ABSTRACT

Dyadic and small group collaboration is an evolutionary advantageous behaviour and the need for such collaboration is a regular occurrence in day to day life. In this paper we estimate the perceived personality traits of individuals in dyadic and small groups over thin-slices of interaction on four multimodal datasets. We find that our transformer based predictive model performs similarly to human annotators tasked with predicting the perceived big-five personality traits of participants. Using this model we analyse the estimated perceived personality traits of individuals performing tasks in small groups and dyads. Permutation analysis shows that in the case of small groups undergoing collaborative tasks, the perceived personality of group members clusters, this is also observed for dyads in a collaborative problem solving task, but not in dyads under non-collaborative task settings. Additionally, we find that the group level average perceived personality traits provide a better predictor of group performance than the group level average self-reported personality traits.

1 Introduction

How we express our personality to others is influenced by many underlying factors such as our relationship to those around us, the social situation in which we are in and our desired intent for the interaction. When describing the personality of an individual, it is common to utilise a trait based description of personality [1]. Within this trait based description, an individual’s personality is composed of the so-called big-five factors: Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism (OCEAN). These traits can be obtained in two ways; from self-report or from other-report. In the field of affective and personality computing the estimation of self-report personality is commonly known as personality recognition. Whereas the estimation of other-reported personality is known as personality perception [2]. Personality perception can be understood as the act of estimating the expression of a persons personality in the big five traits as viewed by an external observer. The perception of personality is influenced by a wide set of sources [3], specific attributes of speech such as speech rate [4], voice quality and intonation [5] have been shown to influence such estimations. Non-verbal cues also play a significant role in the perception of personality [6]. This has been shown in studies of gaze [7], back channels [8] and body language cues [9].

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Growing bodies of evidence have continue to support the relationship between personality and performance across a variety of tasks and both at the level of the individual \[10, 11\] and at the group level \[12, 13\]. While many of these studies focus on the relationship between self-reported personality traits, there are many examples in the current literature which outline the importance of evaluating other-reported perceived personality. While personality traits tend exhibit long-term stability, they are not fixed \[14, 15, 16\]. Studies have shown that within-person variation of personality traits can show significant short-term change \[17\]. However, the resolution at which this variation can be examined is limited by the frequency of questioning which may be used in current experience sampling methods \[18\].

With the introduction of the ChaLearn dataset \[19\], there has been significant progress in the area of automated personality perception from multi-modal sources. We leverage these developments in order to estimate the perceived personality state of individuals from a multiple audio-video sources which focus on dyadic and small group interaction. The automated nature of such methods provide a way to augment the resource and time intensive nature of experience sampling.

Through the evaluation of the time varying first-impression like personality, i.e., estimations of personality in which the perception is not influenced by earlier predictions which exist outside the thin slice of input under consideration. We examine the perceived personality state of individuals taking part in dyadic and group interactions. We examine multiple datasets which focus on dyadic and small group interaction. In order to analyse the generalisability of the developed method we make use of the provided perceived personality annotations present in the MULTISIMO dataset. For the dyadic case we analyse the UDIVA dataset \[20\] and for small groups the Emergent Leader (ELEA) \[21\] and AMI \[22\] meeting corpus. Both the UDIVA and AMI meeting corpus provide the opportunity to explore the potential changes in perceived personality over different tasks. Despite the limitation that the ELEA dataset provides only a single interaction session for each group, it provides a useful metric of group performance for the completed task. For all of these datasets we determine a time-averaged set of personality traits for each individual and evaluate the existence of the emergence of group personality, that is the convergence of individual personality states at a group level, as well as changes in expression of the participants personality across tasks.

In our analysis we first demonstrate the out-of-distribution performance of the trait estimation model performs similarly to human raters. Using estimates on perceived personality applied to both small groups and dyads involved in a task oriented interaction we examine the time-averaged personality states of group members for the existence of group level clustering and the subsequent evolution of the time-averaged personality traits across different tasks. Finally, we compare the predictive capacity of the time-averaged perceived personality and self-reported personality at the group level on a measure of group performance in a collaborative problem solving task.

2 Materials and Methods

2.1 Automatic perceived personality estimation

We estimate the big-five personality traits in a multi-modal fashion, in which we combine information from audio, textual and visual inputs. For the audio modality we compute the eGeMAPS features \[23\] using the OpenSmile \[24\] software. The textual modality is obtained from speech transcripts, from which BERT \[25\] embeddings are generated. The final visual modality comprises of facial action units \[26\] which are obtained using the OpenFace \[27\] software. Action units are used over the raw RGB video content to avoid influence due to visual factors such as clothing, location and background objects visible in the video.

These features are used with a transformer based model \[28, 29\]. An overview of the architecture is given in Fig. \[1\] and full details of the architecture can be found in \[30\]. The architecture is built on multi-head attention units that transform one modality to another. As we utilise three unique modalities, the model comprises of six cross-modal transformers.

This architecture follows that of \[31\], however we replace the quadratic attention modules with linear versions \[32\], providing similar performance \[30\] while being easier to train. The final output of the network is the prediction of the big-five personality traits, however we use emotional stability that refers to the ability that the person can remain balanced. The low end of our scale corresponds to high neuroticism, i.e., the person experiences negative emotions often.

Estimation of the big-five traits is made over a sliding window of duration 15 seconds and a stride duration of 1 second. The estimations are then averaged over a period of 30 seconds, providing a snap-shot of the perceived personality traits. From the big-five traits we determine a higher-order two-factor meta-trait representation of personality based on the suggested combinations of big-five traits as described in \[33, 34, 35, 36\]. These meta-traits are plasticity (PLA) and stability (STA), the former combining the traits of openness and extroversion and the latter conscientiousness, agreeableness and emotional stability. We express our traits of plasticity and stability as linear combinations of the
relevant big-five traits with equal weights set to unity. An example of the extracted meta-trait trajectories for one group is shown in Fig. [2]

2.2 Data sets

Four data sets were utilised in the study, these were the Emergent Leader (ELEA), AMI Meeting corpus, UDIVA and MULTISIMO. The ELEA dataset [21] contains video of small groups (3–4 participants) completing a collaborative task to produce a single ranking of items in terms of importance in a winter plane crash survival scenario. From this dataset we analysed 17 videos containing all three (audio, video, text) modalities. This corresponded to sessions: 12, 14, 16, 17, 21–26, 28, 32, 34, and 36.

The AMI meeting corpus [22] is a multi-modal dataset which aims to explore small group interactions in meetings. In these scenario meetings each group takes part in a series of four meetings with the goal of designing a new remote control. The meeting series starts with an initial kick-off meeting, followed by meetings on functional design, conceptual design and finishing with a detailed design meeting, these meetings are labeled as 'A', 'B', 'C' and 'D', respectively.

Understanding Dyadic Interactions from Video and Audio Signals (UDIVA) [20] is a multimodal, multiview, non-acted dataset that consists of face-to-face dyadic interactions. The participants sit at a table, and they are individually recorded during the sessions. There are 4 different tasks (Ghost, Talk, Animal, Lego) which vary in the level of collaboration and competition. This is a multi-lingual dataset, from which we focus only on the English language component.
MULTISIMO \cite{37} is another multi-modal dataset which is triadic, however the majority of interactions are dyadic. In the dataset, pairs work together to solve a quiz given by the third participant. We do not include this dataset into the analysis, however, as this dataset provides annotation of the big-five traits of the perceived personality estimated by external observers.

2.3 Data analysis methods

Evaluation of the trait estimation model, when applied to out-of-distribution samples (i.e. samples collected at a different time and under different conditions and environments) is conducted on the MULTISIMO dataset. We determine the inter-rater correlation factors by evaluating the average of all raters in which we consider the raters to be randomly selected. A two-one-sided t-test was applied to the distributions of the absolute error from the mean rating between each rater and the trait estimation model to determine equivalence of the model errors and human errors. We conduct this analysis trait-wise, and utilise a bound determined as the mean absolute error of the human rater for the target trait.

In order to evaluate any significance in group clustering we performed a PERMANOVA test with a pseudo f-ratio test statistic as described in \cite{38}. The test statistic is determined as $F = \frac{SS_A}{a-1}/\frac{SS_W}{N-a}$ where $a$ is the total number of groups in the study, $N$ is the total number of observations. $SS_A$ denotes the between-group variance. $SS_W$ is the within group variance and is calculated as the sum over all groups of the sum of the squared distance of individuals in the group to their respective group mean.

We computed the Maulchy’s W for each dependent variable which indicated that the variances were not equal for all dependent variables in the case of individuals and for the stability trait for groups. For these dependent variables we apply the Greenhouse-Geisser correction in our one-way repeated measure analysis of variance (ANOVA). For our post-hoc analysis we perform Welch’s t-test pairwise between meeting types for the case of AMI and between task types for UDIVA. For all pairwise t-test’s we apply a Holm-Bonferroni correction.

For the case of UDIVA, 10 individual participants repeated the tasks with a new partner. An additional repeated measure ANOVA was conducted on the same dependent variables, taking the task as the within factor.

Group performance prediction is conducted as a regression task using a Gradient Boosted Tree method. The performance metric under evaluation is the differences in ordering of the item importance determined by the group compared to an expert. Due to the limited amount of data we apply a leave-one-out cross-validation methodology, and report the average mean-squared error across all splits.

3 Results

Interrater correlation factor ICC(2,k) for the eight external observers surveyed in the MULTISIMO dataset were determined traitwise. Using the interpretation of the ICC values as described in \cite{39} we observe moderate agreement.
for the traits of openness (0.55), conscientiousness (0.62), and emotional stability (0.57). For extraversion (0.81) we find good agreement and we observe poor agreement the trait of agreeableness (0.43), for the meta-traits we see good to moderate agreement with plasticity and stability ICC values of 0.80 and 0.62 respectively.

Comparing the human raters to the predictive model we employed a two one-sided test (TOST) analysis, for both big-five and meta-traits. This analysis showed that for the OCEAN traits, the absolute error of the model from the human rater average is equivalent to at least half of the human raters. In the case of the meta traits, the absolute error of the plasticity is only equivalent with three of the eight raters and stability with seven out of eight raters.

The distribution of participant session averaged meta-traits are shown for ELEA in Fig. 3. For the ELEA and AMI datasets we find the formation of groups to be statistically significant. We perform the PERMANOVA for all datasets on both the big-five traits and meta-traits. The resulting histograms for the PERMANOVA is shown in Fig. 4 with the big-five results in red and the meta-traits in blue. For the ELEA dataset we observe a test-statistic for the five and two factor personality models of $F = 4.31$ and $F = 4.57$ respectively, both with $p < .001$. Similarly for AMI we observe the test-statistics $F_a = 4.41$, $F_b = 3.97$, $F_c = 7.92$, and $F_d = 7.08$ for the big-five and $F_a = 3.26$, $F_b = 5.20$, $F_c = 6.94$, and $F_d = 5.84$ for the meta-traits. For both cases all meetings have $p < .001$. The result on dyads in UDIVA, shows only a significant result for the “animals” task ($F = 6.49, p < .001$).

Repeated measures ANOVA conducted on the AMI dataset for individual participants showed a significant difference for all big-five traits, openness ($F = 16.76, p < .001$), conscientiousness ($F = 20.46, p < .001$), agreeableness ($F = 5.12, p = .002$), extraversion ($F = 19.35, p < .001$) and emotional stability ($F = 21.45, p < .001$). For the meta-traits a significant result was found for stability ($F = 3.88, p = .017$). For the plasticity trait a marginally significant result was obtained ($F = 2.73, p = .053$).

Post-hoc pairwise dependent t-tests across meetings showed significant differences over all combinations of meeting pairs for the trait of openness. The traits of conscientiousness, agreeableness and emotional stability showed a non-significant result between meeting B and C. Finally the trait of extraversion only showed significant difference between
Figure 4: Histograms of the permutation test. For each histogram we show the result for the evaluation of the meta traits in blue and the same evaluation on the raw big five traits in red. The top row shows the result for the ELEA perceived personality (left) and self-reported (right). The middle row shows the results for the four AMI phases from left to right (kick-off, conceptual design, functional design, detailed design). The bottom row shows the results for UDIV A from left to right (Animals, Lego, Talk, Ghost).

sessions A and C and A and D. No significant differences for the variable of plasticity was observed. The dependent variable stability showed a significant difference between meetings A and C.

For the group averaged traits, repeated measure ANOVA, showed significant differences for the big-five traits of openness ($F = 10.19, p < .001$), conscientiousness ($F = 14.64, p < .001$), agreeableness ($F = 10.93, p < .001$), emotional stability ($F = 12.76, p < .001$) and extraversion ($F = 3.15, p = .03$). A marginally significant difference was found for the trait of stability ($F = 2.45, p = .091$) across meeting types. The remaining trait of plasticity was not significant.

Post-hoc tests indicated the traits of openness and agreeableness had significant differences for meetings A and B, A and C, and C and D. Conscientiousness showed significant difference between meeting A and all other meetings. Extraversion like in the case of individuals showed significant differences in the fewest number of pairs. For groups this was only between meeting A and D. All dependent variables based on the meta-traits showed non-significant results.

Repeated measure ANOVA on individuals in UDIV A returned significant results for all dependent variables. For the variables related to the meta-traits both plasticity and stability were significant with $p < .001$. All of the big-five traits were also significant with $p < .001$.

For the group averaged traits in UDIV A the repeated measure ANOVA showed only significant differences for the all dependent variables with $p < .001$. Post-hoc pairwise t-test showed significant differences in plasticity $p < .001$ for the task pairs of Animals-Lego, Ghost-Lego and Lego-Talk. For the variable of stability significant differences were observed with $p < .001$ for all task pairs excluding Animals-Ghost.

In the case of UDIV A, there were 10 participants who repeated the series of tasks with another partner. A repeated measure ANOVA was performed to examine the potential effects due to the presence of a new partner. In this case no significant results for any of the dependent variables on any of the four tasks was observed.

In the case of UDIV A, there were 10 participants who repeated the series of tasks with another partner. A repeated measure ANOVA was performed to examine the potential effects due to the presence of a new partner. In this case no significant results for any of the dependent variables on any of the four tasks was observed.

Having observed across data-sets the emergence of clusters in the perceived personality we evaluated the predictive capability of both the group-level perceived meta-traits and the original big-five traits on the metric of group performance on the ELEA dataset compared to the provided self-reported personality traits. We obtain a mean-squared error (MSE) of $16.17 \pm 0.45$ with the group average perceived meta-traits and $22 \pm 1.26$ for the big-five traits. This is compared to a MSE of $43.88 \pm 1.17$ in the case of self-reported group average meta-traits and $40.68 \pm 1.10$ for the big-five traits.
4 Discussion

By evaluating the equivalence of the absolute error of the estimated perceived personality to that of the human rater, where we calculate the error between the estimate and the average rating of all human raters, we find that in terms of equivalence plasticity has the fewest equivalences with human raters. For this trait we can reject the null hypothesis against only 3 out of 8 human raters. For all other traits we find that there is equivalence within the prescribed bounds with at least 4 out of 8 human raters. For openness, agreeableness and stability we find equivalence with 7 out of 8 human raters, 5 out of 8 for extraversion and neuroticism and 4 out of 8 for conscientiousness. These results suggest that we can have confidence in the application of the model on other distinct but similar datasets which we can access video, audio and text modalities.

Our results on the remaining datasets are framed by the following ideas. Firstly, that personality expression is influenced by the situation experienced by the individual [40, 41, 42, 43, 44]. Secondly, in social interactions, participants may mirror their partners [45]. We found in the case of small groups in the ELEA dataset who are solving an object ranking problem and in all AMI meeting types, the perceived personalities traits of group members formed clusters. However, the analysis of of the dyadic case present in the UDIVA data, only shows this effect in “animals” task. Of the four tasks undertaken by the participants of the UDIVA study, only “animals” and “lego” may be considered somewhat collaborative.

In the case of “animals” the collaboration is achieved by the process of question and answers made by the participants in order to discover the participants assigned animal. While the “lego” task is collaborative, it does not require discussion or high levels of engagement between the participants. In this case the target object to construct is given, and only the process of construction is required. The “ghost” task is purely competitive, with both participants aiming to optimise their score against the other and “talk” present open conversation with no specific goal to be achieved as a group. The nature of these tasks and the findings suggest that the influence of others in a group may be felt even in the case of dyads, but the task and context of the interaction also play a role. The clustering of the perceived personality only occurring in the predominately collaborative tasks may be seen in the context of avoidance of social exclusion, which has been shown to effect personality expression [46].

In the further analysis of the big-five and meta-traits across meeting types in the AMI meeting corpus demonstrates that for many of the big-five traits there is a statistically significant change depending on the meeting type which is being carried out and has an effect both at the level of the individuals and at the group level. At both the individual and group level, the perceived extraversion appeared to be the most stable trait. Conversely, the higher-order traits as a linear combination of the big-five traits appear to exhibit less change across meeting types. The stability of the meta-traits does not extend in our analysis to the case of dyads in UDIVA. This difference in the stability of the higher-order traits may be due to the fact that in AMI all group tasks were collaborative and the context (design of a new product) was consistent between all meetings, with variation in task only being at the level of detail. Whereas UDIVA featured a wider variety of task goals. Further studies of dyads with consistent task goals similar to those in AMI may help explain these variations.

The additional analysis on the UDIVA participants whom repeated the four tasks with a new partner, showed no significant difference in their perceived personality between their first and second attempts at each task. However, due to the low number of participants who had repeated the set of tasks, we could not draw strong conclusions regarding this outcome.

While we have analysed the time-averaged traits in these studies, there remain many open questions about the factors which influence the observed dynamics of the perceived personality and the relationship they have to psychological processes [47]. The work of [48] describes a taxonomy of situations, which describe locations, associations, activities and experienced processes which are relevant to the expression of personality. Such a taxonomy may be useful in future experiment designs and the study of these factors may enable prediction of future changes in a individuals perceived personality state.

In addition to identifying causal factors, there is the question of what group and within group attributes may be predicted from the perceived personality of the group. In our study we compare the predictive capability of the perceived and self-reported traits from the ELEA dataset. We find that the perceived traits result in a more accurate prediction of group performance. While a large body of literature exists examining the relationship between self-reported personality and performance across a variety of tasks [49, 50, 13, 12], these results add further support to the idea that self-report alone may not be sufficient and in fact, other-rated personality traits may be stronger predictors [51, 52, 11].
5 Conclusion

In summary, this paper investigates the perceived personality of individuals in dyads and small groups estimated using deep-learning based methods, across multiple datasets. We first determined the perceived personality traits represented as the big-five traits, using a multi-modal linear transformer model evaluated on thin slices of the recorded meetings. We found that the model used to determine the perceived personality traits performs similarly to human raters present in the MULTISIMO dataset.

Using these estimates of perceived personality we evaluate the significance of the group membership with a non-parametric permutation test. For the ELEA and AMI datasets, we found the clusters centroids to be significantly different between groups with with \( p < .001 \), and for UDIVA a significant result was only observed for a single task out of the four evaluated tasks with \( p < .001 \). The task dependent nature of these results suggest that in small groups and dyads in which the task is collaborative, how personality is expressed clusters around the group. For the ELEA dataset it was observed that this result did not occur for the self-reported personality. Additionally we studied how both group and individual perceived personality traits varied over multiple tasks, we found that in the case of tasks in which the task does not deviate significantly, that the group average perceived personality traits demonstrated fewer significant changes between tasks compared to the individual group members. However, when the task context is significantly different between tasks we observe similar amounts of variation in the individuals and in the group averages.

Finally we evaluated the predictive nature of the perceived traits compared to self-reported traits for the task of group performance prediction. In the winter-survival task presented in the ELEA dataset the group average perceived personality meta-traits of plasticity and stability were a stronger predictor of the overall group performance than the group average self-reported meta-traits.

Author Contributions

KF Conceptualization, Formal Analysis, Software, Writing - original draft. AF Data Curation, Formal Analysis, Software, Writing - original draft. SB Investigation. RS Data curation, Software. CO Writing - review & editing. AL Conceptualization, Methodology, Writing - original draft, Supervision, Project administration.

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