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# **Creating an Explainable AI Tool for First Impression Enhancement in Job Interviews**

Bachelor's thesis (12 ECTS)  
Curriculum Science and Technology

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## **Lühikokkuvõte:**

Tööintervjuude maailmas mängib esmamulje kandidaadi valikul suurt rolli. Siiski jääb praegune inimressursside (HR) tehnoloogia sageli vajaka vahenditest, mis suudaksid pakkuda kandidaatidele mõtestatud tagasisidet nende esmamulje kohta ja pakkuda läbipaistvat, tegevusele suunatud nõuandeid soorituse parandamiseks. See väitekiri tutvustab seletatavat tehisintellekti (AI) tööriista, mis on mõeldud nõuannete pakkumiseks kandidaatidele, kuidas parandada nende esmamuljet tööintervjuudel. Pakutav tööriist kasutab suurte viie isiksuseomaduste mudelit töökandidaatide intervjuusoorituse hindamiseks ja parandamiseks. Väitekiri keskendub sellise tööriista potentsiaali demonstreerimisele, et pakkuda automatiseeritud, kuid spetsialiseeritud tagasisidet kandidaatidele. Tööriista efektiivsuse kinditamine on esitletud läbi mitmete eksperimentide. Täheledatai, et kandidaadid näitasid pärast tööriistaga tegelemist parendatud sooritust.

Leiud viitavad, et sellel AI tööriistal on praktiline väärtus, näidates paljulubavat suunda tulevikuks HR tarkvaraplatvormidele integreerimisel. Selline integreerimine ei suurendaks ainult nende platvormide funktsionaalsust, vaid edendaks ka eesmärki parandada tööintervjuu tulemusi teadliku andmepõhise tagasiside kaudu. Edasist arendust ja täiustamist nähakse ette, et täielikult realiseerida selle tööriista potentsiaal professionaalsetes seadetes, sillutades teed uuendusele HR tehnoloogias, kus esmamuljet ei hinnata mitte ainult, vaid süstemaatiliselt parandatakse.

## **Võtmesõnad:**

AI, Esimene mulje, Tööintervjuu, OCEAN, CNN, Inimressursid, Kasutatavus, Soorituse hindamine, Suur viisik

## **Abstract:**

In the world of job interviews, first impression plays a big role in candidate selection. However, current Human Resources (HR) technology tends to lack tools that can both provide candidates with meaningful feedback on their first impression and offer transparent, actionable advice for performance improvement. This thesis introduces an explainable artificial intelligence (AI) tool designed to provide advice to candidates for improving their first impressions during job interviews. The proposed tool uses the Big Five personality traits for evaluating and improving job candidates' interview performances. The thesis focuses on demonstrating the potential of such a tool to provide automated, yet specialized feedback to candidates. The validation of this tool's effectiveness is showcased through a series of experiments. It was observed that candidates exhibited enhanced performance after engaging with the tool.

The findings suggest that this AI tool holds practical value, indicating a promising direction for future integration into HR software platforms. Such integration would not only augment the functionality of these platforms but also advance the goal of improving job interview outcomes through informed data-driven feedback. Further development and refinement are envisioned to fully realize the potential of this tool in professional settings, paving the way for an innovation in HR technology where first impressions are not just evaluated, but systematically improved.

## **Keywords:**

AI, First Impression, Job Interview, OCEAN, CNN, HR, Usability, Performance Evaluation, The Big Five

# Contents

<b>Terms, abbreviations and notations</b>	<b>6</b>
<b>1 Introduction</b>	<b>7</b>
<b>2 Literature Review</b>	<b>9</b>
2.1 AI in Human Resources . . . . .	9
2.2 The Big Five Model . . . . .	11
2.3 AI and Self-Assessment Practices . . . . .	12
<b>3 The aims of the thesis and requirements</b>	<b>14</b>
3.1 Objective . . . . .	14
3.2 Requirements . . . . .	14
<b>4 Materials and Methods</b>	<b>15</b>
4.1 Dataset . . . . .	15
4.2 Models . . . . .	16
4.2.1 Interpret DAN . . . . .	16
4.2.2 Visual ResNet50 3D . . . . .	18
4.3 Preprocessing . . . . .	20
4.3.1 Interpret DAN . . . . .	20
4.3.2 Visual ResNet50 3D . . . . .	21
4.4 Mechanisms . . . . .	21
4.4.1 General Workflow Mechanism . . . . .	21

4.4.2	Target Score Mechanism . . . . .	22
4.4.3	Feedback Mechanism . . . . .	22
<b>5</b>	<b>Experimental results</b>	<b>26</b>
5.1	Interpret DAN results . . . . .	26
5.2	ResNet50 3D results . . . . .	29
<b>6</b>	<b>Discussion and Future Steps</b>	<b>33</b>
6.1	Discussion . . . . .	33
6.2	Future Steps . . . . .	34
	<b>Bibliography</b>	<b>35</b>
	<b>License</b>	<b>40</b>

# Terms, abbreviations and notations

**HR** Human Resources – a business function focused on the recruitment, management, and direction of people who work in an organization.

**AI** Artificial Intelligence – the simulation of human intelligence processes by machines, especially computer systems. These processes include learning, reasoning, and self-correction.

**NN** Neural Network – a neural network.

**CNN** Convolutional Neural Network – a type of deep neural network primarily used in image recognition and processing that is also increasingly used for other types of data, such as audio and text.

**OCEAN** Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism - a model used in psychology to describe and measure five major domains of human personality.

**NLP** Natural Language Processing – a field of AI that focuses on the interaction between computers and humans through natural language, aiming to read, decipher, understand, and make sense of human languages in a valuable way.

**LLM** Large Language Model.

**ChatGPT** Chat Generative Pre-trained Transformer – an AI model developed by OpenAI, designed to generate human-like text based on the input it receives, often used for conversational purposes.

**NEO-PI-R** The Revised NEO Personality Inventory – a personality inventory that assesses an individual on five dimensions of personality. These are the same dimensions found in the Big Five personality traits.

**FFPI** The Five-Factor Personality Inventory – assesses the Big Five factors of personality, both for self-ratings and for others ratings.

**SEFI** Seeking external feedback through inquiry.

**DAN** Descriptor Aggregation Network.

# Chapter 1

## Introduction

Job interviews are a key part in the hiring process, where both applicants and employers evaluate each other [1, 2]. Studies show the profound impact of first impressions in this context, influencing hiring decisions significantly [3]. Despite the advancements in Human Resources (HR) technology, such as job interview text simulations or advancements in deep learning methods to predict first impressions [4, 5] a conspicuous gap remains: the lack of tools aimed at enhancing qualitative feedback on first impressions. Existing video-based assessment tools, while using automated first impression recognition and Big Five personality traits analysis, fall short as they fail to provide candidates with feedback or insights into their performance [6, 7].

This study aims to bridge this technological divide by proposing a tool designed to offer candidates insights into their non-verbal communication and actionable recommendations to refine their first impressions during the job interviews. This not only fills a notable gap—where quantitative advancements have traditionally outpaced qualitative enhancements—but also sets the stage for future innovations in this field.

The central challenge this work addresses is the shortage of innovative tools that qualitatively enhance job interviews by focusing on first impressions and the nuanced aspects of human interaction. Existing HR technologies, despite their advancements, primarily emphasize simulation and automation, overlooking the crucial domain of impression management [8]. The methodology utilizes neural networks to analyze job candidates' non-verbal cues. This process involves constructing personality profiles aligned with the Big Five personality traits model and further analysis of the profile using large language model, which later provides detailed feedback and recommendations for improvement.

Preliminary findings indicate that candidates receiving feedback from the tool show improvements in their presentation skills during mock interviews. This feedback mechanism enables candidates to understand and adapt their non-verbal

communication, thereby enhancing their presentation styles and non-verbal cues, such as body language and mimics, based on the AI-generated feedback. The plateau observed in performance at a point during the trials may suggest that there is a learning curve and that after a certain number of iterations, additional feedback may have diminishing returns.

The significance of these findings lies in their demonstration of the practical utility of such personalized tools in professional development, particularly for job interview preparation or self-introduction prerecordings. This study not only fills a critical gap in HR technology by providing qualitative feedback on first impressions but also encourages a paradigm shift towards developing more personalized and nuanced tools that take into account the complexity of human perception of feedback and the differentiation of individual learning dynamics [9]. Future research should explore extending the capabilities of AI in HR, further enhancing the qualitative aspects of the hiring process.

The paper is structured as follows: Chapter 2 reviews related literature, Chapter 3 outlines the methodology, Chapter 4 presents the results and their implications, Chapter 5 demonstrates results and Chapter 6 concludes with a discussion on the impact of the study and directions for future research.

# Chapter 2

## Literature Review

The fast progress of Artificial Intelligence raised the new era in many industries, fundamentally changing the way complex problems are addressed and solved. And the rapid development is led by the field of natural language processing, which has made remarkable progress through the creation of large language models (LLMs). These models have improved our capacity to engage with digital systems in a more instinctive manner and exerted widespread influence across various areas. In particular, the sector of job interviews is being transformed by the integration of AI technologies.

### 2.1 AI in Human Resources

The advancement of natural language processing has significantly changed the perception of Artificial Intelligence, especially with the release of large language models such as OpenAI's ChatGPT and Google's Gemini [10]. This progress improves our interactions with digital technologies and expands its influence to various domains, including recruitment processes. One of the key areas where AI can greatly impact HR is in job interviews [11]. The incorporation of AI algorithms into systems like Applicant Tracking Systems [12] platforms can be an example of this broad impact across different fields. These systems evolve candidate screening and evaluation by bringing analysis and decision-making capabilities to levels that were previously unreachable.

Advancements in information technology (IT), predictive analytics, AI, and machine learning have irreversibly changed the automation of administrative processes such as payroll processing, employee time monitoring, and benefits management [13], which were previously time-consuming and prone to human error. Recent studies have shown that AI-powered systems can perform this work with high speed and accuracy, freeing HR employees from monotonous clerical work [14]. This change frees up human resources departments to focus on more strate-

gic aspects of their jobs, such as employee engagement and talent development. AI is changing recruitment processes in addition to administrative duties. Traditional recruitment methods include sorting through a large number of applications and resumes to discover the most suitable candidates [15]. AI and its ability to process massive datasets in a shorter amount of time can help. It can go through hundreds of resumes to discover applicants with the necessary skills and experience, and can even forecast which candidates are more likely to succeed in a particular position. Thus, successful integration of AI can potentially speed up the hiring process and offer a level of impartiality, thereby eliminating unintentional prejudices that human recruiters may have [16].

Another important area in which AI is having an impact on HR is data analysis for strategic decision-making [17]. The modern HR department is exposed to massive amounts of data, and AI technologies are ideal for analyzing this data and proposing actionable recommendations. For example, AI can help discover patterns in employee turnover, forecast future staffing needs, and assess employee feedback to determine overall happiness. Such possibilities are invaluable to HR professionals making decisions about talent management and organizational policies [11]. While AI has the potential to take the recruiting process to the next level of development, there are several challenges that need to be addressed when developing AI-based interview tools. One of the main sources of concern is data privacy [18]. Because AI systems require access to massive volumes of employee data, there is a certain risk of data leakage or misuse of personal information. One of the other primary concerns is the ethical use of AI in evaluating and scoring human interactions [19]. AI decisions, like applicant selection or performance assessments, can still be influenced by inherent biases in the data or algorithms, resulting in unjust employee treatment [20]. The need for extensive and diverse data exists to train AI models effectively. The quality and diversity of the data used to train the AI algorithms directly impact the tool's ability to provide accurate feedback to candidates [21]. Furthermore, the interpretability of AI-generated feedback is essential. Candidates should be able to understand and act upon the recommendations provided by the tool, ensuring that the feedback is constructive and actionable [22]. The ability of an AI system to be fair, free from bias, and privacy-safe is critical to credibility and acceptance among both candidates and employers.

The importance of first impressions in recruiting cannot be overstated. In a competitive job market, candidates often have only one opportunity to make a positive impression on the employers. From the initial application to the interview stage, first impressions play a critical role in shaping an employer's perception of a candidate [23]. Therefore, it is important for candidates to understand how to effectively present themselves and make a strong initial impact during the recruitment process [24]. In recruitment, psychological strategies, such as impression management, are often used to influence hiring decisions. These can include techniques such as self-promotion and ingratiation [25].

As recruitment methods evolve to incorporate digital and online interactions, with the advancement of AI-based tools, there is potential to improve first impressions in job interviews [26].

## 2.2 The Big Five Model

The Big Five, also known as the Five-Factor Model or OCEAN model, is a widely accepted framework for understanding personality. It postulates that human personality traits are based on five broad dimensions: Openness to Experience (creativity, intellectual curiosity, and appreciation for art and new experiences), Conscientiousness (organization, discipline, and dependability), Extraversion (sociability, assertiveness, and enthusiasm), Agreeableness (compassion, cooperation, and trustworthiness) and Neuroticism (associated with emotional instability and negative emotions such as anxiety and sadness) [27]. These factors are thought to represent the basic structure of personality and they are relatively stable across cultures and languages. Instruments such as the NEO-PI-R [28] and the FFPI [29] have been developed to measure these dimensions, and a vast body of research has linked the Big Five to various life outcomes and behaviors. For example, conscientiousness is a strong predictor of job performance and academic achievement [30] and higher levels of neuroticism together with lower levels of agreeableness, conscientiousness, extraversion, and openness are associated with increased levels of employee burnout [31]. The Big Five provides a foundation for comparing personality across cultures and has been used to study the relationship between personality traits and other psychological constructs, forming what is known as a nomological network [32]. The Big Five model can help to understand employee behavior and productivity and can be used to assess candidate and job compatibility. There are notable variations in personality characteristics between employees, supervisors, managers and entrepreneurs. Recognizing these traits can be advantageous when determining a suitable role for individuals based on their personalities. Entrepreneurs and managers generally display decreased Neuroticism, but heightened Openness and Conscientiousness compared to regular employees. At the same time, managers demonstrate reduced Agreeableness and increased Extraversion. By understanding these traits and their various combinations, guidance to hiring teams can be offered to assist in the selection of candidates whose personality traits match the job requirements [33].

State-of-the-art methods in assessing the Big Five personality traits from video data are proof of the advancements in the field of AI, particularly machine learning and computer vision. Video-based personality assessment has made a move towards more specific and automated methods that combine different data streams to build a broad picture of an individual's personality [34].

One approach that has made progress in this area is the use of convolutional neural networks (CNN), which have been successfully used to analyze facial expressions

during video interviews [35]. The models are trained to detect micro-expressions and subtle facial expressions that correlate with the Big Five personality traits. By analyzing these nonverbal signals, the CNNs can presumably describe a candidate's interpersonal communication style and personality, which may otherwise not be discernible through traditional assessment methods.

Besides facial expressions, these state-of-the-art systems also incorporate speech analysis to evaluate prosody, tone, pace, and inflection in a subject's voice, all of which can give information about their personality traits [36]. Additionally, body language and gesture analysis is another growing area in which all body movements and postures captured in video interviews are analyzed to identify personality indicators.

Furthermore, multimodal approaches combining visual, textual and auditory data are being developed, such as deep learning and natural language processing to parse speech content and analyze semantic structures, which in combination with visual and acoustic features can provide a more solid personality assessment [34].

## 2.3 AI and Self-Assessment Practices

Self-assessment practices are crucial components of the learning process across various professional domains and act as an internal regulatory mechanism that can significantly influence learning outcomes [37]. When learners evaluate their own performance and seek constructive criticism or feedback, they engage in a reflective process that can help identify strengths and weaknesses, thereby directly affecting their professional development and skill acquisition [38]. The manner in which learners seek feedback is an essential determinant of the training's impact. Specifically, the study [39] found that learners who actively seek external feedback on their interview skills, particularly from experts or those with greater knowledge in a particular field (defined as seeking external feedback through inquiry, SEFI), tend to learn more effectively from training programs compared to those that rely solely on internal cues or static course materials. This finding underscores the importance of fostering environments that encourage interactive feedback mechanisms and continual professional dialogue.

Moreover, the study found relationships between personal characteristics such as age, profession, previous experience and training outcomes [39]. These results stress the need for training programs to accommodate varying self-assessment practices and to tailor support for individual learning needs effectively. Through the utilization of these practices early in the training process, organizers can better structure their programs to integrate suitable self-assessment interventions, which could range from more explicit instruction to fostering opportunities for peer interaction, enhancing training effectiveness.

Integrating self-assessment practices with AI into training models has significant potential to improve personal development and professional growth [40]. By using AI technology, training programs can offer personalized and adaptive feedback to individuals, complementing their self-evaluation efforts [41]. The utilization of AI algorithms to analyze self-assessment inputs and tailor feedback for learners is a concept rooted in the capability of AI to handle vast amounts of data and identify complex patterns within it [42].

This becomes evident in the case study [43] of the personal AI tutor app used at UniDistance Suisse. By generating personalized questions and adapting to each student's proficiency, AI demonstrated an understanding of individual learning progress and knowledge retention. Through machine learning techniques, these systems can adapt and refine their feedback over time. AI algorithms can analyze self-assessment inputs from individuals and provide feedback based on their unique learning styles, strengths, and areas for improvement, thereby assisting in the creation of adaptive learning paths that align with individuals' self-assessment results and maximize their learning outcomes. AI can use this synthesized information to form adaptive learning paths that reflect the learner's self-assessment and align with empirically successful learning strategies such as spaced repetition and retrieval practice. The AI tutor's neural network demonstrates the capability to forecast a learner's grasp on different concepts—predictive modeling that inherently takes into consideration the learner's self-assessment to refine its predictions and feedback. For these purposes, the study demonstrates the created "learnnet", which visually signifies areas of strength and topics needing further review. Furthermore, deploying AI allows continual processing of the adaptive learning paths as learners progress. As students interact with the AI tutor, their performance data streams into the system, allowing the AI to recalibrate the learning pathway, thereby ensuring that the feedback remains relevant and optimal for each individual's skill development [43]. By integrating self-assessment with ongoing performance analytics, AI algorithms can become more and more proficient at offering suggestions that learners might not discern on their own. This can result in an educational experience that is highly personalized and also dynamic, adjusting in real-time to maximize learning outcomes and enhance educational efficacy. This evolution in educational methodology can be reached through the transformative potential of AI in crafting highly individualized and effective learning experiences.

# Chapter 3

## The aims of the thesis and requirements

### 3.1 Objective

The goal of this research is to create and test an assistive tool for candidates to improve their first impressions on a job interview. The tool uses automated first impression recognition (FIR) techniques to create an OCEAN profile based on brief introductory videos submitted by job candidates. By analyzing created OCEAN profiles, this tool aims to offer candidates personalized feedback and practical suggestions to enhance their initial impression in video interviews. Then, the influence of the feedback will be analyzed on the next video in chronological order. A main aspect of this research is looking at how the feedback changes the way candidates present themselves over time, thereby quantifying the benefits of the feedback provided. The ultimate aim is to ascertain a marked improvement in candidates' interview performance through the strategic application of feedback recommendations. Upon successful evaluation, the tool could potentially be integrated into larger HR software platforms in the future.

### 3.2 Requirements

- A feature within the tool that generates OCEAN personality profiles from provided video using neural networks.
- A feedback mechanism that offers personalized recommendations based on the generated OCEAN profile.
- Assessing the tool's impact on the candidates' first impressions during introductory videos.

# Chapter 4

## Materials and Methods

### 4.1 Dataset

Attempt	Actor 1	Actor 2	Actor 3	Actor 4	Actor 5	Actor 6
1	31	36	17	41	31	28
2	32	34	39	47	45	24
3	35	29	53	51	34	30
4	34	31	46	64	33	25
5	32	31	40	29	32	24
6	31	40	44	34	34	28
7	34	45	42	28	34	21
8	36	36	36	30	35	35
9	31	38	37	26	35	22
10	31	33	45	36	35	26

Table 4.1: Duration of Videos in Dataset in seconds

Acquisition of the dataset consisted of iterative process to gather ten video recordings. Each set of recordings was created under consistent conditions by the same individual, who was instructed to introduce themselves as if they were applying for a bank worker position. After each session, the individual received feedback and recommendations from the advising tool, which were then incorporated into subsequent recordings, creating a continuous cycle of performance improvement. The use of a single participant ensured consistency in the dataset, while algorithmic feedback introduced dynamic elements. Participants were advised to ensure consistency in their video recordings by maintaining the same posture, optimal lighting conditions, and minimalist environmental background across all sessions. This methodology allowed us to analyze individual performance improvement over time and provided information about the effectiveness of AI-assisted coaching in enhancing communication skills relevant to professional scenarios.

It consists of 60 videos with 6 participants, where each one recorded 10 videos, with an average durability of 34.6 seconds. The resolution of videos for 4 participants is  $720 \times 1280$  and for the other 2 was  $1920 \times 1080$ .



Figure 4.1: Examples of original frames in dataset. Faces blurred for privacy

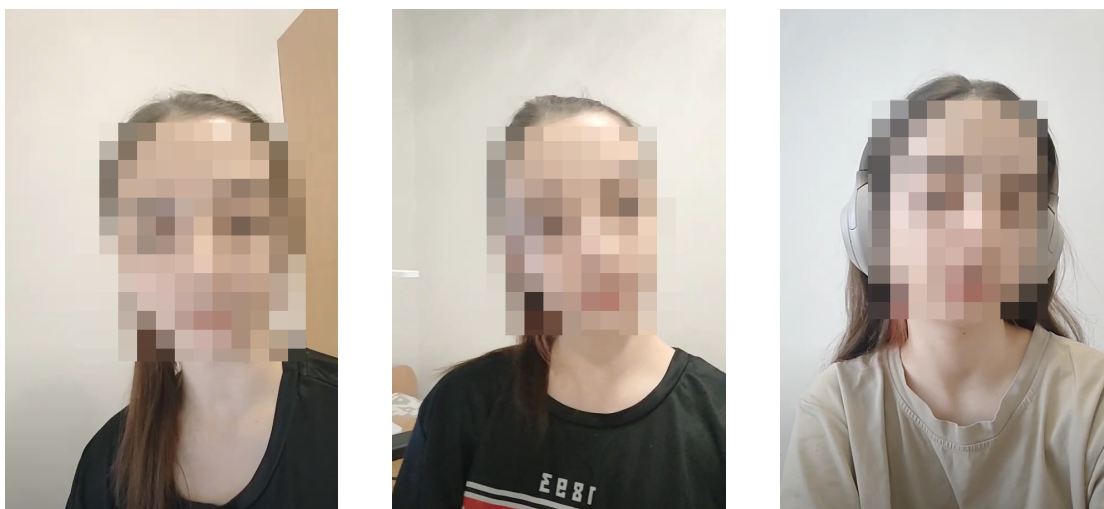


Figure 4.2: Examples of original frames in dataset. Faces blurred for privacy

## 4.2 Models

### 4.2.1 Interpret DAN

DAN is a CNN model that infers personality from each static image (including both face and background). It consists of several convolution-ReLU blocks and an additional block that is equipped with both average-pooling and maxpooling,

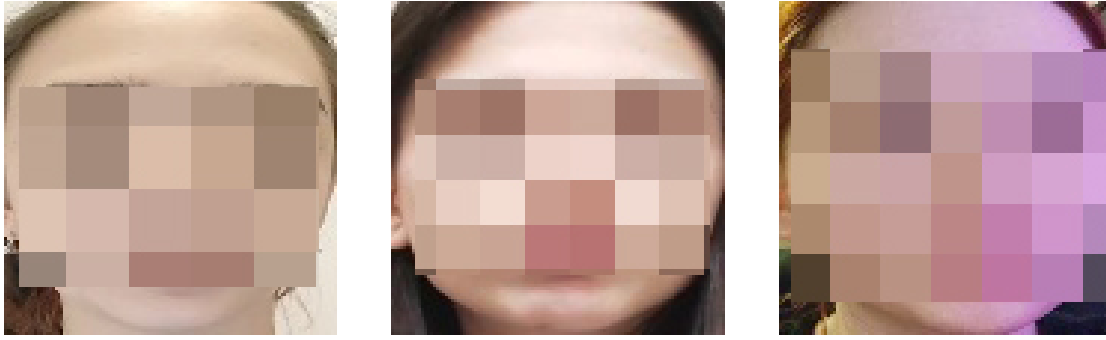


Figure 4.3: Example of extracted faces in dataset. Faces blurred for privacy

which is added between the last convolutional layer and the final FC layer. Before being fed to the model, each image is resized to  $456 \times 256$  resolution. The training process is conducted using the SGD optimizer with initial learning rate of 0.05, weight decay of 0.0005 and momentum of 0.8, where MSE is employed as the loss function. [44]

The Interpret DAN model is a specialized neural network architecture developed using PyTorch, primarily based on the VGG16 model. This architecture is tailored for image analysis, particularly focusing on extracting interpretable features for specific applications, potentially in personality interpretation or similar areas. [44]

The model consists of a sequential layer of features generated using the `make_layers` function with a VGG16 backbone. This setup typically comprises multiple convolutional layers, each followed by batch normalization and ReLU activation functions, designed for deep feature extraction. After processing through these layers, the network employs a global average pooling layer (`nn.AdaptiveAvgPool2d`), reducing each feature map to a singular value and summarizing spatial information efficiently. This reduction is key for managing model complexity and enhancing generalization.

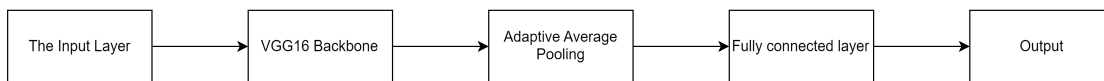


Figure 4.4: Interpret DAN model architecture

At the heart of Interpret DAN lies a fully connected layer (`nn.Linear`) that transforms the pooled features into an output vector corresponding to the number of classes, defaulted to five in this model. An optional sigmoid activation function can be applied to the output, making the model suitable for tasks that require outputs in a  $[0, 1]$  range, such as binary classification [44]. Additionally, the model offers the flexibility to return the flattened feature vector from the global average pooling layer, which can be instrumental in interpreting the model's learning process.

The model’s design allows for significant configurability, including the option to initialize with or without pretrained weights, a choice that can facilitate transfer learning. This adaptability makes Interpret DAN a robust tool for image-based analysis tasks where both accuracy and interpretability of results are paramount. Its architecture, featuring the ability to return intermediate features and use sigmoid activation, positions it well for applications demanding deep insight into the model’s decision-making processes, such as nuanced image classification or personality trait analysis. [44]

## 4.2.2 Visual ResNet50 3D

ResNet 3D, or 3D Residual Networks, is an extension of the original 2D Residual Networks for application in 3D data such as videos. The primary goal of ResNet 3D is to better capture spatio-temporal features by incorporating the temporal dimension into the neural network architecture, hence enabling more effective action recognition in video sequences.

In 2D ResNets, the architecture utilizes residual blocks—combinations of layers with shortcut connections that allow the network to learn identity functions as needed, which eases the training of deep networks and helps mitigate the vanishing gradient problem. Each block consists of sequences of convolutional layers, activation functions, and batch normalization, with a shortcut that bypasses these layers. The output of the shortcut is then added to the output of the convolutional block, helping in training deeper networks by ensuring that the gradients can flow through these shortcuts. [45]

The key difference in ResNet3D architecture is the use of 3D convolutional kernels and 3D pooling layers, in contrast to their 2D counterparts, allowing the network to process temporal information present in multiple consecutive video frames. Convolutions in ResNet3D are performed in three dimensions—spatial height, width, and temporal depth—which means the network can learn features that describe the appearance and movement of objects in videos over time. [44]

ResNet3D networks have been found to perform well on large-scale video datasets like Kinetics, showing good generalization capabilities without suffering from overfitting—despite having a large number of parameters. This performance is attributed to the 3D convolutions’ ability to capture dynamic information and the powerful feature-learning capabilities of deep residual networks. The ResNet3D models achieve state-of-the-art results in action recognition tasks and have become a critical component in video analysis and related applications. [46]



Figure 4.5: ResNet50 3D model architecture

At the core of the ResNet50 3D architecture lies its capability to handle 3D tensors as input. This is reflected in its initial layer, a 3D convolutional layer, which is designed to capture complex spatial and temporal features from the input data. The kernel size of this layer, (`conv1_t_size`, 7, 7), along with a stride of (`conv1_t_stride`, 2, 2), allows the model to effectively process a series of 2D frames as a cohesive 3D volume. [44]

Following the initial convolutional layer, the model incorporates batch normalization and ReLU activation, standardizing the outputs and introducing non-linearity. An optional max pooling layer can be included, serving to reduce the spatial dimensions of the data. This not only increases the network's receptive field but also significantly reduces computational demands, making the model more efficient. [44]

The distinctive feature of the ResNet50 3D model, however, lies in its use of residual blocks. These blocks form the backbone of the model, with each set containing either BasicBlocks, used in shallower versions of ResNet, or Bottleneck blocks, employed in deeper versions. The Bottleneck block, in particular, is composed of a series of convolutions, including a 1x1x1 convolution for dimensionality reduction, a 3x3x3 convolution as the primary feature extractor, and another 1x1x1 convolution to restore dimensions. This arrangement is pivotal in enhancing the model's feature extraction capabilities. [44]

To facilitate the addition of residual connections, downsampling is performed within these blocks as necessary. This ensures that dimensions and channels are matched, allowing for seamless integration of the residual connections. These connections are crucial as they help mitigate the vanishing gradient problem, thus enabling effective training of deeper network architectures. [44]

Concluding the architecture, the model employs an adaptive average pooling layer, which distills each feature map to a singular value, encapsulating both spatial and temporal information effectively. The final layer, a fully connected layer, maps these pooled features to the number of classes desired in the output. [44]

The number "50" in ResNet50 3D refers to the depth of the network, specifically indicating the number of layers in the network that have trainable weights. In the context of neural networks, layers with trainable weights typically include convolutional layers, fully connected layers, and other similar types of layers that contain parameters (weights and biases) which are updated during the training process.

For ResNet architectures, the depth is typically associated with the number of convolutional layers. In ResNet50, there are 50 such layers. This includes:

- The initial convolutional layer.
- Convolutional layers within the residual blocks (Bottleneck blocks in the case of ResNet50). Each Bottleneck block in a ResNet50 contains 3 convolutional layers. Since the configuration of ResNet50 includes 16 Bottleneck blocks, this results in  $16 \times 3 = 48$  convolutional layers from these blocks.
- The final layer in the network is usually not counted in this total, as it is a fully connected layer rather than a convolutional layer.

Thus, the "50" in ResNet50 3D signifies a deep architecture composed of 50 layers with trainable parameters, allowing the network to learn complex features and patterns from the input data. This depth is a key factor in the network's performance, enabling it to effectively capture and learn from both spatial and temporal data, making it well-suited for tasks that require detailed feature extraction from 3D inputs. [44]

## 4.3 Preprocessing

### 4.3.1 Interpret DAN

Each video, sourced from the dataset described in section 4.1, underwent a preprocessing stage. This stage was important for ensuring that the videos were in a suitable format for analysis by the deep learning model.

Main part of the preprocessing is the utilization of the OpenCV library (cv2) [47]. Each video undergoes a process where frames are extracted and stored for further analysis in automatically created folders.

During the frame extraction process, videos are accessed frame by frame using OpenCV's `cv2.VideoCapture` method. The system is designed to extract a specific number of frames (5/6ths of the total frame count), typically aiming for a comprehensive representation of the video content without overburdening the storage or processing resources. The frames are then resized to a uniform dimension of  $456 \times 256$  pixels. A central sub-region of  $224 \times 224$  pixels is extracted from the full frame for analysis. [44]

At the same time face region is cropped differently from a video directly. Upon receiving an image, the FaceDetection class uses dlib's [48] frontal face detector to identify faces within the image. After detecting a face, the script calculates facial landmarks using dlib's shape predictor. The script calculates the bounding box

for the face based on the landmarks, specifically focusing on the distance between the eyes and other key facial points to determine the box's dimensions. [44]

After rotation and landmark re-calculation, the face image is cropped from the rotated image using the newly defined bounding box, ensuring that the face is centered and occupies a significant portion of the image. Finally, the cropped face image is resized to the predefined dimensions (112x112 pixels), standardizing the size for all extracted face images to have consistent dimensions. The result of this process is a face image that has been detected, aligned, cropped, and resized to a standard size, ready for further analysis or use as input to machine learning models focusing on facial features. [44]

### 4.3.2 Visual ResNet50 3D

Initial processing is a bit different for this model due to its spatial-temporal nature. Two parts of processing exist. The first part, a short segment-level system, where each video was divided into several segments, each containing 32 frames. These segments are individually processed to generate predictions for personality traits, which are then averaged to obtain a final prediction for each video.

In the video-level system, each video was divided into 32 segments where only the first frame of each segment is chosen for being assembled into a sequence. This sequence is the input for ResNet50 3D, which then predicts personality traits based on this condensed representation of the video. The personality trait prediction of each test video is computed by averaging both part predictions.

Both systems use the preprocessing steps, described earlier for Interpret DAN model. [44]

## 4.4 Mechanisms

### 4.4.1 General Workflow Mechanism

The conducted experiment follows an iterative process to refine a candidate's ability to make strong first impressions during interviews. This process begins with candidates recording introductory videos, which are then analyzed by tool utilizing neural networks.

After the initial analysis of OCEAN scores, ChatGPT provides personalized feedback to the candidates, highlighting areas of strength and opportunities for improvement in their presentation and communication styles. The feedback is tailored to enhance the candidate's performance in alignment with what is generally perceived positively in job interviews.

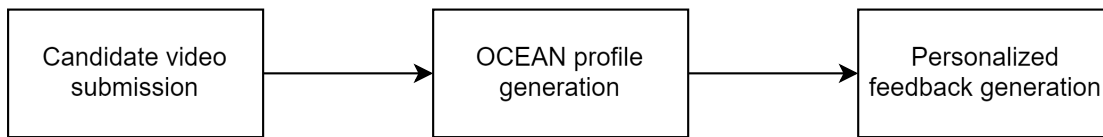


Figure 4.6: General Workflow Mechanism

Candidates then iterate on their performance by incorporating the feedback into new recordings, and submitting these to the AI for subsequent rounds of analysis and feedback. With each iteration, the AI tool refines its evaluations, and the candidates adjust their presentations, entering a cycle of continuous improvement. The iterative nature of the experiment allows for tracking the evolution of the candidates’ presentation skills.

#### 4.4.2 Target Score Mechanism

In light of the progressing utilization and continuous improvement of Large Language Models (LLMs), this study utilizes ChatGPT-4, recognized as one of the premier LLMs as of early 2024 according to LMSYS Chatbot Arena Leaderboard [49], for the generation of target OCEAN values specific to the role of a bank worker. By using the capabilities of LLMs, we aim to create target personality profiles without necessitating direct manual input from HR professionals or psychologists. The targeted OCEAN values established for this occupation are Openness (0.25–0.4), Conscientiousness (0.85–0.95), Extraversion (0.55–0.7), Agreeableness (0.65–0.8), and Neuroticism (0.15–0.3).

These values were proposed by the model within a predefined range (0 to 1), in which used neural network models operate. The model provided justifications for these proposed scores and proposed the scientific research, thus employing an evidence-based approach. The proposed synthesis of over 50 meta-analyses indicated that specifically, conscientiousness emerges as the trait with the largest positive effect on overall job performance. Openness, on the other hand, has the smallest effect size. Extraversion and agreeableness exhibit some positive effects on job performance. Neuroticism is the only trait among the Big Five to consistently show a negative effect on job performance, highlighting the potential challenges that high levels of emotional instability or stress sensitivity may pose in the workplace. [30]

#### 4.4.3 Feedback Mechanism

We utilized ChatGPT-4, a state-of-the-art language model, as a central component of our recursive feedback loop. Initially, ChatGPT-4 was instructed with a specific prompt designed to contextualize its feedback within the framework of our

study. This prompt was crafted to ensure that the model understood the nature of the task: evaluating a video intended for a simulated bank worker job short application, rather than preparing for a real-life interview. ChatGPT-4's role was twofold: firstly, to interpret the OCEAN scores obtained from the videos, and secondly, to provide tailored advice based on these interpretations.

*Imagine you are a psychologist working in HR. Offer your advice based on the OCEAN results to an employee, aiming to improve their scores where necessary. This guidance will be provided according to the results you share with me. Focus on advice that enhances scores in a recorded CV video, considering aspects such as mimicry, voice, and gestures. Keep in mind that the individual is applying for a bank worker position, and evaluate their performance accordingly.*

- **Role and Context Clarification:** The prompt clearly identifies the role of the responder (a psychologist working in HR) and the context (providing advice based on OCEAN results). This specificity helps ChatGPT to tailor the response according to the perspective of a professional who is familiar with psychological assessments and their application in a workplace setting.
- **Objective Definition:** The prompt outlines a specific objective – to offer advice aimed at improving an employee's OCEAN scores, especially in the context of a recorded CV video. This narrows down the response to focus on personality traits and their expression through verbal and non-verbal communication, which are critical for CV videos.
- **Inclusion of Relevant Details:** By mentioning that the advice should consider aspects such as mimicry, voice, and gestures, the prompt provides direction on the type of feedback expected. This encourages a response that includes practical tips on improving non-verbal communication, which is particularly relevant for video presentations and do not pay attention to such things as outfit.
- **Application Context:** Stating that the individual is applying for a bank worker position adds an important layer of context. It implies that the advice should not only aim to enhance the OCEAN scores but also consider the specific attributes valued in the banking sector, such as trustworthiness, attention to detail, and customer service skills.
- **Why Contextual Clarity Matters:** ChatGPT's understanding is significantly enhanced by prompts that are detailed and contextualized. A well-defined prompt enables the model to generate responses that are more closely aligned with the user's expectations. In this case, the additional details about the role, objectives, and specific application scenario allow ChatGPT to tailor its advice to be both psychologically informed and relevant to the banking industry.

When evaluating the OCEAN score, ChatGPT-4 considered what each score meant in the context of the individual's presentation.

Subsequently, ChatGPT-4 provided specific advice aimed at enhancing the individual's performance in the recorded video. This advice was unique and contextual, taking into account the constraints of the medium, such as the lack of real-time interaction and the limited time available to make an impression. The model offered suggestions on improving various aspects, such as body language and speech clarity to better align the individual's presentation with the expected standards of a bank worker position.

Example of feedback given based on OCEAN score with the used prompt:

- Openness (0.3971):

*Evaluation: This score suggests a moderate level of openness to experience, indicating some degree of creativity and willingness to embrace new ideas, though still leaning towards traditional approaches.*

*Visual Advice: To convey openness, the individual should aim to demonstrate curiosity and a readiness to learn and adapt. This can be visually communicated through an engaged posture, using hand gestures that suggest exploration (such as open palms) and nodding in agreement or understanding when discussing new ideas or experiences.*

- Conscientiousness (0.3828):

*Evaluation: Slightly below the ideal range for roles requiring high levels of organization and reliability. This score indicates a need for improvement in showing attention to detail and task management.*

*Visual Advice: The individual should focus on presenting a well-organized and meticulous environment in their video. Dressing professionally and ensuring a tidy background can help convey conscientiousness. Using a structured format for the presentation, with clear transitions between points, can also visually underscore an organized mindset.*

- Extraversion (0.3111):

*Evaluation: Indicates a more introverted personality, with potential challenges in expressing energy and enthusiasm in social settings.*

*Visual Advice: Despite the lower extraversion score, the individual can practice displaying a more outgoing demeanor through their body language and facial expressions. Smiling, maintaining eye contact with the camera, and using expressive gestures can help convey a more extroverted and engaging presence.*

- Agreeableness (0.4120):

*Evaluation: Close to the moderate range, suggesting a reasonable level of cooperativeness, warmth, and empathy towards others.*

*Visual Advice: To enhance the appearance of agreeableness, the individual should focus on maintaining a warm and friendly facial expression, nodding to convey understanding, and using open gestures. Sharing examples of teamwork or situations where they helped others can also visually communicate this trait.*

- Neuroticism (0.3457):

*Evaluation: This score is within a moderate range, indicating some level of emotional stability but also highlighting the importance of managing stress effectively.*

*Visual Advice: The individual should aim to project calmness and composure throughout the video. Techniques such as deep breathing before recording, speaking at a measured pace, and maintaining a steady posture can help convey emotional stability and resilience. [50]*

# Chapter 5

## Experimental results

This part examines the data from experiments and evaluates how well the AI tool can help improve first impressions in job interviews. We analyze the results that come from using this AI approach. By using quantitative analysis, we can see how much the candidate's way of presenting themselves in interviews changes with each attempt, illustrating the learning curve and changes over time.

The calculation of absolute differences between the target and actual scores for each trait across all attempts for each participant was completed using formula  $\text{abs}(\text{target OCEAN value} - \text{obtained OCEAN value})$ . Averages were employed for their simplicity and effectiveness in this context, serving as a good demonstrative technique. Following this initial step, participant averages for each attempt were aggregated to produce a global average for every attempt. This aggregation offers a more generalized perspective on overall performance to smooth individual variances in order to present a clearer depiction of the overall trend.

### 5.1 Interpret DAN results

We observed a certain trend in the performance scores obtained through the feedback loop, as analyzed by Interpret DAN model. Participants' averaged performance measured across a series of attempts was compared to the proposed by ChatGPT range.

Collected values demonstrate a notable decrease in the average distance in the third attempt, decreasing from 0.2625 to 0.2505. This third attempt marked the peak of the best performance in our experimental data. This can suggest an assimilation of the feedback provided by ChatGPT and a corresponding enhancement in the subject's presentation skills, as per the OCEAN criteria.

However, following this apex, there was a significant decline in the scores (0.2613) during the fourth attempt. This drop might indicate a point of over-adjustment or

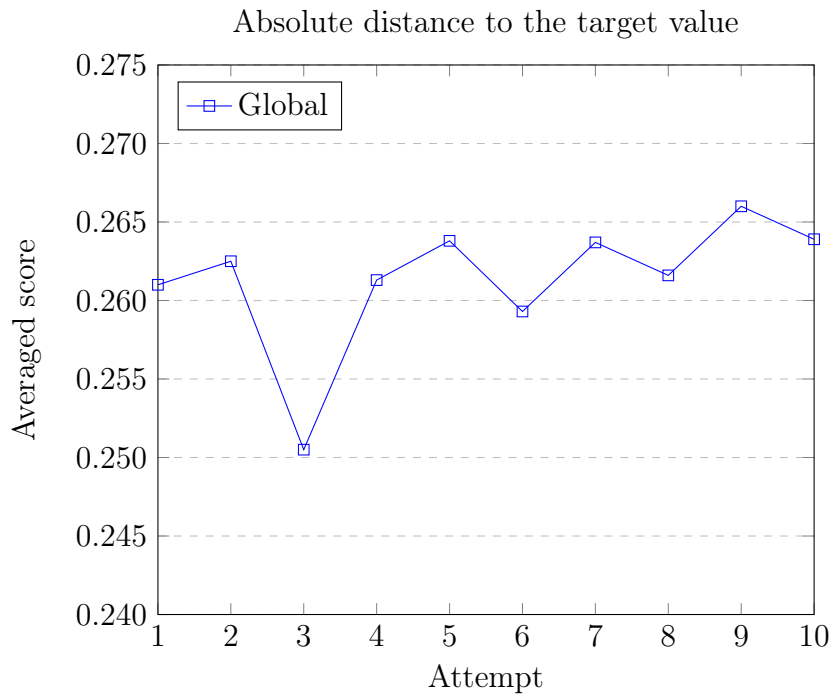


Figure 5.1: Global average of absolute distances to the target value across multiple attempts for Interpret DAN model.

a deviation from optimal presentation strategies, potentially caused by an overemphasis on certain feedback aspects. After this decline, the data showed fluctuations in bigger distance values for the rest of the attempts having the 9th attempt (0.266) as the biggest average distance. This decline in the later stages could be indicative of several factors, such as fatigue or the complexity of continuously adapting to the feedback.

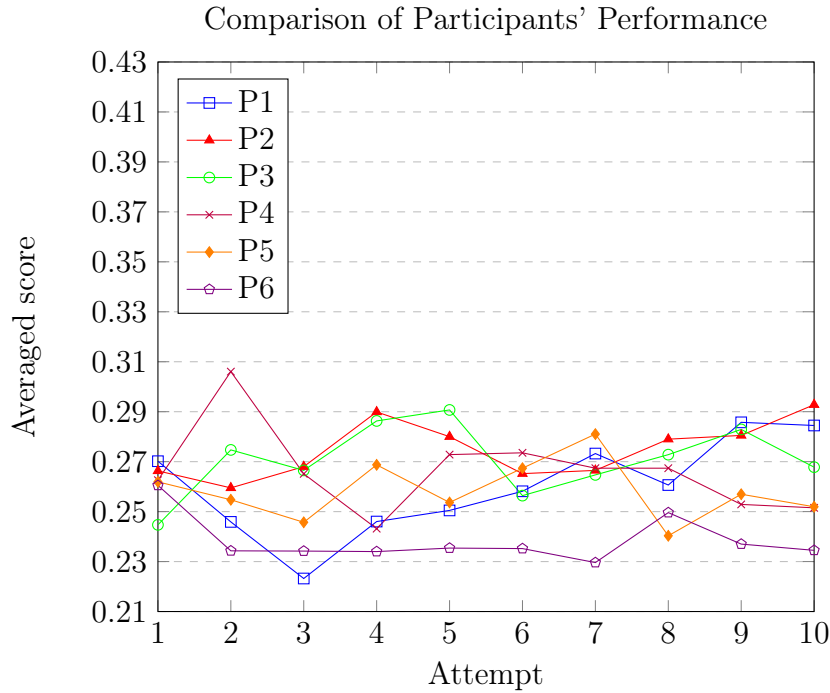


Figure 5.2: Average of absolute distances to the target value across multiple attempts for Interpret DAN model per participant.

Figure 5.2 illustrates the average of absolute distances to the target value with each line representing one of six participants (labeled P1 through P6) across 10 attempts.

- P1: This participant's performance has the best score at the 3rd attempt and then demonstrates general growing trend.
- P2: Starting around 0.27, this performance shows the second attempt as the best, then an increase with fluctuations.
- P3: The performance begins just below 0.25, rises significantly towards the third attempt, and then demonstrates a mixed pattern of ups and downs. It is the only example when the first attempt was the most successful.
- P4: This participant's line shows an initial increase, followed by a sharp decline, achieving the best result, another rise, and ends with a significant drop until the end.
- P5: Starting just below 0.27, this participant shows the best result around the 8th attempt and the second best result around the 3rd attempt.
- P6: This participant's performance improves steadily until the 7th attempt.

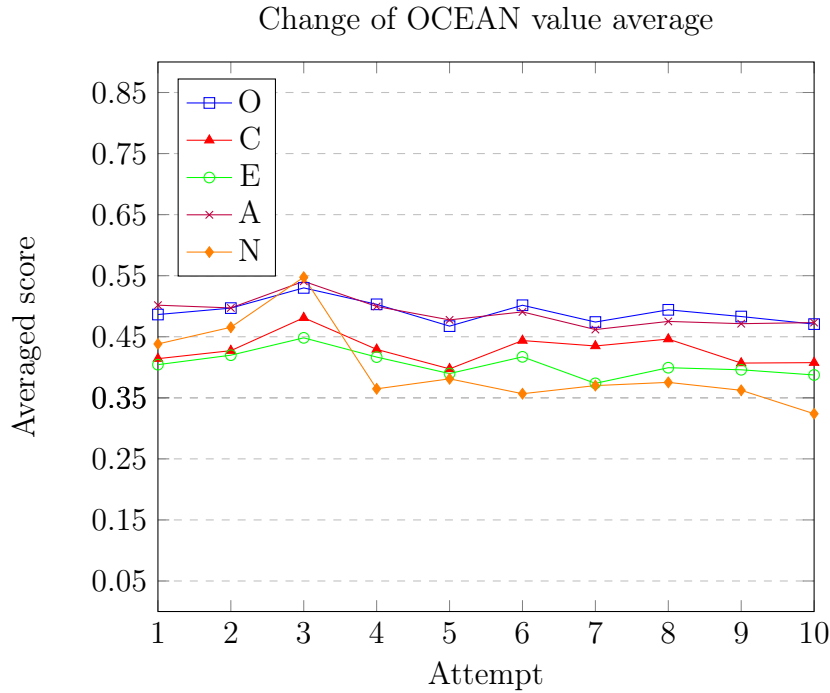


Figure 5.3: Change of OCEAN value average separately across multiple attempts for Interpret DAN model, where bigger score of all the values except N means better score.

Figure 5.3 shows changes in average scores associated with the OCEAN personality traits over a series of 10 attempts. For all the values except Neuroticism, a higher score is considered to be better one. For Neuroticism, this is reversed. The overall trend for these values can be observed in a way that the best scores for O, C, E, and A values were achieved at the 3rd attempt together with the worst observed value of N, while the best N-value is reached only by the 10th attempt. We can think about such patterns in a way, that participants had the highest score when they intensively tried to implement the feedback, while it could be the certain stress at the same time. Then there are decreased trend for all values which can be explained by tiredness from the process.

## 5.2 ResNet50 3D results

In contrast to the Interpret DAN results, where a sharp peak and decline in performance were observed, the ResNet50 3D outcomes present a more gradual trend until the best attempt but a sharp rise afterward.

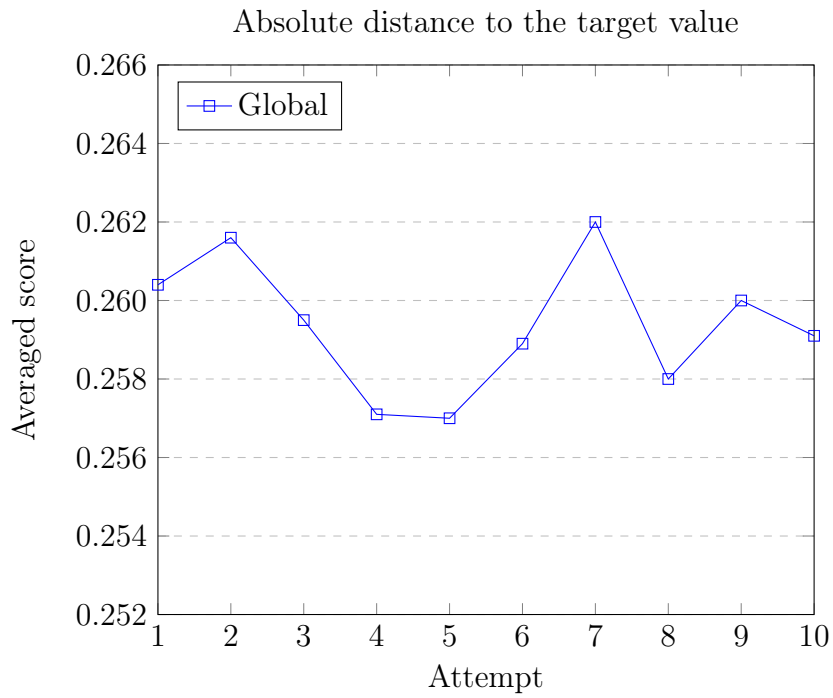


Figure 5.4: Global average of absolute distances to the target value across multiple attempts for ResNet50 3D model.

These results indicate gradual improvement by the fourth (0.2571) and fifth (0.257) attempts, marking the peak performance period.

Post-peak, the analysis notes a significant increase in the global average, where this can demonstrate potential challenges such as over-adjustment. The largest average distance (0.262) was reached by the 7th attempt.

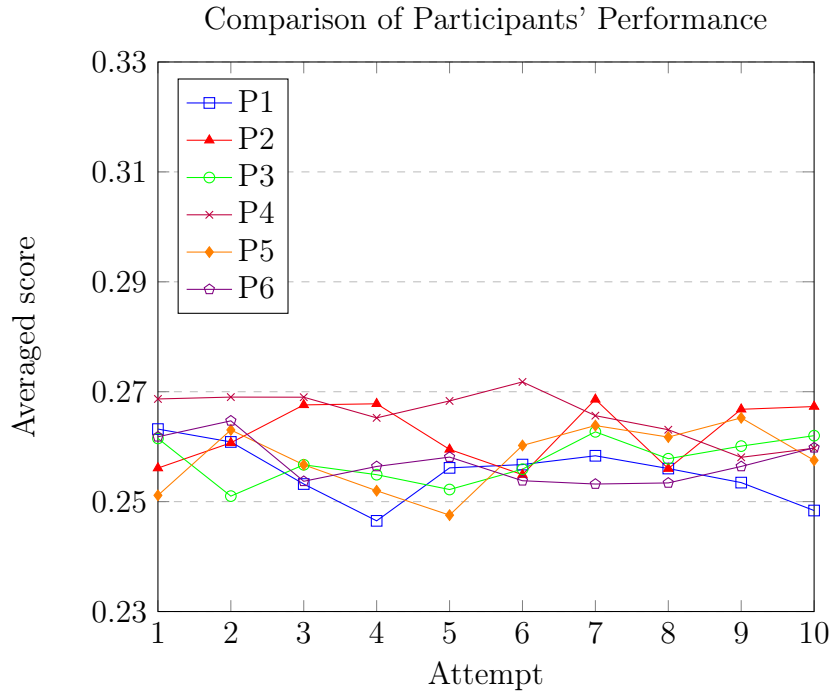


Figure 5.5: Average of absolute distances to the target value across multiple attempts for ResNet50 3D model per participant.

- P1: The scores fluctuate and demonstrate general downward trend. The lowest score is achieved on the 4th attempt.
- P2: Scores start lower, rise to a peak at the 3rd and 4th attempts, and then vary with a tendency to fluctuate. The first and the sixth are considered to be the best.
- P3: Less variability compared to P2, the lowest score is seen early in the 2nd attempt.
- P4: Scores are generally higher, with the lowest points occurring around the 4th and 9th attempts.
- P5: Scores start low, peak towards the middle, and end with moderate scores. The best performances are seen in the 5th attempt and near the 1st attempt.
- P6: The trend with minor fluctuations. The worst score is observed by the second attempt, while better performance is notable in the later attempts, from the 6th to the 8th.

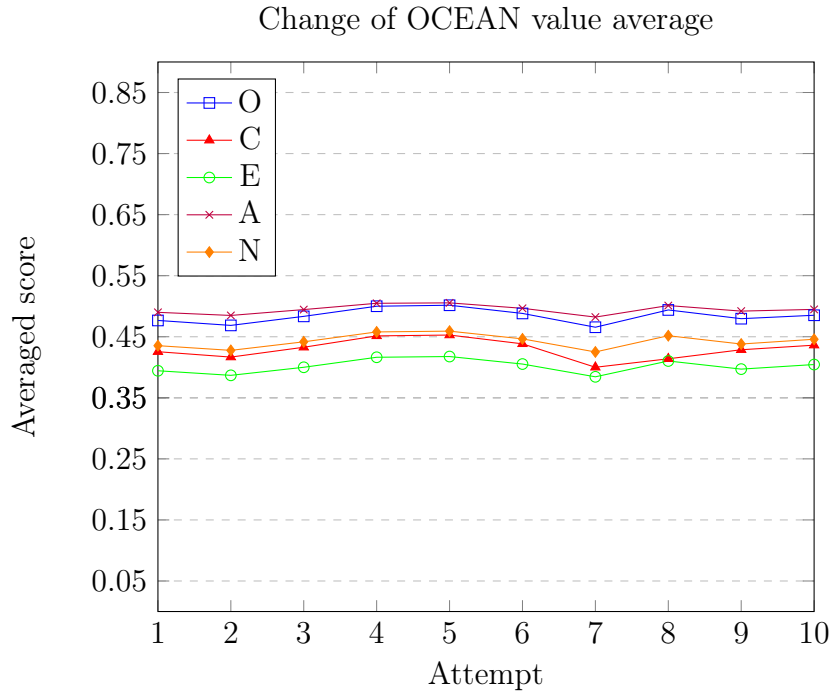


Figure 5.6: The change of each OCEAN value average separately across multiple attempts for ResNet50 3D model, where bigger score of all the values except N means better score.

Figure 5.6 demonstrates some peak for all the values around the 4th and the 5th attempts, including N value. Then, there is a decrease at the 7th attempt with hardly a trackable pattern afterward.

# Chapter 6

## Discussion and Future Steps

### 6.1 Discussion

In the observed trend where the DAN model's performance typically peaked on the third attempt, it can indicate that candidates were able to rapidly integrate and apply the initial feedback provided by ChatGPT. This quick adaptation likely reflects the initial straightforward improvements that were most apparent and easily correctable as well as feedback format was clear. It is worth mentioning that the 3rd attempt leads not only to the best performance attempt but also to the highest observed averaged Neuroticism score. Initially, the feedback provided by the AI tool likely heightened the candidates' arousal to an optimal level, enhancing their focus and ability to incorporate feedback effectively, leading to peak performance on the third attempt.

The subsequent decline in performance following the third attempt can be attributed to several factors. First, the complexity of continuing to adapt to feedback might have increased. After initial improvements, further adjustments suggested by the feedback could be repeatable and therefore challenging to implement, which might lead to less effective application. This was one of the complaints from almost all participants.

The smaller variance in the amplitude of acquired scores can be observed for ResNet50 3D. Interpret DAN, rooted in the VGG16 architecture and designed for image analysis, specifically focuses on extracting interpretable features from static images, and higher amplitude in scores can be attributed to its sensitivity to static image features, including subtle variations within individual frames. On the other hand, Visual ResNet50 3D extends the principles of 2D Residual Networks into the temporal domain, employing 3D convolutions to process video data which could result in a more consistent performance across attempts, as it integrates information over a sequence of frames, potentially smoothing over frame-to-frame variations and resulting in less dramatic fluctuations in performance scores.

Additionally, there could be a potential issue of overfitting the feedback. Candidates might overly focus on specific areas highlighted by the feedback, which could lead them to neglect other important aspects of their performance or to perform in a manner that appears rehearsed and less natural and they might experience increased anxiety about adhering to these aspects precisely, leading to a decrease in overall performance due to the pressure to perform perfectly in those areas.

Candidate fatigue is another important factor to consider. Continuous adaptation and the mental effort required to integrate feedback can lead to fatigue, which in turn may reduce the effectiveness of further attempts. The cognitive load of processing and applying complex feedback continuously can degrade performance over time due to heightened psychological pressure or fatigue.

Therefore, while immediate feedback from AI tools can significantly enhance performance initially by providing clear, actionable points for improvement, its effectiveness might decrease over time.

## 6.2 Future Steps

Future research could explore strategies to maintain the effectiveness of feedback over longer interactions, perhaps by varying the type of feedback to better sustain engagement and effectiveness. Developing adaptive feedback systems that correct the type and intensity of feedback based on the learner's performance, emotional state, and feedback receptivity could lead to better outcomes as well. To avoid the scenario of self-repeating feedback, future research could look into advanced prompt engineering techniques. This can be in a way that a specific AI-chatbot can be created with more precise and context-aware definitions, also, for example, adding shortcuts for initial calibration for each participant individually together with incorporating insights from psychology, especially related to motivation, emotion, and cognitive load. Potentially, audio-information processing can be also added to make the video analysis more complete.

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