An Unsupervised Approach for Study of the Relationship Between Behavioral Profile and Facial Expressions in Video Interviews

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Abstract: The use of Behavior Mapping (BM) questionnaires to analyze the Behavioral Profile (BP) of employees can lead to biased responses, incompleteness, and inaccuracies, especially when information such as reactions, facial expressions, and body language cannot be captured. Thus, methods with the ability to recognize and characterize BP automatically and without direct inference of bias can minimize the impact of erroneous assessments. Intensity clustering of Facial Action Units (AUs) from the Facial Action Coding System (FACS), extracted from video interviews of PACE BPs, was proposed. Features were extracted from 500 videos and effort was targeted to profiles whose probability was equal to or greater than 40% of the individual belonging to the profile. An analysis of the relationship between BPs and intensities throughout the video was presented, which can be used to support the expert's decision in the BM.

1 INTRODUCTION

Organizations are complex environments that require tactical development, meeting deadlines and making profits. In particular, managers and Human Resources (HR) professionals are interested in using data visualization and predictive analysis to make faster and more efficient decisions about employee performance, and profiles (Tursunbayeva et al., 2018). In this effort, Behavioral Profile Mapping (BPM) can be used to identify and understand the employee's behavioral profile within the organization. By mapping the behavior of employees, both during the hiring process and throughout the employee journey, BPM helps identify strengths and weaknesses and ensures that the right people are placed in the right roles.

Two strong BPM models, BigFive and DISC, stand out and are widely used in the literature (Ng, 2016; Grosbois et al., 2020; Kohút et al., 2021; Rengifo and Laham, 2022; Denissen et al., 2022). In these studies, the primary approach of HR professionals in BPM is highly dependent on the individual analyzed. The process consists of capturing information through reports, questionnaires, and tests developed by experts in the field, as shown in Figure 1.

This approach is prone to the cognitive biases of those involved in the process, which can cause differences in the understanding and interpretation of the answers, for example, by lack of sincerity or lack of self-knowledge of the employee when answering the questionnaire. These can cause inaccuracies and incompleteness in the BPM experts' assessment of the individuals studied. Several studies attempt to capture information less dependent on individuals' cognitive bias (Jerritta et al., 2011; Chernorizov et al., 2016; Al-Nafjan et al., 2017). Research on facial expressions, reactions, and body language, can be important clues about an individual's behavior profile (BP).

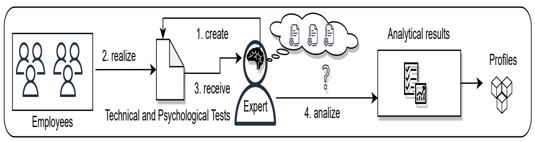

Figure 1: MPB process. The expert prepares questionnaires based on BP models, characteristics required of the candidate to fill the vacancy, and expertise. Candidates are submitted to the questionnaires and later this same specialist or others evaluate the answers analytically, outlining the BP and skills of the individuals.

The premise is that distinct individuals with the same BP carry similar behaviors and characteristics. Although BP depends on internal and external factors, it is changeable due to the complex nature of human beings. This means that BP can change as a function of the individual's experiences. The BP is con-

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sidered to be a state composed of several other stable states that repeatedly appear over time. A profile does not change suddenly and tends to stabilize by showing some statistically significant distribution.

Other types of data can be used to trace the BP of individuals during recruitment and selection of people. Multimedia data includes video interviews, written text from candidates, and information from resumes and previous jobs. Another important detail is that this type of data tends to be little exploited due to the complexity of manipulation, processing, and storage (Silberschatz et al., 1996; Kumari et al., 2018).

From a candidate's video interview, it is possible to capture important information such as facial expressions, reactions, and body language. This work focuses on associating the intensity of facial muscle movements throughout a video with the BP of individuals. The facial muscle movements are defined through facial Action Units (AUs) described in the Facial Action Coding System (FACS). The intensities of facial actions extracted from different individuals over videos can be understood as a multivariate time series that will be modeled in 3.1 object of analysis of this work.

The main contributions of this work are: (i) Using data extracted from video interviews, we propose a BP clustering methodology based on AUs; (ii) We provide an analysis of the relationship between BP and AUs, which can be used for decision-making by HR professionals; (iii) We make the database available to the community in the hope that it can support BP and FE related investigations.

The rest of the paper is organized as follows: Section 2 (Background) presents an overview of BPM; Section 3 (Related Work) introduces concepts about AUs and MTS analysis; In Section 4 (Experimental Setup) we present the dataset and applied methodology. We discuss the Experimental results in Section 5. Finally, conclusions and future works on this study are shown in Section 6.

2 BACKGROUND

2.1 Overview of BPM Studies

The first studies to understand personality and BP date back to before the Judeo-Christian period (Perrotta, 2019). Generally, human behavior is divided into four categories. For example, during ancient Greece, human behavior was related to the four classical elements of nature: fire, water, earth, and air. It was common to associate these elements with human faculties, such as morality as fire, aesthetics and soul with water, intellectual with air, and physics with earth. Hippocrates, the father of medicine, associated certain temperaments with the balance of body fluids: blood, black bile, yellow bile, and phlegm. Later, these temperaments were used by Galean to create BP nomenclatures choleric, sanguine, phlegmatic, and melancholic (Yahya et al., 2020).

Carl Gustav Jung refined Galean proposal, advocating the existence of four main psychological functions through which the individual experiences the environment (Bradway, 1964). These are the functions of sensation perception, intuition, the functions of feeling judgment, and thought. Jung argued that only one of these functions was dominant most of the time and that being a dominant function was characterized as conscious behavior, while the repressed opposite was unconscious (Wilsher, 2015).

A large number of psychometric tests have been developed over time for use in psychological assessments, particularly during the selection and recruitment process. One of the most famous is the Myers-Briggs Type Indicator (MBTI), which is a self-report assessment tool that analyzes a person's personality and behavior in specific situations (Henderson and Nutt, 1980; Murray, 1990; Sak, 2004). In the early 20th century, many other methodologies for personality assessment were also developed.

In 1932, the psychologist McDougall proposed the BigFive model, which defines five main factors that influence personality: Neuroticism, Extroversion, Amiability, Conscientiousness, and Openness to experience. Several studies present applications of BigFive in their assessments of behavioral responses, such as performance and care preferences (Tapus et al., 2014), emotions (Kohút et al., 2021), moral disinterest, unethical decision-making (Rengifo and Laham, 2022), and pro-social versus antisocial personality traits (Denissen et al., 2022).

The DISC was proposed by psychologist William Moulton Marston (Weiming, 2011). His approach defines four main types of behavior: (i) Dominance; which refers to control, power, and assertiveness, (ii) Influence; related to communication and social relationships, (iii) Stability; which refers to patience and persistence, and (iv) Conscientiousness; related to organization and structure. Applications such as personality assessment of students to send feedback to counselors and teachers about teaching methods, motivations, suggestions (Agung and Yuniar, 2016), assessment of students' response to videos during testing (Genc and Hassan, 2019), and assessment of users' tweets to determine PCs (Setiawan and Wafi, 2020; Utami et al., 2021) are presented in the literature. These and other models are widely applied, and others arise due to them. This is the case of the PACE model, which is inspired by DISC and other methodologies and which will be presented in Subsection 2.2.

2.2 PACE Behavioral

The PACE is a BPM approach that combines elements from the DISC personality assessment and other methods. It has gained popularity in Brazil due to its simplicity and ability to reflect cultural characteristics in profile assessments accurately. It is based on a questionnaire where the individual is asked to answer two questions. These questions are designed to assess the individual's internal and external self-perception. The answers to these questions are used to determine the individual's BP. The PACE BP are Planner (P), Analyst (A), Communicator (C), and Performer (E) and their combinations. All have four BPs, and the system assigns the respondent a probability for each BP. Thus, according to these probability assignments, the weighting of the dominance or combination of profiles is done to determine that individual's ranking by the system.

Profiles P have marked patience, stability, thoughtfulness, and persistence. They are calm, quiet, prudent, and controlled. They like to follow the rules and routines, interacting with active, dynamic people and formal environments. They need stable, secure work environments, support when working in teams and changing priorities, and develop emotions related to self-confidence, stubbornness, excessive worry, and greater flexibility to change.

Profiles A are precise, insightful, responsible, discreet, observant, quiet, concerned, detail-oriented, and rigid. They are calm, centered, intelligent, and can be perfectionists (skilled at tasks that require detail and risk management). They need to be stimulated to put their projects into practice, as they suffer from fears and conflicts when making mistakes and not thinking through possibilities. They tend to be quiet or withdraw momentarily when under pressure, but overcome this by deepening their knowledge.

Profiles C are sociable, enthusiastic, confident, outgoing, adapt quickly, and dislike monotony. They have ease of communication and change, with movement and autonomy, work best in teams, are imaginative, have artistic feelings, and need interpersonal contact and a harmonious environment. They don't like to go unnoticed, they are festive, lively, relaxed, travel and go out. They dislike routine, details, and understatement, and they are agile and quick-witted. They can be immature, impetuous, and need help to finish what they start.

E profiles are determined, independent, self-motivated, active, competitive, dynamic, take risks and challenges, are hard workers with great physical dispositions, and demonstrate perseverance. They have a logical and deductive attitude, obstacles stimulate them to act more and more, their imagination and judgment are balanced. They give priority to execution rather than thinking about how to do it, they prefer autonomy, independence and know-how to impose themselves on others. They must learn to be more flexible, they can be inflexible and authoritarian.

We note that the PACE BPM is not intended to discriminate between employees, but to understand the BP, due to the obvious differences in behavior, to support management decisions and thus better manage the organization's workforce. In this paper, we build a dataset whose profile classification follows the PACE methodology described above. More details about the dataset will be discussed in the section 4.

3 RELATED WORK

3.1 Facial Expression Analysis

The application of face and action recognition can be found in many areas, such as biology, neuroscience, psychology, disease detection, human emotions, security, learning systems, and surveillance. However, face recognition is challenging as many variations in head posture, lighting, and scale can affect the accuracy of the results. Facial Expressions (FEs) reveal intent, affect, and emotion (Baltrusaitis et al., 2018).

It is possible to extract FE features in videos, such as facial markings, head pose estimation, Action Unit (AU) recognition, gaze estimation in using e.g., the OpenFace tool[1]. OpenFace was built on the basis of the Face Action Coding System (FACS), first published in 1978 by Paul Ekman and Wallace V. Friesen. FACS is useful for identifying and measuring any FE that a human being might make. It is an anatomically based system for describing all observable facial movements in a comprehensive manner. Each observable component of easy movement is called AU and an EF can be divided into its constituent AUs.

Similar FEs follow the same pattern of relaxation and contraction of muscles in specific regions of the face (Lifkooee et al., 2019). For this reason, it is possible to define some units of action based on the area of the face whose muscles are contracted and relaxed. Facial units are defined as the variation of muscles in different locations of the face, eyes, mouth and eyebrows. These units follow patterns such as re-

[1] https://github.com/TadasBaltrusaitis/OpenFace

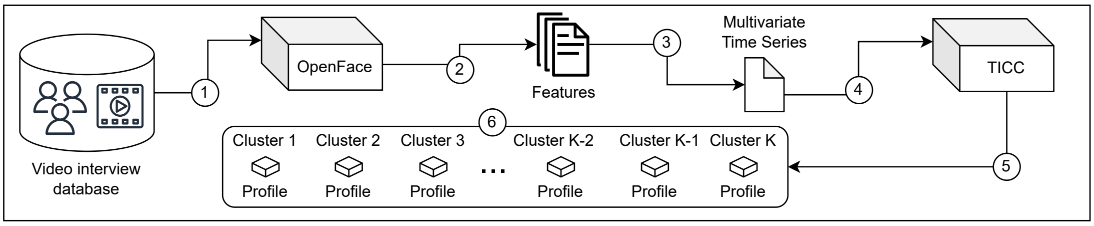


Figure 2: Facial Expression Analysis Approach as Multivariate Time Series (FEAA-MTS).

laxation and contraction in different FE. The AUs are described in Table 1.

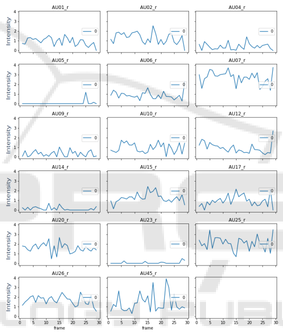
This variation in muscle movements is important temporal information for identifying the AUs presented according to the dynamics of the face 46 AUs describe 7000 FE. The advantage of using them is that they allow for representing a large number of FEs using a limited number of units. However, it can sometimes be challenging for classifiers to understand the spatial relevance of the action units as a class label since each belongs to a specific region of the face (Lifkooee et al., 2019). Facial activity is a dynamic event where activation and movement of facial muscles can be expressed as a function of time. AUs have activation velocities, intensity or magnitude, and orders of occurrence that are key to distinguishing movement (Tong and Ji, 2015).

Table 1: Description of AUs (Baltrusaitis et al., 2018).

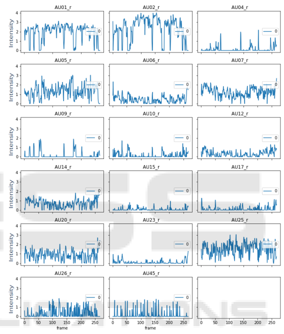
Action Unit	Description
AU01_r	*Inner Brow Raiser*
AU02_r	*Outer Brow Raiser*
AU04_r	*Brown Lowerer*
AU05_r	*Upper Lid Raiser*
AU06_r	*Cheek Raiser*
AU07_r	*Lid Tightener*
AU09_r	*Nose Wrinkler*
AU10_r	*Upper Lip Raiser*
AU12_r	*Lip Corner Puller*
AU014_r	*Dimpler*
AU15_r	*Lip Corner Depressor*
AU17_r	*Chin Raiser*
AU20_r	*Lip Stretched*
AU23_r	*Lip Tightener*
AU25_r	*Lips Part*
AU26_r	*Jaw Drop*
AU45_r	*Blink*

The extraction intensity provided by the OpenFace tool is always a value between 0 and 5 (low and high intensity). These features can be modeled as Multivariate Time Series (MTS), as multiple variables are being recorded over time from multiple individuals with different BP. The AUs have features that are key to distinguishing movement (Tong and Ji, 2015), including patterns of relaxation and contraction in different FEs.

A MTS is a set of variables observed and measured at regular intervals of (Hallac et al., 2017). Each variable is a function of time, and typically, they are correlated with each other. This set of variables collected over time form a MTS (Hallac et al., 2017; Kapp et al., 2020; Gui et al., 2021) that contains a collection of unique series called components, which are represented by vectors or matrices. Statistical techniques are used to analyze the relationships between multiple variables over time.

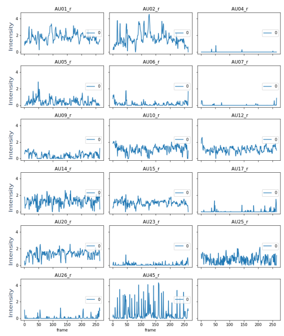


(a) Behavior for BP P



(b) Behavior for BP A

(c) Behavior for BP C



(d) Behavior for BP E

Figure 3: Behavior MTS for profiles PACE.

These techniques involve identifying patterns, trends, and correlations in data, which can be used to make predictions of values of variables. This methodology has been used in many fields, including economics, finance, meteorology and biology, engineering (Hallac et al., 2017; Li, 2019). The application of MTS is seen in the contexts of analyzing the behavior of automotive and synthetic sensor data (Hallac et al., 2017), detecting failure patterns in factory parts (Kapp et al., 2020), and extracting human action (Gui et al., 2021).

Analysis of multivariate distributions makes it possible to describe the behavior of several variables simultaneously, investigating the relationship between them, describing temporal and spatial dependence structures, and also condensing the information from several variables into a small number of latent factors (Hallac et al., 2017). Clustering of MTSs can be useful for identifying patterns and trends in data that may not be visible when looking at individual TSs, such as the behavior of the MTS of AUs in Figure 3. Such clustering can also help identify correlations between different variables, can be used to identify anomalies in the data, reduce data complexity, reduce the number of variables that need to be considered, and ultimately predict future values.

4 EXPERIMENTAL SETUP

This section aims to answer the following question: is it possible to relate the intensity of FE to PACE BP? The rest of this section describes the experimental setup used for this investigation.

4.1 Dataset

Candidates were instructed to voluntarily submit a video presentation and answer a PACE MBP form. The BP used in this paper are P, A, C, E, and combinations. Asynchronous video interviews of job candidates generally present data such as name, address, past experiences, goals, competencies, image of the professional, voice, etc. These are personal data protected by LGPD (Potiguara Carvalho et al., 2020; Carauta Ribeiro and Dias Canedo, 2020; de Castro et al., 2022) and therefore is disclosure is forbidden by the authors. Another implication that justifies the non-disclosure of the video base is the explosion of DeepFakes (Westerlund, 2019; Yu et al., 2021).

These are fake videos created with free machine learning-based software whose facial exchanges result almost perfect or leave little trace of manipulation (Güera and Delp, 2018), thus individuals could be targeted by hackers or malicious people. However, the database of AUs intensity and presence and absence properly anonymized, as well as the individuals' BP was made available as a contribution.

Also, since these are videos collected from candidates demographic data (age, ethnicity, gender, etc.) present many incompleteness and therefore were not the focus of this work, nor were data on this presented in the results. The Figure 4 shows the distribution of the videos in relation to the BPs. It is possible to see that the database adds up to 49% for the EC, CE, PA and AP profiles, representing a certain bias in relation to these profiles. One can also observe the presence of the dominant BPs P, A, C, and E, in much smaller quantities in relation to the previously mentioned BPs.

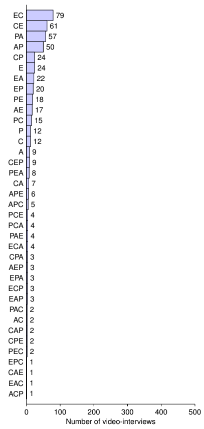


Figure 4: Distribution of BP from the database *PACE*.

From the database of 500 video interviews, ranging from 13s to 528s, about 94 were separated using the criterion of 40% or greater probability of the individual belonging to one of the profiles. The MTS were extracted from the intensities of the AUs using the OpenFace tool, then clustering experiments were performed using the TICC tool, and finally, comparisons with other techniques were performed. The feature file has about 121.965 lines containing intensity information of 17 AUs described in 3.1, frame and instant of extraction. In addition, the BP was incorporated after clustering for eventual analysis.

4.2 FEAA-MTS Approach

In Figure 2 one observes the FEAA-MTS approach consisting of 6 steps. They are: (1) Select a sample of video interviews (in the case of this work the database has 500 videos), (2) Extract features from the video interviews using the OpenFace tool (intensity of AUs, presence, absence frame and instant of extraction), (3) Filter extractions with 95% confidence and aggregate the extractions to a single file (MTS-AUs), (4) The generated MTS-AUs file will be input to the TICC tool [2], (5) Aggregation of the BP and clustering result of the TICC into the MTS-AUs file, and finally (6) Analyses and visualization of the MTS-AUs file data

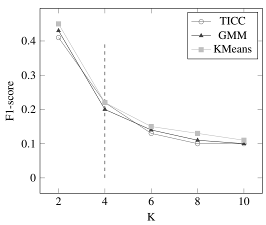
[2] https://github.com/davidhallac/TICC

for understanding the BP of the individuals.

The TICC is an algorithm that combines two optimization techniques which are Expectation-Maximization (EM) (Dempster et al., 1977) and Alternate Direction Method of Multipliers (ADMM) (Boyd et al., 2011) and has the ability to learn states and how they are partitioned. The EM technique is simple to implement and works basically by performing missing value estimation, updating the parameters and repeating until convergence. ADMM, on the other hand, solves convex optimization problems by dividing the problem into smaller problems, where at each step the problem is approximated by a quadratic programming problem.

Each state is a correlation network that is used to group and segment the MTS. What distinguishes TICC from other techniques is this correlation network created using covariance, also called a Markov random field (MRF), which is characterized by independence between the different observations in a subclass (Hallac et al., 2017). It is this MRF that is used by the algorithm to perform clustering, given the window size information w. This MRF represents the state that is repeated throughout the analyzed data and will be used by the algorithm to perform the separation of the instances. In addition, the Gaussian Mixture Model (GMM) (Xuan et al., 2001) and KMeans algorithms (Syakur et al., 2018) are used to compare the clustering performance of TICC. The difference between them and TICC is the metric that each uses. While TICC uses covariance, GMM uses mean and standard deviation and KMeans uses Euclidean distance.

After processing, we obtain the clustering of the MTS in relation to the intensity of the facial AUs of the sample. With this, it is possible to perform the aggregation of the cluster and the profile and then perform analysis and visualization of patterns that relate cluster, with profiles, intensities and instants of occurrence in the videos.



(a) Elbow method

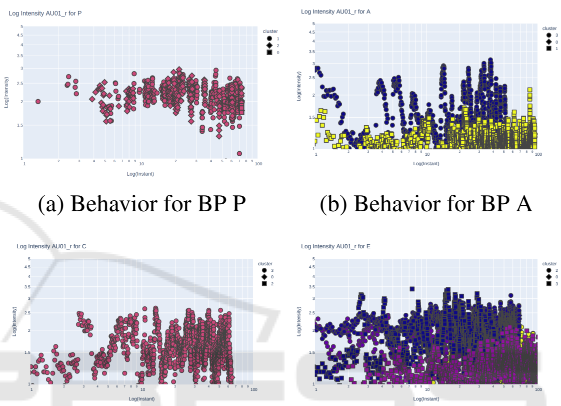
K	F1-score		
	TICC	GMM	KMeans
2	0.41	0.43	0.45
4	0.22	0.20	0.22
6	0.13	0.14	0.15
8	0.10	0.11	0.13
10	0.10	0.10	0.11

(b) Clustering results

Figure 5: Comparison of TICC, GMM and KMeans.

5 EXPERIMENTAL RESULTS

An experiment was conducted using basically three algorithms: TICC, GMM and KMeans. The two main parameters investigated were the K relative to the number of clusters and the size of the window used (followed by the value of K). In Table 5 in (a) we see the results of the F1-score metric presented by the three algorithms. It can be noted that TICC did not behave by presenting a higher value than the others, however, we recall here that the purpose of its use was to investigate the possibility of interpreting states from the clustering of the multivariate time series of AUs intensities.



(a) Behavior for BP P (b) Behavior for BP A

(c) Behavior for BP C (d) Behavior for BP E

Figure 6: Behavior MTS for profiles PACE.

In Figure 5 in (b) we see that $K = 4$ is the optimal value in the experiments performed and the performance is very similar. The elbow (Syakur et al., 2018; Cui et al., 2020) method was used, which basically tests the variance of the data against the number of clusters. You can see the elbow when you plot the results on a graph, and this value indicates that there is no gain with respect to increasing clusters. It should be noted that only a portion of the data was used due to limited resources in developing the research. However, the opportunity was observed to explore TICC on features extracted from video interviews, as a mechanism to understand and relate the behavior of the studied profiles in a less biased way.

In general, there are differences between frequencies, concentrations, and intensities of AUs among the PACE BPs throughout the video interviews, as seen in Figure 3 and one can observe the clustering behavior in Figure 6, where the states identified by TICC for AU01 are seen and the colors represent distinct individuals. It can also be stated that in all the profiles analyzed, the predominant AUs were of low intensity, except at the end of the video interviews, where a more significant increase occurs. A possible justification for this may be the need to have an impact at the end of the presentation, a fairly common mindset for those who are giving a presentation competing for a job opportunity.

6 CONCLUSIONS AND FUTURE WORKS

The study allowed the investigation of the behavior of AUs in video interviews of candidates, as a way to characterize the PACE BP of these individuals. The FEAA-MTS approach was proposed and applied, which is an attempt to cluster MTS of AUs extracted from FEs and thus try to identify states and associate them with profiles. We found evidence of frequencies and concentrations of AU intensities among the different profiles, but due to the sample size and resource limitations we should avoid generalizations.

As future work, we intend to expand the investigations, using more data, re-evaluate different ways of visualization to find different patterns and make the approach more effective and consequently the study less biased. Verify the impact of video summarization on the FEAA-MTS approach, since applying this method can generate processing savings.

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APPENDIX

More information, database, details and analysis are available at https://drive.google.com/drive/folders/1m4_78jlexsTtiYDuE-cOtnHQ1rQ_oh8M?usp=sharing by permission and approval of the authors.