteneffizient ist.

Hintergrund zur Verhandlung

Vor einigen Tagen habt ihr euer erstes Angebot per E-Mail eingereicht, das jedoch nicht den Erwartungen entsprach. Aufgrund eures guten Rufs hat die ABC-Vertrieb GmbH beschlossen, euch eine zweite Chance zu geben und euch die Anforderungen nochmals zukommen lassen. Eure Aufgabe besteht nun darin, ein neues Angebot zu erstellen und es während der Verhandlung zu präsentieren. Dabei gelten folgende Vorgaben: Aufgrund einer firmeninternen Richtlinie muss jedes Fahrzeug mit einem **Parkassistenten** ausgestattet sein. Die Gesamtkosten sollten im optimalen Fall unter denen des vorherigen Angebots liegen. Zudem sollen die Fahrzeuge auf die entsprechende Vertriebsklasse angepasst werden. Insgesamt werden **10 Fahrzeuge** für verschiedene Einsatzbereiche benötigt:

- **1 Fahrzeug** für den Manager
- **3 Fahrzeuge** für Vertriebler, die wichtige Großkunden betreuen
- **4 Fahrzeuge** für Vertriebler, die kleinere Unternehmen betreuen
- **2 Pool-Fahrzeuge** für allgemeine Besorgungen

Ziel der Verhandlung:

Euer Ziel ist es, ein überzeugendes Angebot zu erstellen, das die Anforderungen der ABCVertrieb GmbH erfüllt. Dabei sollt ihr darauf achten, durch geschickte Argumentation das Unternehmen davon zu überzeugen, ein höheres Budget zu investieren. Berücksichtigt, dass ihr durch Provisionen profitiert, daher sollte euer Angebot so gestaltet sein, dass es für beide Seiten attraktiv ist – für euch gewinnbringend und für das Unternehmen wertvoll.

Preisliste für Autotypen und Features

Autotypen und Grundpreise:

Autotyp	Grundpreis pro Auto (k€)
Hochklassig	20,0
Mittelklassig	15,0
Niedrig	8,0

Features und Zusatzkosten:

Feature	Zusatzkosten pro Auto (k€)
Parkassistent	1,0
Infotainment	1,5
Hybrid-Antrieb	3,0

Das alte Angebot:

1. Hochklassige Autos:
   - Anzahl: 4
   - Features: Infotainment, Parkassistent, Hybrid
   - Kosten pro Auto: 25,5 k€
   - Gesamtkosten: 102 k€
2. Mittelklassige Autos:
   - Anzahl: 4
   - Features: Infotainment, Hybrid
   - Kosten pro Auto: 19,5 k€
   - Gesamtkosten: 78 k€
3. Weitere Mittelklassige Autos:
   - Anzahl: 2
   - Features: Infotainment
   - Kosten pro Auto: 16,5 k€
   - Gesamtkosten: 33 k€

Gesamtkosten für das alte Angebot: 213 k€

Appendix 1.2: Case for the Industrial Expert

Verhandlungssimulation: Case für den Profi-Verhandler

In dieser Verhandlungssimulation repräsentiert ihr die ABC-Vertrieb GmbH, ein mittelständisches Unternehmen, das Fahrzeuge für die eigene Vertriebsflotte beschafft. Die Verhandlungen werden von Ihnen, [redacted] dem Flottenmanager geführt. Ziel ist es, ein Fahrzeugangebot zu erhalten, dass die unterschiedlichen Anforderungen der Vertriebler erfüllt und gleichzeitig kosteneffizient ist.

Ihr steht im Austausch mit dem Autohaus CarNova Motors, das euch ein Angebot für eure Vertriebsflotte unterbreiten soll. Dabei ist es wichtig, dass die vorgeschlagenen Fahrzeuge den verschiedenen Einsatzbereichen gerecht werden und innerhalb des vorgegebenen Budgets liegen.

Eure Aufgabe ist es, während der Verhandlung ein überzeugendes Angebot zu sichern, das die Bedürfnisse eurer Vertriebler optimal abdeckt und wirtschaftlich sinnvoll ist.

Hintergrund der Verhandlung

Vor einigen Tagen hat das Autohaus CarNova Motors ein erstes Angebot per E-Mail eingereicht, das unseren Erwartungen nicht entsprach. Aufgrund des guten Rufs von CarNova Motors haben wir uns entschieden, ihnen eine zweite Chance zu geben und unsere Anforderungen nochmals klar zu definieren.

Unsere Aufgabe ist es, während der Verhandlung sicherzustellen, dass das neue Angebot unsere Vorgaben erfüllt. Dabei gelten folgende Anforderungen:

Aufgrund einer firmeninternen Richtlinie muss jedes Fahrzeug mit einem Parkassistenten ausgestattet sein. Die Gesamtkosten sollten im optimalen Fall unter denen des vorherigen Angebots liegen. Zudem müssen die Fahrzeuge an die unterschiedlichen Vertriebsklassen angepasst sein. Insgesamt benötigen wir 10 Fahrzeuge für folgende Einsatzbereiche:

- 1 Fahrzeug für den Manager
- 3 Fahrzeuge für Vertriebler, die wichtige Großkunden betreuen
- 4 Fahrzeuge für Vertriebler, die kleinere Unternehmen betreuen
- 2 Pool-Fahrzeuge für allgemeine Besorgungen

Vorgaben vom Manager:

Vor der Verhandlung hat euer Manager euch folgende zusätzliche Vorgaben mit auf den Weg gegeben:

- Das Angebot sollte idealerweise zwischen **180.000 € und 200.000 €** liegen.
- **Klare Fahrzeughierarchie:** Es muss eine deutliche Trennung zwischen den Fahrzeugtypen geben. Der Manager erwartet die bestmögliche Ausstattung, während für Pool-Fahrzeuge einfache Modelle ausreichend sind.
- Für die Vertriebler wäre eine **Freisprecheinrichtung** wünschenswert, um den Arbeitsalltag effizienter zu gestalten.

Ziel der Verhandlung:

Das Ziel der Verhandlung besteht darin, ein Fahrzeugangebot zu erhalten, das die Anforderungen der **ABC-Vertrieb GmbH** vollständig erfüllt. Die Fahrzeuge müssen den verschiedenen Einsatzbereichen gerecht werden und optimal auf die Bedürfnisse der Vertriebler abgestimmt sein. Gleichzeitig soll das Angebot wirtschaftlich überzeugend sein und idealerweise innerhalb des Budgetrahmens von **180.000 € bis 200.000 €** liegen.

Darüber hinaus sollen klare Argumente für die Preisgestaltung geliefert werden, um sicherzustellen, dass die Investition einen hohen Mehrwert für das Unternehmen bietet. Es
gilt, eine kosteneffiziente Lösung zu verhandeln, ohne Abstriche bei Qualität und Funktionalität der Fahrzeuge zu machen.

Das alte Angebot:

1. Hochklassige Autos:
    - Anzahl: 4
    - Features: Infotainment, Parkassistent, Hybrid
    - Kosten pro Auto: 25,5 k€
    - Gesamtkosten: 102 k€
2. Mittelklassige Autos:
    - Anzahl: 4
    - Features: Infotainment, Hybrid
    - Kosten pro Auto: 19,5 k€
    - Gesamtkosten: 78 k€
3. Weitere Mittelklassige Autos:
    - Anzahl: 2
    - Features: Infotainment
    - Kosten pro Auto: 16,5 k€
    - Gesamtkosten: 33 k€

Gesamtkosten für das alte Angebot: 213 k€

Mögliche Fragen während der Verhandlung

- (Opener Frage) Eine andere Firma hat mir ebenfalls ein gutes Angebot gemacht. Können Sie mir bitte erläutern, wie Ihr neues Angebot besser auf unsere Bedürfnisse zugeschnitten ist, da das letzte nicht ideal war?
- Können Sie mir das Angebot einmal bitte zeigen?
- Wie setzt sich der Preis zusammen?
- (Wenn keine klare Trennung zwischen den Autos erkennbar ist) Inwiefern beachten Sie die unterschiedlichen Positionen der Mitarbeiter?
- (Gemeine Frage, eher gegen Ende stellen) Wie hoch ist die Marge bei Ihnen?

Appendix 2: Surveys

Appendix 2.1 PANAS before the Negotiation

I-PANAS-SF mit Abfrage der Verhandlungsskills

Anleitung:

Bitte bewerten Sie, wie stark Sie **in diesem Moment** jeden der folgenden Zustände empfinden. Verwenden Sie die folgende Skala:

1 = Überhaupt nicht
2 = Ein wenig
3 = Mäßig
4 = Ziemlich stark
5 = Sehr stark

Positive Affekte

1. Wachsam
2. Inspirierend
3. Bestimmt
4. Freudig
5. Aktiv

Negative Affekte

1. Verärgert
2. Schuldgefühle
3. Beschämt
4. Nervös
5. Ängstlich

Wie schätze ich meine Skills beim Verhandeln ein:

Sehr gut
Gut
Durchschnitt
Schlecht

Appendix 2.2 Survey after the Negotiation

Fragebogen zur Selbsteinschätzung nach der Verhandlung

Allgemeine Informationen

• **Datum:** ______________________________

Selbsteinschätzung zur Verhandlungsleistung

1. **Vorbereitung**
   a. **Wie gut fühltest du dich auf die Verhandlung vorbereitet?**
      ☐ Sehr gut vorbereitet
      ☐ Gut vorbereitet
      ☐ Teilweise vorbereitet
      ☐ Nicht gut vorbereitet
   b. **Was hätte am Case besser erklärt werden können?**

___

___

2. **Verhandlungsstrategie**
   a. **Hattest du eine klare Strategie für die Verhandlung?**
      ☐ Ja, vollständig
      ☐ Teilweise
      ☐ Nein
   b. **Wie konsequent hast du deine Strategie umgesetzt?**
      ☐ Sehr konsequent
      ☐ Überwiegend konsequent
      ☐ Teilweise konsequent
      ☐ Nicht konsequent
   c. **Was hättest du an deiner Strategie ändern können?**

___

___

3. **Kommunikation und Argumentation**
   a. **Wie klar und verständlich hast du deine Position vertreten?**
      ☐ Sehr klar
      ☐ Klar
      ☐ Teilweise klar
      ☐ Nicht klar
   b. **Wie überzeugend waren deine Argumente?**
      ☐ Sehr überzeugend
      ☐ Überzeugend
      ☐ Teilweise überzeugend
      ☐ Nicht überzeugend
   c. **Welche Argumente haben besonders gut funktioniert?**

___

___

   d. **Wo siehst du Verbesserungspotenzial in deiner Kommunikation?**

___

___

4. **Flexibilität und Kompromissbereitschaft**

a. **Wie flexibel bist du auf unerwartete Situationen eingegangen?**
   ☐ Sehr flexibel
   ☐ Flexibel
   ☐ Teilweise flexibel
   ☐ Nicht flexibel
b. **Hast du sinnvolle Kompromisse gefunden?**
   ☐ Ja, vollständig
   ☐ Teilweise
   ☐ Nein

5. **Welche Kompromisse waren besonders wichtig für den Verhandlungserfolg?**

____

____

____

____

6. **Zielerreichung**
   a. **Hast du die Ziele erreicht, die du dir für die Verhandlung gesetzt hast?**
      ☐ Ja, vollständig
      ☐ Teilweise
      ☐ Nein
   b. **Welche Ziele wurden nicht erreicht und warum?**

____

____

____

____

7. **Gesamtbewertung**
   a. **Wie zufrieden bist du mit deiner gesamten Verhandlungsleistung?**
      ☐ Sehr zufrieden
      ☐ Zufrieden
      ☐ Teilweise zufrieden
      ☐ Nicht zufrieden
   b. **Was hast du aus dieser Verhandlung gelernt?**

____

____

   c. **Welche konkreten Schritte wirst du unternehmen, um deine Verhandlungsfähigkeiten zu verbessern?**

____

____

Vielen Dank für deine Selbsteinschätzung! Diese Reflexion hilft dir, bei zukünftigen Verhandlungen noch erfolgreicher zu sein.

Hochschule Düsseldorf
University of Applied Sciences
HSD

Eidesstattliche Versicherung

[redacted]
Name, Vorname

[redacted]
Matrikelnummer

Hiermit versichere ich an Eides Statt, dass ich die in elektronischer Form abgenommene schriftliche Prüfung

Bezeichnung der Prüfung: Bachelor Thesis, [redacted]
(Modul, Prüfungsnummer)

Prüfer/in: Frau Prof. Dr. Kati Lang & Herr Prof. Dr. Robert Scheidweiler

Prüfungs-/Abgabedatum: 19.02.2025

eigenhändig erbracht habe. Bei der Bearbeitung habe ich keine unzulässigen Hilfsmittel benutzt und mich nicht der unerlaubten Hilfe Dritter bedient. Ich habe keine anderen als die angegebenen Quellen benutzt und, soweit von der Aufgabenstellung vorgesehen, die aus fremden Quellen direkt oder indirekt übernommenen Inhalte als solche kenntlich gemacht.

Ich bin darüber belehrt, dass die vorsätzlich oder auch nur fahrlässig falsche Abgabe einer eidesstattlichen Versicherung nach §§ 156, 161 StGB* strafbar ist.

Düsseldorf, 19.02.2025
Ort, Datum

[redacted]
Unterschrift

* **§ 156 StGB - Falsche Versicherung an Eides Statt**

Wer vor einer zur Abnahme einer Versicherung an Eides Statt zuständigen Behörde eine solche Versicherung falsch abgibt oder unter Berufung auf eine solche Versicherung falsch aussagt, wird mit Freiheitsstrafe bis zu drei Jahren oder mit Geldstrafe bestraft.

§ 161 StGB - Fahrlässiger Falscheid; fahrlässige falsche Versicherung an Eides Statt

(1) Wenn eine der in den §§ 154 bis 156 bezeichneten Handlungen aus Fahrlässigkeit begangen worden ist, so tritt Freiheitsstrafe bis zu einem Jahr oder Geldstrafe ein.

(2) Straflosigkeit tritt ein, wenn der Täter die falsche Angabe rechtzeitig berichtigt. Die Vorschriften des § 158 Abs. 2 und 3 gelten entsprechend.