A Multimodal Workflow for Modeling Personality and Emotions to Enable User Profiling and Personalisation

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Abstract: The Personality Emotion Model (PEM) is a workflow for generating quantifiable and bi-directional mappings between 15 personality traits and the basic emotions. PEM utilises Affective computing methodology to map this relationship across the modalities of self-report, facial expressions, semantic analysis, and affective prosody. The workflow is an end-to-end solution integrating data collection, feature extraction, data analysis, and result generation. PEM results in a real-time model that provides a high-resolution correlated mapping between personality traits and the basic emotions. The robustness of PEM's model is supported by the workflow's ability to conduct meta-analytical and multimodal analysis; each state-to-trait mapping is dynamically updated in terms of its magnitude, direction, and statistical significance as data is processed. PEM provides a methodology that can contribute to long-standing research questions in the fields of Psychology and Affective computing. These research questions include (i) quantifying the emotive nature of personality, (ii) minimising the effects of context variance in basic emotions research, and (iii) investigating the role of emotion sequencing effects in relation to individual differences. PEM's methodology enables direct applications in any domain that requires the provision of individualised and personalised services (e.g. advertising, clinical care, research).

1 INTRODUCTION

The interdisciplinary field of Personality science is concerned with identifying, taxonomizing, and understanding the key aspects of personality. Personality traits are the foundation for Personality science (McAdams and Pals, 2006) (John et al., 2008). Traits are the cognitive, behavioural, emotional, and motivational characteristics of a person that are stable across situations (McAdams, 2015). Each person varies along a continuum on any given trait (e.g. a person can range from highly introverted, to a cross between introverted and extraverted, to highly extraverted). And while a person's traits can and do change during their lifetime, the person's relative position on each trait's continuum remains stable (e.g. a highly extraverted child will also be a highly extraverted adult, even if their absolute levels of extraversion has decreased (Little, 2014)). Therefore, personality traits provide information about the enduring and unique structure of a person's psyche relative to other people[1].

There is an increasing demand for individualised and personalised technology and services that better realise and meet the idiosyncratic needs of each individual (Vinciarelli and Mohammadi, 2014b) (Subramanian et al., 2016). Personality science is a valuable tool for meeting this demand, as personality traits indicate the characteristic way a person thinks, acts, feels, and desires relative to other people. Personality enables researchers and professionals to apply client-centred approaches given the personal characteristics of their client-base, thereby gaining an advantage over those that use blanketed approaches. (El Bachari et al., 2010).

Personality is displayed via a variety of detectable cues (Mehl et al., 2006). These cues span across multiple modalities, ranging from central-nervous system activity, speech and language patterns, behaviour across a variety of settings (e.g. consumer behaviour, workplace behaviour), and self/peer report. To harness the potential of personality in user adaptation, there is a need to identify cues that (i) reliably indicate personality across situations and (ii) can be detected

[1]Personality is hereafter used as a shorthand for the collection of traits a person has. For information about the other aspects of personality, see (McCrae and Costa Jr, 1999).

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automatically and accurately.

This paper argues that emotions meet both of these conditions. The relationship between personality and emotions has been (i) likened to that between the climate and the weather: "*what one expects is personality [climate], what one observes at any particular moment is emotion [weather]*" (Revelle and Scherer, 2004). A significant body of both psychological and neuropsychological research supports this analogy (Wilson et al., 2017) (Davis and Panksepp, 2018). Emotions can be (ii) detected automatically across multiple modalities (e.g. writing, expressions, neurophysiological activity, behaviour, etc). Therefore emotions provide an opportunity for automatic personality recognition and categorisation research.

The field of Affective computing (AC) is well-positioned to avail of this opportunity. AC is concerned with the development of technological systems that can automatically detect, process, categorise, and display human emotion (Picard, 2000). Significant advances in automatic emotion detection have led to successful AC applications in multiple domains, such as in healthcare and education (Poria et al., 2017) (D'Mello et al., 2018). The relationship between personality and emotions provides an avenue for AC research to extend its reach. AC methodology enables automatic extraction of emotive-states, which can be statistically correlated with personality traits, to gain information about the enduring characteristics of users.

The goal of the Personality Emotion Modelling (PEM) workflow is to provide an end-to-end solution that enables researchers to map personality and emotions via AC methodology at scale. This workflow identifies the key components for both personality and emotion that have been validated and are readily accessible via predefined interfaces. Additionally, this workflow is automated in that the appropriate AC methodology for extracting and categorising emotive-states would be built into the workflow, enabling researchers to upload their data for analysis. The analysed data would then be correlated with the personality-traits of their participant sample and the resulting state-trait mappings are visualised in terms of their magnitude, significance, and direction.

The remainder of the article is organised as follows. Section 2 defines the key psychological phenomena of the workflow. Section 3 presents the workflow of the model. Section 4 discusses the value of PEM in contributing to open research questions and the sustainability of the workflow. Section 5 discusses the potential applications of PEM and provides a direct use case scenario. Section 6 summarises the work and presents conclusions.

2 PERSONALITY TRAITS AND THE BASIC EMOTIONS

Personality traits are typical expressions of emotion, cognition, behaviour, and motivation across time (Costa and McCrae, 1995). Personality traits reliably and accurately predict important life outcomes concerning health, relationships, and career success (Soto, 2019). Personality traits represent our unique general temperament or disposition towards the world (DeYoung, 2015).

The Five Factor Model (FFM) is considered an overarching paradigm from which to view Personality science (John et al., 2008). The FFM provides a taxonomy of personality based on five broad traits: Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism (McCrae and John, 1992). These five traits are considered to be at the highest level of the trait hierarchy with each factor being an aggregate of multiple lower-level facets (i.e. a specific aspect of personality) that correlate highly with one another (e.g. Agreeableness is made up of facets such as empathetic, co-cooperativeness, and modesty (Graziano and Tobin, 2009)). This aggregation provides a greater bandwidth that strengthens the accuracy of predictions across situations, but it weakens the accuracy of predictions in specific situations (Soto and John, 2017).

A potential solution to this limitation is the provisioning of an intermediate level between the FFM and their facets. This intermediate level would (i) retain adequate generalisability to assess cross-situational psychological consistency (ii) but would also be "narrow" enough to enable specific behavioural prediction. Candidates for such an intermediate level have been identified; psychometric and genetic research have demonstrated that each FFM trait can be broken down into two further aspects, defined here as "sub-traits" (DeYoung et al., 2007).

The benefit of using this intermediate level has been demonstrated in experimental studies (Allen et al., 2018) (Leon et al., 2017). For example, researchers that previously investigated the relationship between the FFM factor Agreeableness and political orientation found inconsistent results. However, research that incorporated the sub-trait hierarchy demonstrated that the two sub-traits of Agreeableness - Compassion and Politeness - correlated with left-wing and right-wing political orientation respectively (Hirsh et al., 2010). The importance of sub-traits in identifying new links between personality and life-outcomes has also been showcased in clinical and educational domains (Allen et al., 2018) (Leon et al., 2017). These are promising indications that sub-traits

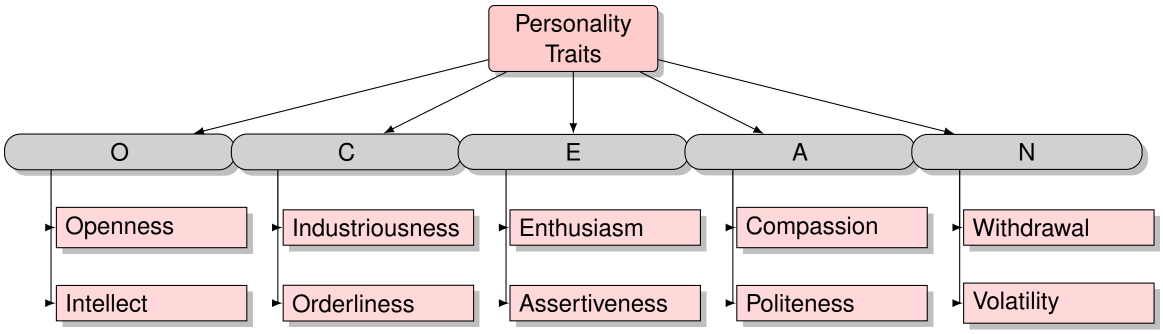

Figure 1: The Five Factor Model's five broad traits (Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism; OCEAN) and the associated sub-traits as specified by (DeYoung et al., 2007). The five broad traits represent the highest level of the personality trait hierarchy. The foundational level of the trait hierarchy are facets, which aggregate to form each of the five broad factors. The sub-traits operate in an intermediate level between these two levels and enable a higher resolution analysis of an individuals personality.

are an integral component for assessing the influence of personality in applied research settings.

Therefore, the PEM workflow incorporates the sub-trait level of personality to (a) enable investigation of the particular influence of sub-traits in user-tailoring and targeting and (b) to assess the claim that the sub-traits offers a higher level of specificity than the FFM without sacrificing generalisability. If (a) and (b) can be empirically demonstrated, then this supports the presupposition that this intermediate level is the next necessary component for future FFM theories. PEM's primary focus is to assess both (a) and (b) in relation to the basic emotions.

2.1 The Basic Emotions

Basic Emotion Theory (BET (Hutto et al., 2018)) states that there exists a set of emotions that are considered distinct from one another (Ekman, 1999). These distinct emotions are labelled basic because they are (i) deeply rooted in subcortical areas of the brain and have been the most influenced by evolution (Ekman and Cordaro, 2011) and (ii) are the foundation for more cognitive and culturally mediated emotions, such as shame or guilt. BET asserts that for an emotion to be considered basic it should be coupled with highly consistent and distinct psychological, behavioural, and physiological patterns (Ekman and Rosenberg, 1997).

Therefore, emotion is defined here as the subjective experience of a particular emotion coupled with physiological and behavioural activity that occurs simultaneously (Ekman and Rosenberg, 1997). This definition encapsulates both the "raw" subjective feeling of each emotion and the associated activity that researchers can objectively measure (Ekman, 1999). PEM considers the following emotions to be the basic emotions: Anger, Anxiety, Disgust, Fear, Joy, Sadness, Surprise. Donovan et al. (2020) discuss the rationale behind this selection.

In the basic emotion literature, there is an ongoing debate about the universality of emotions and whether emotions have culturally independent and universal signals (Lewis et al., 2010) (Barrett et al., 2016) (Barrett, 2017) (McDuff et al., 2017). A strong position on the universality of these emotion signals is not taken by the authors, as the validity of PEM is not dependent on the apriori assumptions of BET. PEM focuses on the basic emotions for pragmatic purposes, as the basic emotions are well-defined and have been thoroughly researched. However, PEM is seen as a tool for providing insights into this debate. The meta-analytical and multimodal approach provides a means for robust analysis that can add clarity to this debate.

3 THE PEM WORKFLOW

The primary goal of the PEM workflow is to provide an end-to-end solution for personality-emotion modelling that results in a live instance. Live instances will provide (a) empirical insight into multiple open questions surrounding Personality science; (b) providing a high-resolution understanding of the specific emotive nature of personality traits; (c) providing an analytical dashboard to enable a meta-analysis of the magnitude and direction of results across research groups. The varied nature of these insights reflects the multi-purpose uses of the PEM workflow.

Two primary groups are envisaged as users of PEM, namely theoretical researchers and industry professionals. Researchers will consist mostly of psychology and Affective computing practitioners. Similarly, industry users will consist mostly of psychological professionals in various domains (e.g. education) and those interested in user-profiling (e.g. advertising

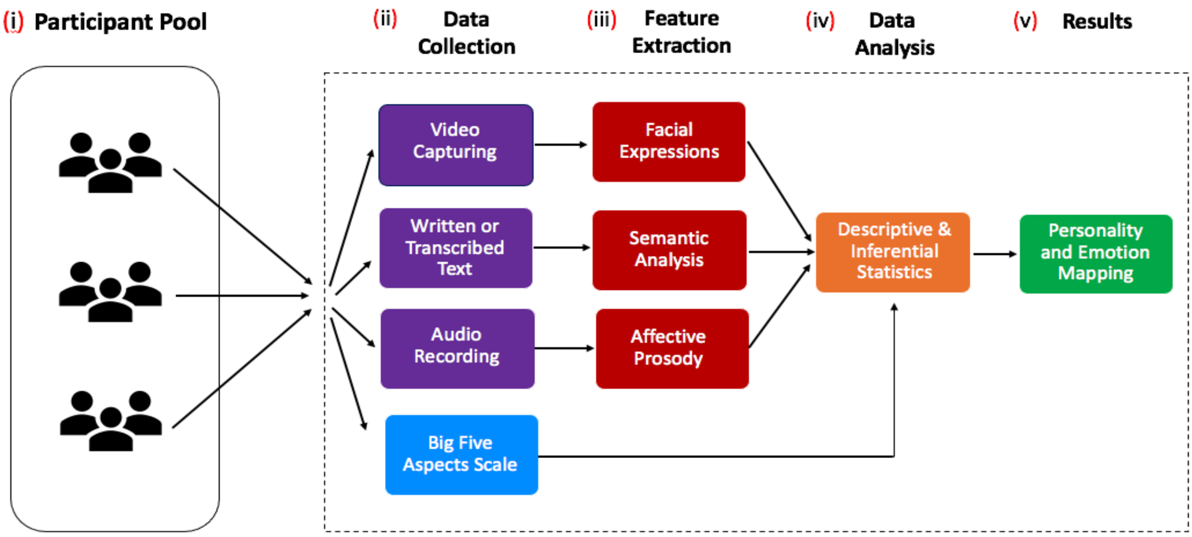

Figure 2: The PEM Workflow.

15 Personality Traits	Fear	Anger	Joy	Anxiety	Sadness	Surprise	Disgust
Openness to Experience	X	X	X	X	X	X	X
Openness	X	X	X	X	X	X	X
Intellect	X	X	X	X	X	X	X
Conscientiousness	X	X	X	X	X	X	X
Industriousness	X	X	X	X	X	X	X
Orderliness	X	X	X	X	X	X	X
Extraversion	X	X	X	X	X	X	X
Assertiveness	X	X	X	X	X	X	X
Enthusiasm	X	X	X	X	X	X	X
Agreeableness	X	X	X	X	X	X	X
Compassion	X	X	X	X	X	X	X
Politeness	X	X	X	X	X	X	X
Neuroticism	X	X	X	X	X	X	X
Withdrawal	X	X	X	X	X	X	X
Volatility	X	X	X	X	X	X	X

Figure 3: Analytical dashboard for visualising statistical correlation of state-to-trait mappings for a PEM live instance. Note: the magnitude and direction indicated by this figure were generated randomly. For an example of the analytical dashboard based on empirical research, see (Donovan et al., 2020b) and (Donovan et al., 2020c).

or political campaigning). In both cases, PEM enables a holistic comprehension of the needs and characteristics of target populations.

The PEM workflow consists of several stages as depicted in Figure 2:

(i) Participant Pool: A suitable participant pool, which is dependent on the aims of the specific study, is recruited by the user groups for data collection.

(ii) Data Collection:

The PEM workflow necessitates two types of data input:

1. *Personality Data Types.* The hierarchical trait model used in PEM requires the use of data from the Big Five Aspects Scale (BFAS). The BFAS breaks down the personality of the participant based the Five Factors and their sub-traits as described in Section 2.

2. *Emotive Data Types.* PEM necessitates data collection from at least one of the emotion modalities. Data collection can either be conducted directly or taken from already existing data-sets. The modalities are video capturing, written or

transcribed text, audio, and self/peer report.

(iii) Feature Extraction: Features are extracted for emotional content based on the modality of the data. For example, from video capturing PEM extracts facial landmarks points that indicate emotional expressions (e.g. muscle movements around the face, eyebrows, nose, and mouth). This process is currently automated by a support vector machine classification trained on two different datasets (Healy et al., 2018).

(iv) Data Analysis: Descriptive statistics are derived from the underlying features to compute the mean for each basic emotion per person. The data is also assessed to ensure that it matches parametric assumptions of the inferential statistical tests.

The processed emotion data is then statistically correlated via a Pearson R correlational test with the personality traits of the participants contributing a live instance. Currently, the PEM method for conducting correlations is Pearson R. Pearson R measures the linear relationship between two variables via the R effect size, ranging from a score of -1 (indicating a complete negative linear relationship between two variables) to +1 (a complete positive linear relationship), with 0 indicating no linear relationship (Field et al., 2012).

(v) PEM Model Instance: Figure 3 depicts an example of the analytical dashboard of a live instance with correlations between each of the 15 personality traits and the 7 basic emotions.

The nature of the relationship (positive, negative, or no relationship) and the strength of that relationship is represented by the colours green, red, and white. Green indicates a positive relationship, red indicates a negative relationship, and white indicates no relationship. Darker shades indicate a stronger relationship. This shading is based on the magnitude of the Pearson R effect size (Cohen, 2013).

Each live instance dynamically updates the analytical dashboard as new data is inputted. This enables live analysis of state-trait mappings in terms of statistical significance, magnitude, and direction.

4 DISCUSSION

An experimental study with 38 participants was carried out to validate the PEM workflow (Donovan et al., 2020b). The results of the study demonstrated that 4 of the 7 basic emotions (Disgust, Joy, Sadness, and Surprise) considered in PEM correlated significantly and substantially with one or several personality traits. Two further basic emotions approached statistical significance (Fear and Anger) in their correlations with personality traits.

Several of the significant relationships found between personality traits and basic emotions either only (i) emerged at the sub-trait level, or (ii) the magnitude of the relationship was greater at the sub-trait level than the Five Factor level. This result supports the need for high-resolution analysis of personality incorporated by PEM, as otherwise these findings would have been undetected [2].

4.1 PEM's Contribution to Longstanding Research Questions

PEM can provide contributions to several research questions. These research questions include:

1. What is the emotive nature of personality?
2. How to minimise the effects of context variance in basic emotion studies?
3. What are the main emotion sequencing effects and how do they differ with respect to individual differences?

4.1.1 What is the Emotive Nature of Personality?

Outside of a few research studies, e.g. (Donovan et al., 2020a) and (Gavrilescu, 2015), the relationship between personality and emotion outside of Extraversion and Neuroticism has been overlooked. This is unfortunate, because understanding the relationship between these two phenomena is important, as research that can detect this relationship has the potential to enable greater user adaptability in both theoretical and practical domains.

PEM addresses this question by explicitly modelling the interaction between personality and emotions across modalities. The results of PEM studies - once pooled together into an analytical dashboard - will enable one to draw empirically driven observations of the emotive nature of personality traits.

4.1.2 How to Minimise the Effects of Context Variance in Basic Emotion Studies?

The debate regarding the influence of cultural differences on the BET warrants further empirical study and analysis. PEM contributes to this debate by (i) enabling comparisons between real-time PEM dashboard instances across modalities. This enables a comparison between populations from different cultures for differences in emotional expressions. PEM

[2]See also (Donovan et al., 2020c). This preprint compares personality to emotion mappings across the modalities of self-report and facial expressions.

also contributes to this debate by (ii) enabling a multimodal perspective, enabling researchers to assess emotions based on a broad spectrum of input, including voice, facial expressions, language, and self/peer reports. This contribution (ii) avoids the criticism targeted at BET research, that the BET field is over-reliant on using subjective self-report methodology for collecting data (Barrett, 2017). Both contributions represent means of either minimising and/or understanding the effects of culturally based variances concerning basic emotions.

4.1.3 What Are the Main Emotion Sequencing Effects and How Do They Differ with Respect to Individual Differences?

A common experimental protocol in BET research is to separate emotional stimuli with a neutral task to bring participants back to a "baseline" state. This is done to avoid sequencing effects, where the experience of one emotion either increases or decreases the likelihood of experiencing subsequent emotions. For example, the emotions Anger and Disgust have been shown to have sequencing effects with one another, where the experience of one makes the experience of the other emotion more likely to occur (Salerno and Peter-Hagene, 2013). However, it is not clear whether there exist sequencing effects across other basic emotions, and whether personality plays any mediating role for such effects. PEM provides a platform for researchers to design future studies to test such hypotheses and to assess sequencing effects with respect to individual differences.

4.2 The Sustainability of the PEM Workflow

The sustainability and reusability of the workflow are differentiated between the two primary user groups - theoretical researchers (both in AC and Psychology) and industry professionals.

PEM provides researchers with a workflow for generating, testing, and developing applications to improve human-computer interaction. For instance, in semantic analysis research the challenge of distinguishing between emotional states in the presence of sarcasm or jokes is a difficult one. However, personality has been successfully applied to determine the meaning of ambiguous statements (Poria et al., 2016). AC researchers could utilise personality data to minimise ambiguities in content from client or user groups (Mehta et al., 2019) resulting in higher accuracy.

PEM provides professionals with a workflow for a better understanding of the emotional states or personality traits of a target audience. For example, to gauge the personality of a target audience, text from the audience could be collected. Semantic analysis can then be conducted to assess the basic emotional states of the audience, which can then be used to infer their associated personality traits.

5 PEM USE CASE: A NON QUESTIONNAIRE METHOD OF PERSONALITY ASSESSMENT

There are several potential applications for the PEM workflow. One potential application is in the domain of personality assessment. The current methodology for assessing personality is the use of Likert-scale questionnaires (Anglim and O'Connor, 2018). These questionnaires ask participants to rate how well statements regarding typical patterns of thought, behaviour, emotion, and motivation apply to themselves or another person. The accuracy of questionnaires as a personality assessment tool indicates that they report quite well on both accounts, but they are not exhaustive (Vinciarelli and Mohammadi, 2014a).

There are several deficiencies with questionnaires that inhibit an exhaustive detection of personality:

- Highly accurate personality questionnaires are time-consuming and monotonous to complete (e.g. the NEO-FI-R contains over 200 questions and takes over an hour to complete on average). Shorter questionnaires can take less than 10 minutes to complete, but they are significantly less accurate (Anglim and O'Connor, 2018).
- Questionnaires assume a level of cognitive competence that effectively excludes several groups of people (e.g. young children, people with literary issues, and cognitive disorders).
- Results also show that repeatedly taking personality questionnaires decreases its accuracy for the results of that person, a phenomenon known as a "retest artifact" (Durham et al., 2002).
- Personality questionnaires are a secondary source. Questionnaires require participants to sit and focus on a set number of questions for a length of time, rather than assessing personality "in the wild" from real-world interactions (Baumeister et al., 2007).

PEM provides a foundation for non-questionnaire-based inferences of personality via state-to-trait mappings. Interested parties can acquire and analyse data via stages (ii) - (iii) to extract information about emotion states. Users can then use this information along with a state-to-trait live instance (v-vi) to infer the likely personality traits of each member of the participant pool, given their observed emotive states.

There are several advantages to such an approach, as it would (a) be inclusive to all members of the population, and (b) it enables continuous personality assessment based on data acquired from multiple modalities. The value of assessing personality via the modalities listed in stage (i) is that such signals can indicate personality in natural settings (e.g. semantic analysis of text messages). This would constitute a valuable personality assessment tool.

6 CONCLUSIONS

The Personality Emotion Model (PEM) workflow enables automated and quantified bi-directional personality-emotion mappings. PEM specifies a standardised approach for data collection, specifying the required data input for personality and emotion to enable mappings. PEM identifies methods of feature extraction to identify the emotive content per modality that is needed for inferential statistical analysis. The appropriate statistical tests to correlate these phenomena and to generate a model instance is also identified in the workflow. Overall, PEM provides automation for many of these aspects, providing a tool for extracting emotive states and correlating them with personality traits that are built-into the workflow.

PEM provides several advantages over modern approaches in personality/emotion research: (i) PEM utilises a meta-analytical and data-driven approach to quantify and reduce the impact of sampling/cultural variance; (ii) PEM provides a methodology that facilitates contributions to research questions in the fields of Personality science and Affective computing; (iii) PEM assesses personality at a high-resolution level of the trait hierarchy increasing the likelihood of capturing statistically significant relationships between personality traits and the basic emotions; (iv) PEM facilitates multi-purpose applications of results across research and industrial domains; (v) PEM is flexible, enabling the model to be used in domains relating to personality and/or emotions; (vi) PEM is adaptive, in that the model will be refined as more data is collected; (vii) The results of PEM will be open-sourced and available online for interested groups to use.

PEM enables practical applications. One potential application is the establishment of a non-questionnaire method of personality assessment. Such a method of personality assessment would enable researchers to study personality in more naturalistic settings, using a combination of modalities to extract information and identify personality in natural settings.

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