UNIVERSITY OF PADOVA

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Final Dissertation

‘The Face of the Other: Investigating the Psychological and Neurophysiological Predictors of Emotion Authenticity Discrimination’.

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Abstract

While emotion recognition has been extensively studied, the ability to distinguish between genuine and posed facial expressions remains largely underexplored. This study examined behavioral and neurophysiological predictors of emotion authenticity discrimination, using dynamic, ecologically valid stimuli from the Padova Emotional Dataset of Facial Expressions. Forty healthy psychology students underwent a resting-state electroencephalography (RS-EEG) recording, followed by the Emotion Authenticity Recognition (EAR) task. Behavioral performance was analyzed alongside standard periodic oscillations, aperiodic baseline EEG parameters, and socio-cognitive assessments, specifically evaluating Alexithymia (via the TAS-20) and Theory of Mind (via the RMET). Results revealed no overall "truth bias"; instead, authenticity discrimination appeared to be highly emotion-specific and modulated by perceived stimulus intensity. Moreover, higher externally oriented thinking (EOT), a specific aspect of alexithymia, was associated with a better ability to detect simulated expressions. At the neurophysiological level, while periodic oscillations yielded null effects, baseline aperiodic parameters revealed distinct predictive neural strategies: a higher temporal Exponent predicted recognition of genuine expressions, suggesting automated processing, whereas higher parietal Offset and Exponent values predicted recognition of posed emotions, indicating complex integration and increased metabolic effort. Interestingly, no predictive effects were observed in the motor cluster. These findings emphasize that authenticity discrimination is a complex, context-dependent cognitive skill supported by different neurophysiological dynamics.

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Chapter 1

Introduction

We spend most of our lifetime surrounded by people, engaging with and interacting with them. As we don’t have direct access to other people’s thoughts, we constantly try to unravel the true meaning of their words and actions. To do this, we strongly rely on facial expressions to identify movements, however subtle, that may give us even a glimpse into the true nature of other people's actions and choices.

Emotions play a pivotal role in our social life: the ones we feel are significant clues that act as a compass drawing us toward or distancing us from others. Similarly, observing the emotional expressions of those around us provides vital context that shapes our decisions. Being able to correctly interpret such powerful signals is essential for healthy social functioning. However, while much is known about the emotional recognition process, one major aspect of human social practices has often been overlooked: the role of deception. By lying, feigning emotions, and concealing our intentions, we change the outcome of social interactions. Are we really capable of “unmasking” others? Are there individual characteristics that make us experts? How does our brain integrate this information?

This work aims to present, analyze, and discuss these questions.

1.1 Evolution of Face Perception

The human face has always been of interest. A great variety of fields have dedicated time and effort to grasp its essence. Faces are one of the most informative stimuli we can perceive, in that they present us with a significant amount of socially relevant information (e.g., identity, sex, mood, age, race, focus of attention, intention) essential to carry out tasks beyond mere identification, such as inferring other people's emotions and interpreting people's intentions. As pivotal as it is, face perception is perhaps the most advanced visual perception ability we possess and is one of the first abilities to emerge after birth: newborns' predilection for face-like arrangements with the substantial presence of their caregiver's faces in their early visual world paves the path to becoming face experts (Barrett et al., 2019; Sugden & Moulson, 2016; Young & Burton, 2018). How do we make sense of all this information? To investigate the complexity of authenticity perception, I would like to start by observing the trajectory of face perception models.

Research in this field has its roots in the influential model by Bruce and Young (1986): 'Understanding face recognition', in the British Journal of Psychology. Largely based on behavioral observations, their cognitive model postulated the existence of distinct, functionally independent routes for identity extraction and facial expression (Bruce & Young, 1986). Their work established a theoretical framework that has since shaped the debate regarding how we process faces and the steps involved in this process. (Calder & Young, 2005; Haxby et al., 2000). Technical advances in brain imaging techniques have made it possible to study non-invasively and with greater anatomical precision the brain regions involved in face processing, allowing us to observe their dynamics and interplay.

The influential neurobiological model proposed by Haxby, Hoffman, and Gobbini (2000) mapped onto a neurological framework the functional architecture proposed by Bruce and Young (1986). They defined a hierarchical mechanism encompassing a *core system* for the visual processing and analysis of faces, and an *extended system* that supports face perception, incorporating other brain areas (Figure 1). The core system entails three regions of the occipitotemporal visual extrastriate cortex: inferior occipital gyri (IOG), superior temporal sulcus (STS), and lateral fusiform gyrus, which have been found to take diverse roles depending on the nature of facial information; precisely, the posterior STS is associated with the representation of changeable aspects of the face (i.e., eye gaze, expression, and lip movement) and the lateral fusiform gyrus seems to respond to invariant aspects of faces (i.e., perception of unique identity) (Haxby et al., 2000). Indeed, it is in the core system that the dissociation for the processing of facial identity and expression is proposed to stem, localizing the former in the ventral stream and the latter in the dorsal stream.

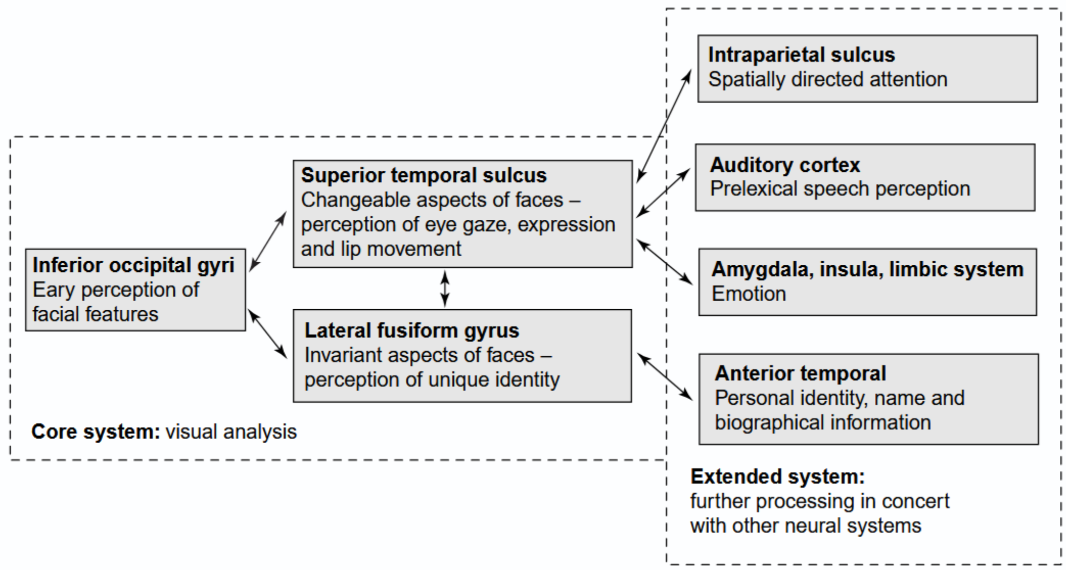

Figure 1. Functional architecture of the face processing system (Haxby et al. 2000).

As empirical evidence began to grow, the rigidity of this framework emerged. Calder and Young (2005) in their paper "Understanding the recognition of facial Identity and facial Expression" tackled the dominant framework by questioning the evidence in support of the strict dichotomy between an "identity route" and an "emotional route". As a matter of fact, the existence of neurologically independent systems found strong support in documented cases of patients with prosopagnosia, showing a double dissociation with a selective impairment in emotional recognition and identity recognition (Tranel et al., 1988; Young et al., 1993), which however have been shown to be based on misleading assessments, probably demonstrating a trend dissociation[1], where a single system is damaged, but the effects are unequal because facial identity tasks are generally more difficult than expression tasks (Calder & Young, 2005). Also, psychological findings on how motion aids in identity recognition (O'Toole et al., 2002) prompted the need to integrate the role of motion in the visual recognition model provided by Haxby and colleagues (2000), as the standard in early research was to use static stimuli (Foley et al., 2012). For instance, in real-life conditions, faces and people do not appear static, but rather in constant motion. This intrinsic dynamism has been theorized to contribute to facial recognition process by providing an additional "dynamic facial signatures" peculiar for each individual (supplemental information hypothesis) and by enhancing the processing of invariant features of the face (representational enhancement hypothesis) (O'Toole et al., 2002). These findings, along with a growing body of heterogeneous neuroimaging data regarding the roles and functions of the face processing areas, led to the need to revise the hegemonic model.

1.1.1 Redefining the neural framework of face perception

In Haxby's model, the fusiform face area (FFA), in the lateral fusiform gyrus, was defined as the central module of the ventral stream, responsible for processing unique identity (Haxby et al., 2000). Although subsequent findings supported the role of the FFA in identity extraction

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[1] Neuropsychological dissociations are empirical observation of impairment in specific tasks across patients. They can be of different types, although only a *double dissociation* allows to support strong claims about the functional architecture of the brain, as it refers to two distinct patterns of impairment observed across two different patients: patient A exhibiting good performance in Task A, but performing bad in a task B, while the other showing the opposite pattern. Thus implying that the two tasks rely on different independent systems. However, *trend dissociation* represent a peculiar kind of data, mimicking double dissociations. Specifically, it is the case when patients, with respect to the healthy population, are impaired both task A and B, however, their degree of impairment varies on the two tasks, which suggest differences in task demands, which could anyway be modulated by one single system (Shallice Tim, 1988).

(Bernstein & Yovel, 2015), this central tenet faced a challenge as the FFA was later found to be sensitive to facial expression, a feature theoretically relegated to the dorsal stream (Bernstein & Yovel, 2015; Ganel et al., 2005; Pessoa et al., 2002). The integration of dynamic stimuli in the experimental setting was crucial to comprehend the activation pattern of these areas (Bernstein & Yovel, 2015; Foley et al., 2012; O'Toole et al., 2002). As noted in the review by Bernstein and Yovel (2015), the FFA shows similar activation to both static and dynamic faces, suggesting a lack of sensitivity per se. Conversely, the pSTS responds consistently to moving faces, regardless of the content conveyed by the motion (Bernstein & Yovel, 2015). Thus, the functional definition of the pSTS as a processor of "changeable aspects" of the face turned out to be limited, failing to integrate its tuning to biological motion (Bernstein & Yovel, 2015). These inconsistencies called for a new understanding of the ventral and dorsal visual pathways. Bernstein and Yovel (2015) proposed shifting the functional division between the dorsal and ventral stream away from semantic categories (identity vs expression) toward the physical properties of the stimulus: motion versus form.

This re-evaluation of face processing architecture also involved areas beyond the core visual stream, pushing the debate toward a dynamic face perception network. (Foley et al., 2012). The IOG, which was initially thought to act as an "entry point" for visual information projecting both to the FFA and the STS (Haxby et al., 2000), was found to be strongly connected to the FFA and only weakly to the STS by structural connectivity studies (Bernstein & Yovel, 2015). Later, studies integrating dynamic stimuli revealed the functional plasticity of this region, which although structurally connected to the form pathway, contributes to the recruitment of the motion-sensitive STS, allowing the integration of early visual perception with higher-order motion processing (Foley et al., 2012).

The amygdala, initially integrated by Haxby et al. (2000) as part of the extended system, has gone beyond its classic definition of a module responsible for fear recognition, as several studies have revealed its broader involvement in the processing of facial affect (Foley et al., 2012). This area is highly interconnected with other relevant regions of the limbic system (e.g., insula), which are vital for the processing of socially salient information, and also the STS and inferior frontal gyrus (IFG), to interpret the social relevance of dynamic stimuli (Foley et al., 2012). The IFG has been integrated in the dynamic face perception network, as it shows activation to dynamic stimuli and present clear connections not only with the amygdala but also with areas involved in the mirror neuron system, implicated in action observation and imitation, suggesting a cooperation between these areas to process and generate knowledge about facial signaling (Foley et al., 2012).

It is crucial to note that the connections and recruitment of the areas that make up this network depend on the presented task demands, thus, it could also be informative to identify those areas that are consistently recruited, regardless of task instructions or stimulus type, and those that are clearly task-dependent (Müller et al., 2018). A meta-analysis by Müller et al. (2018) identified an occipito-frontal-amygdalae system which shows regular activation, and other areas found to be active in specific task conditions, such as STS and posterior fusiform gyrus (e.g., evaluating gender vs emotion).

As mentioned above, the information that can be deciphered from our faces is changeable, subtle, complex, and not at all straightforward. Our brains must find a way to juggle all these clues, especially when it comes to socially relevant information. It is not enough to simply recognize and categorize what is presented to us (i.e., the emotions of the person in front of us): in order to navigate successfully in a social environment, it is necessary to determine the authenticity of such signals (Zloteanu & Krumhuber, 2021). Although largely overlooked, there has been growing interest in research into how our brain integrates and discriminates authenticity, and it is precisely in this area that this investigation aims to contribute.

1.2 Emotions and Authenticity

The study of face perception has, since ancient times, been connected with the investigation of emotions. The visage is not just a surface, it represents the most immediate and powerful means for conveying our inner states and deciphering those of others (Barrett et al., 2019). The emotional component of facial expressions is of particular social relevance, as communicative in its nature, what is conveyed through facial expression has been commonly regarded as a reliable gateway to the inner state of who we are observing (Ekman, 1971). As a matter of fact, it was Darwin in the 19th century who, observing remarkable parallels in facial expression patterns across diverse animal and human species, argued that emotions are biologically rooted and universally shared (Darwin, 1872). This laid the foundations for a longstanding line of research involved in identifying facial features and movements that can be traced back to specific emotion categories. Central to this view is the Basic Emotion Theory (BET), which argues that a specific set of discrete emotions - typically anger, disgust, fear, happiness, sadness, and surprise - are innate and expressed through evolutionary conserved facial patterns (Damasio & Carvalho, 2013; Ekman, 1992). Under this framework, expressions are considered to act as “emotional fingerprints”: straightforward cues to decode others’ inner personal state, which can vary to a certain degree, but only around a specific set of movements (namely a *prototype*) (Barrett et al., 2019). These variations are attributed to mechanisms such as “display rules”, and culture-specific dialects, unrelated to the emotion itself (Ekman & Cordaro, 2011; Ekman & Friesen, 1971).

Building on this foundation, the desire to clarify and categorize facial behavior has led to the development of analysis tools - most notably the Face Action Coding System (FACS) proposed by Ekman & Friesen (1978) - to categorize expressions in terms of movement patterns and intensity. These beliefs, also referred to as the “common view”, have been widely adopted outside the psychological domain (Barrett et al., 2019): legal actors often rely on facial demeanor to determine if a defendant is remorseful, which can significantly impact sentencing severity; FBI and TSA agents are trained to detect micro-expression, and more and more tech companies are investing in “emotion reading” that infer affective states from static or dynamic facial images (Barrett et al., 2019).

Despite its undeniable scientific contribution of the common view, recent reviews have challenged this one-to-on mapping, pointing out how this interpretation of facial expressions risks to rely on “expressive *stereotypes*[2]” rather than the variable reality of human behavior (Barrett et al., 2019). As a matter of fact, studies involving heterogenous samples (e.g., infants, blind participants, and members of remote cultures) showed a wide variability in emotional configurations strongly dependent on context an culture (Barrett et al., 2019). This openly challenges the above mentioned belief that such demeanors can be regarded as diagnostic “fingerprints”, that isolate facial display from the person enacting it (Barrett et al., 2019). This shift was supported by a recent meta-analysis, in which Duran and Fernandez-Dols (2021) tested the assumption of co-occurrence, that is the idea that feeling an emotion necessarily triggers its predicted facial configuration and their results suggested that the classic basic emotions do not consistently co-occurred with their expected facial movements (Durán & Fernández-Dols, 2021). Consequently, Barrett’s Theory of Constructed Emotion (Barrett, 2017) offers a broader framework integrating cultural context and learning as pivotal in the creation of the emotion-expression relationship (Barrett et al., 2019). In this view facial configurations are not fixed communicative tools *per se*; instead, they are raw signals that require the observer’s brain to actively construct meaning (Barrett et al., 2019).

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[2] A *stereotype* is a generalized, oversimplified belief about a trait, whereas a *prototype* refers to the most typical example of a category. The risk of the classical view identified by Barret is that of treating facial expressions in a stereotypical way, moving further and further away from the extensive variety with which people move their faces (Barrett et al., 2019).

This theoretical shift invites a rethinking of the functional role of facial movements: if expressions are not exclusively designated to communicate survival-critical information (*encoding-decoding perspective*), they may instead act as deliberate signals used not only to communicate emotional states, but also to exert social influence (*affect-induction perspective*) (Zloteanu & Krumhuber, 2021). This introduces a critical layer of complexity to social cognition: if facial expressions are communicative tools rather than obligatory reflexes, the observer is faced with the challenge of discerning whether a display reflects a "genuine" underlying affect or a "deliberate" social strategy (Zloteanu & Krumhuber, 2021b).

1.2.1 Genuine vs Posed Emotions

Accurate discrimination of authenticity in emotional expressions, that is, knowing whether an emotional display matches a person's true underlying affect, is a crucial ability as it reveals relevant information regarding, not only the environment, but also the people we are in relationship with, allowing us to navigate our social surrounding quickly and cleverly. The perceived nature of the witnessed emotional experience has a direct influence on the observer's decisions and behaviors. In everyday social exchanges the authenticity of a smile can act as a reliable marker of cooperative intent and elicit higher ratings on behavioral intentions (Johnston et al., 2010). Similarly, the authenticity of a negative emotion can guide the evaluation of the target's credibility prior to engaging in prosocial and empathic responses (Reed & DeScioli, 2017). Sensitivity to authenticity and genuineness perception plays a crucial role also in the therapeutic setting, as it promotes therapeutic alliance (Lu et al., 2020). Conversely, misinterpreting a posed expression for a genuine display, or vice versa, can lead to negative outcomes for the perceiver, as being exposed to manipulation or confrontation (McLellan et al., 2010). This highlights how the ability to correctly process *all* the information provided by the face seems to be a key prerequisite to a healthy social functioning (Santamaría-García et al., 2020). Given these social risks, current literature hypothesized that impairment in authenticity discrimination to play a causal role in the breakdown of interpersonal abilities - one of the most prominent and disabling features in psychiatric and neurological disorders - leading to difficulties in social engagement (Scarpazza et al., 2025).

The scientific investigation on the authenticity of emotions can be traced back to Darwin's observations on emotions (Darwin, 1872). He introduced the idea that we don't have full control over all the muscles contributing to the expression of an emotion, thus, when attempting to mask the expression, these muscles will inevitably escape the effort and show the true affect (*inhibition hypothesis*) (Ekman, 2003). This proposal paved the way for a subsequent line of research pivoting on the idea of "reliable face muscles", difficult to voluntary activate and therefore suppress (Ekman, 2003; Ekman & Friesen, 1978). Early research strongly relied on specific static morphological cues to differentiate genuine and posed displays, with the most exemplar ones being the simultaneous contraction of the orbicularis oculi muscle and the zygomaticus major muscle, a combination characterizing the hallmark of genuine positive affect: the *Duchenne smile* (Duchenne, 1990; Ekman & Friesen, 1978; Frank et al., 1993).

As research on face perception grew, the limitations created by the sole use of static, isolated stimuli, became clear. Only relying on static images to investigate face perception not only exhibits poor ecological validity, but also limits the understanding of face perception in all its nuances, from identity extraction to authenticity discrimination (Miolla et al., 2023; Scarpazza et al., 2025). Moreover, facial expressions do not appear in a vacuum, they are a crucial, but always just a part of the paramount information we perceive and integrate to decode our social environment (Straulino et al., 2023). Consequently, various methodological efforts have been made to revise the stimuli used for investigating emotion perception and authenticity discrimination. To overcome their limitations, two main integrations have been proposed: the use of dynamic displays to reflect the dynamic complex patterns of facial movement (Namba et al., 2018), and the use of multi-modal elicitation strategies to capture genuinely felt affective states, allowing the study emotional behavior in a highly ecologically valid manner(Miolla et al., 2023; Zloteanu & Krumhuber, 2021).

1.2.1.1 Authenticity Expression

The shift toward dynamic stimuli revealed how spontaneous and deliberate facial expressions differ fundamentally in their kinematic execution and temporal trajectory. One robust difference lies in their smoothness, with genuine expression being more smooth and reflex-like, while posed emotions appear irregular and with intensity changes during execution (Hess & Kleck, 1990). Further empirical measurements demonstrated that temporal features can be a marker of authenticity (Krumhuber & Manstead, 2009; Schmidt et al., 2006). Genuine expressions, although they can occur in milliseconds (e.g., micro-expressions) (Straulino et al., 2023), exhibit smoother temporal trajectories than deliberate ones (Hess & Kleck, 1990). In contrast, deliberate displays are characterized by abrupt onsets and irregular offsets, presenting very brief or unnaturally long expressions, signaling lower perceived authenticity (Ekman, 2003; Hess & Kleck, 1990; Krumhuber & Manstead, 2009; Schmidt et al., 2006).

These kinematic variations, together with the historical attention devoted to the activation of specific “reliable” muscles, suggest the possibility of two distinct communication pathways at a neural level. The movements linked to genuine, involuntarily felt emotion are believed to stem from subcortical brain areas, which provide excitatory stimuli to the facial nerve nucleus in the brainstem via the extrapyramidal motor tracts (Ekman, 2003; Straulino et al., 2023). Supporting this connection is the fact that extrapyramidal tract has been linked with smoother, more synchronized motions characteristic of genuine affect (Ross et al., 2019). As deliberate expressions are voluntarily controlled, they are initiated by impulses originating in the motor cortex that travel through the pyramidal tracts, accounting for them beinge less fluid than their counterparts (Ross et al., 2019; Straulino et al., 2023).

It is crucial to consider that the extent to which individuals modulate, suppress, or pose emotional displays is heavily influenced by socio-cultural norms (display rules) (Ekman & Friesen, 1971). Facial behavior is frequently shaped by culture-specific "dialects" and social motives, and specific facial movements can communicate entirely different social messages depending on the cultural context (Barrett et al., 2019). Research reveals that a society's migratory history profoundly shapes its expressive norms: historically heterogeneous cultures (with diverse populations lacking a shared background) rely heavily on clear, easily recognizable emotional expressions to build trust among strangers, whereas homogeneous cultures tend to favor the dissimulation or suppression of emotional displays (Barrett et al., 2019; Wood et al., 2016). Modern affective neuroscience views these voluntary displays as strategic communicative signals used to convey social intent and navigate interpersonal interactions (Zloteanu & Krumhuber, 2021).

1.2.1.2 Authenticity Recognition

How observers perceive, process and evaluate emotional authenticity is still a fairly overlooked area of research (Scarpazza et al., 2025). Methodologically, operationalizing recognition accuracy has been a subject of current scientific debate. The type of stimuli chosen and used (e.g., static or dynamic), as specified in the previous sections, has a major impact on the phenomenon that is then under investigation, and the same rationale applies to the type of task chosen (e.g., free labeling, forced response) (Barrett et al., 2019; Zloteanu & Krumhuber, 2021). To capture the messy diversity of real-world facial display, and therefore guarantee a higher degree of ecological validity to the study of accurate emotion recognition, current research has focused over time on the use of dynamic stimuli that show a truly experienced expression (Scarpazza et al., 2025; Straulino et al., 2023; Zloteanu & Krumhuber, 2021). The Padova Emotional Dataset of Facial Expressions (PEDFE) is an example of a modern stimulus library designed to overcome the historical limitations, as not only it provides dynamic clips, but also these recorded emotional reactions have been achieved through an multimodal elicitation protocol based on the sender veracity, ensuring that the genuine expressions strictly reflect actual, spontaneous responses to emotion-evoking events rather than simulated portrayals (Miolla et al., 2023; Zloteanu & Krumhuber, 2021).

Current empirical evidence showed that people are generally not very good at determining if an expression is genuine or posed when relying on visual cues alone (Miolla et al., 2023; Namba et al., 2021; Zloteanu & Krumhuber, 2021), effect that is suggested to be intertwined with the *"truth-bias",* a psychological tendency to believe that interaction partners are being honest, regardless of whether they are actually being truthful (Mccornack & Parks, 1986). Moreover, research suggest a distinct asymmetry in authenticity judgments: observers tend to classify posed emotions as genuine much more often than they classify genuine emotions as posed, a trend that is particularly enhanced when evaluating dynamic rather than static stimuli (Miolla et al., 2023; Namba et al., 2018).

Despite the complexities just discussed, it is clear that in real-word contexts, humans possess mechanisms to identify these subtle signs. An influent proposal to explain how humans decode authenticity is the *sensorimotor simulation hypothesis* (Wood et al., 2016). According to this model, when observing a facial expression, we recreate the motor production of the witnessed expression within ourselves (Wood et al., 2016). This mechanism requires the involvement of the observer's own somatosensory and motor neural systems, which should allow him to simulate the facial component of an emotion and to activate the corresponding emotional state (Wood et al., 2016). It is postulated that this internal affective feedback provides basis from which the perceiver can implicitly infer the true underlying emotional state of the expresser (Wood et al., 2016). Importantly, this automatic simulation is not strictly hardwired, rather it is sensitive to social context and cultural learning; observers engage in sensorimotor simulation much more readily with in-group members than with out-group members (Wood et al., 2016). Consequently, when attempting to decipher emotional displays from unfamiliar cultures or out-groups, this internal simulation process is less effective, which accounts for the well-documented drop in recognition accuracy across different cultural boundaries (Barrett et al., 2019; Wood et al., 2016). Ultimately, evaluating the authenticity of an expression goes beyond merely detecting a "reliable muscle" or a kinematic irregularity; it requires the observer to grasp a strategic social signal that is deeply embedded in the sender's specific socio-cultural environment (Zloteanu & Krumhuber, 2021).

1.2.2 Neural correlates of Emotions and Authenticity Recognition

In the previous section the efforts to investigate the neural bases of face perception have been presented, along with the crucial role of the visage as one of the most important and common mediums of emotion expression. The extraction of emotional significance relies on a highly interconnected, domain-general architecture rather than isolated emotion-specific modules (Xu et al., 2021).

In the transition from visual perception to emotional evaluation the STS plays a crucial role as functional bridge (Foley et al., 2012). Connectivity analyses demonstrated how STS mediates the flow of information from early visual processing areas to emotional processing centers (Foley et al., 2012). The gathered sensory information is not directly assigned meaning in this region, instead kinematic data is projected to an extended system of the distributed face network, where the amygdala operates as the central hub (Foley et al., 2012; Xu et al., 2021). The amygdala seems to be consistently recruited during facial emotion recognition to evaluate the biological and social relevance of the incoming signal across different valences, acting as a domain-general processor rather than a module restricted to specific discrete emotions (Foley et al., 2012; Xu et al., 2021). Through its dynamics connections to higher order regions such as the prefrontal cortices and the insula, these signals are translated into conscious emotional categories (Xu et al., 2021). Specifically, the insula mediates amygdala activity by forwarding information coming from cortical regions (Foley et al., 2012). Indeed, the prefrontal cortex operates within the brain's extended affective systems, with its different subdivisions providing the necessary cognitive control to consciously categorize an observed emotion (Xu et al., 2021). Specifically, areas such as the ventrolateral prefrontal cortex (vlPFC) and the dorsolateral prefrontal cortex (dlPFC) contribute to this process allowing the subject to direct attention to socially salient facial cues and consciously evaluate their emotional meaning (Xu et al., 2021). Moreover, areas involved in action observation and imitation, such as the IFG and the middle frontal gyrus (MFG) were found to be active during the perception of dynamic facial expressions, suggesting their involvement in the generation of conceptual knowledge about the specific emotion being signaled (Foley et al., 2012). Moreover, although historically clinical research heavily supported a right-hemisphere hypothesis, which postulates that the right cerebral hemisphere is dominant for the expression and perception of emotion, regardless of whether the emotion is positive or negative (Borod et al., 1998), contemporary findings challenge this straightforward dominance hypothesis(Xu et al., 2021), pointing to a rather flexible asymmetrical network, where structures like the amygdala lean left, and frontal regions like the ventromedial PFC, dynamically shift their hemispheric engagement depending on the specific emotion being decoded (Xu et al., 2021).

As previously noted, the emotions conveyed by others represent critical social cues essential for navigating daily interactions. However, the neural mechanisms underlying the perception of emotional authenticity are not fully understood yet. Findings from functional MRI suggest that evaluation of genuine facial display recruits areas involved in high-level emotion perception and mentalizing such as left medial superior frontal and right inferior temporal gyrus, whereas for posed stimuli results reveal a rather decreased neural response (McLellan et al., 2012). Moreover, the observed neural signatures seem to depend not only on the nature of the stimulus, but also on the specific emotional valence being decoded (McLellan et al., 2012). Authenticity has been investigated also among other modalities, such as vocal prosody; specifically, one fMRI study investigating authenticity in vocal prosody found increased activation in the Theory of Mind (ToM) network – specifically, the mPFC, the right and left temporoparietal junction, and the retrosplenium – when explicitly trying to judge the authenticity of a vocal emotional expressions (Drolet et al., 2012). In addition, it was found that even without explicit instructions to evaluate authenticity, simply listening to authentic recordings intrinsically enhanced activity in ToM regions when compared to play-acted recordings (Drolet et al., 2012), result in line with the decreased neural response to posed stimuli found by McLellan et al. (2012).

Although such findings are crucial and promising, authenticity research is often limited by the use of static, two-dimensional stimuli, often displaying not truly felt emotions (Namba et al., 2018; Scarpazza et al., 2025; Straulino et al., 2023; Zloteanu & Krumhuber, 2021). Moreover, these studies do not methodically investigate uniform range of emotional displays (Namba et al., 2018; Scarpazza et al., 2025), preventing the formulation of a fully generalized model of emotional authenticity.

1.2.3 Neurophysiological correlates of Emotion and Authenticity

To fully grasp the neural dynamics of face perception it is crucial to integrate spatial information with the temporal data provided by electroencephalography (EEG). Human interactions require fast evaluations and the brain actually reacts to such social stimuli with remarkable speed. Tracking neurophysiological changes allows to map the sequential cascade of cognitive processes involved in the detection and extraction of the multi-faceted information conveyed by faces.

1.2.3.1 Event-Related Neural Dynamics

The brain extracts facial dimensions "following a coarse-to-fine trajectory" where basic categorical distinctions are computed before finer, identity-level details are resolved (Dobs et al., 2019). At around 100 milliseconds after the stimulus onset, face perception evokes a positive peak (P1), reflecting an initial visual detection (Güntekin & Başar, 2014) and attentional allocation (Hillyard & Anllo-Vento, 1998; Valt & Stürmer, 2018). Even at this early stage integration of affective information occurs, with eempirical evidence demonstrating that occipital areas show distinct neural signatures for fearful versus happy expressions within just 80 milliseconds post-stimulus, while frontal regions begin to differentiate threat from neutrality by 100 milliseconds (Güntekin & Başar, 2014; Palermo & Rhodes, 2007). This early emotional discrimination seems to be driven primarily by low-spatial-frequency cues (i.e., coarse visual information) (Vlamings et al., 2009), which draw perceptual resources toward signs of threat, as shown by the increased amplitude of the P1 component in response to expressions of fear or anger compared to neutral stimuli (Valt & Stürmer, 2018). It has been hypothesized that in this first pass analysis, these visual inputs bypass slower cortical processes, traveling through a rapid subcortical pathway directed to the amygdala, which subsequently modulates the visual cortex via feedback loops before the structural encoding of the face is complete (Vuilleumier & Pourtois, 2007).

After an initial detection, the hallmark of face processing emerges between 130 and 200 milliseconds: the N170 component (Hinojosa et al., 2015). Initially, influenced by the cognitive framework of Bruce and Young (1986) proposing the parallel processing of facial identity and expression in distinct independent routes, also early electrophysiological research adopted this strict functional dichotomy (Martens et al., 2010), with early studies converging on the interpretation of the N170 component as correlate of structural identity encoding, blind to affective valence (Hinojosa et al., 2015; Vuilleumier & Pourtois, 2007). As presented in section

1.1.1, this strict theoretical segregation underwent revision also pivoting on new neurophysiological research findings on face perception. Critically, a thorough meta-analysis concluded that the "N170 was found to be sensitive to facial expressions, supporting proposals arguing for integrated rather than segregated mechanisms in the processing of identity and expression" (Hinojosa et al., 2015), sensitivity which was shown to be heterogeneous as anger, fear, and happiness were the emotional expressions eliciting the largest amplitudes, suggesting a functional mechanism, directed by social meaning, behind the N170 component (Hinojosa et al., 2015). Moreover, as the N170 amplitude was found to be modulated by both identity and expression simultaneously, it was suggested that at this stage the differential encoding for identity and expression analysis has not occurred yet (Martens et al., 2010). In addition, simultaneous EEG-fMRI studies showed that most likely the N170 amplitude correlates with activity in regions like the STS and the FFA, supporting the notion that these regions appear to operate together within an interactive network to concurrently process both structural and affective cues (Nguyen & Cunnington, 2014).

There are other two components often associated with emotional processing, the early posterior negativity (EPN) and the late positive potential (LPP) (Vuilleumier & Pourtois, 2007). Following the N170, the Early Posterior Negativity (EPN) emerges between 200 and 300 milliseconds over bilateral occipito-temporal regions (Vuilleumier & Pourtois, 2007). Its amplitude was found to increase with emotionally salient stimuli – specifically angry or threatening faces – hinting to an enhanced recruitment of perceptual resources for a more detailed sensory processing (Martens et al., 2010; Vuilleumier & Pourtois, 2007). Later in the face processing stream, the LPP, a large sustained positivity which encompasses the P300 and extends between 400 and 900 milliseconds post-stimulus, manifests predominantly over centro-parietal sites (Vuilleumier & Pourtois, 2007).This component was shown to yield stronger slow wave response when presenting emotional stimuli compared to neutral ones (Güntekin & Başar, 2014; Vuilleumier & Pourtois, 2007). The manifestation of these late emotion-specific differences was shown to be task-dependent as research indicates that late-latency differences (between 250 and 750 ms) to various emotional expressions emerge only when observers actively direct their attention to the emotion, but not when they merely judge the face's gender (Krolak-Salmon et al., 2001). Functionally, these sustained late responses were interpreted to reflect a transition of the face network, from from bottom-up analysis to a top-down cognitive evaluation triggered by the emotional stimulus (Güntekin & Başar, 2014; Vuilleumier & Pourtois, 2007).

The analysis of strictly time-locked ERPs is not the only possible area of investigation using EEG. Research also considered the oscillatory activity of the brain to gain deeper insights into the functional state of the neural network dynamics during emotion perception (Güntekin & Başar, 2014). Usually EEG signal is decomposed into canonical frequency bands: alpha (8-13 Hz), beta (14-30 Hz), theta (4-7Hz), gamma (28-48 Hz) and delta (0.5-3.5 Hz). A core finding across this frequency spectrum is that the brain exhibits increased oscillatory synchronization when processing emotional stimuli compared to neutral ones, with a robust and rapid increase in responsiveness toward negative or threatening expressions (Güntekin & Başar, 2014). Closely analyzing the above mentioned frequency bands reveals a functional division where the lower frequency bands (delta and theta) primarily track the arousal dimension and late cognitive integration, while the higher frequency bands (beta and gamma) are heavily involved in affective valence and rapid threat detection (Güntekin & Başar, 2014).

In the case of authenticity perception, the neurophysiological response is a fairly underexplored area and the specific patterns of cortical activity supporting its discrimination are still unknown. It has been suggested that incongruence of posed emotion might be detected early on the visual processing stream, as the P1 component shows larger amplitude for non-genuine ambiguous stimuli (Valt & Stürmer, 2018). Contrarily, the N170 components was shown to be insensitive to smile authenticity (Valt & Stürmer, 2018). Such preliminary findings are important to discuss, however they are contextual to the experimental design and the specific kind of stimuli used. Indeed, as discussed earlier, most of research on emotional perception, as well as the limited work on authenticity perception, has strictly focused on static posed emotions and stereotypical displays, which coupled with a lack in methodological standardization, makes it hard to generalize these results.

1.2.3.2 Resting-State EEG as Index of Neural Predisposition

Although historically brain's activity was thought to be determined by incoming stimuli, this view has been challenged by the discovery that the brain possesses a high level of intrinsic, or resting-state, activity that is continuously ongoing (Northoff et al., 2010). This opened the possibility to a new understanding of the neural activity we observe, which might be an ensemble of both the brain's resting state activity level and the stimulus-induced activity (Northoff et al., 2010). Crucially, research investigating Resting-State EEG, which measures the brain's spontaneous intrinsic activity in the absence of an explicit task, demonstrated that this intrinsic activity modulates the intensity of subsequent stimulus-induced activity and can reliably predict trial-to-trial variability in behavioral performance and reaction times, therefore suggesting that an individual's baseline neural architecture can be an index of neural predisposition (Northoff et al., 2010).

Evaluating the pre-stimulus canonical frequency bands provides vital clues about this neural predisposition as an individual's task-related brain responsiveness is heavily dictated by their baseline spontaneous activity (Güntekin & Başar, 2014; Northoff et al., 2010). A review by Güntekin & Başar (2014) explicitly suggest that this dependency is particularly evident in the alpha frequency range, where task-related reactivity is strictly proportional to the amplitude of pre-stimulus resting alpha activity. Spontaneous alpha oscillations are intrinsically linked to working memory, intelligence, and active cortical processing (Klimesch et al., 2000; Lejko et al., 2020), and they support baseline alpha power as marker of cognitive capacity. Beyond alpha activity, Güntekin & Başar (2014) found that spontaneous parietal beta asymmetry significantly predicts a subject's subsequent attentional response to angry facial expressions, suggesting that resting beta networks directly prime the brain for rapid threat detection.

Recognizing the functional significance of this resting-state architecture naturally raises a critical methodological question: what specific features should be extracted from the RS-EEG signal to accurately capture this neural predisposition?

Traditionally, RS-EEG literature has focused on the extraction of periodic oscillations, such as the standard frequency bands discussed above (Donoghue et al., 2020). However, these rhythmic peaks do not appear isolated, rather they are embedded within a broad, 1/f-like background[3] signal known as the aperiodic component, often treated as noise (Donoghue et al., 2020). Recent methodological advances made it possible to disentangle the periodic oscillatory peaks from the aperiodic slope through a mathematical algorithm called FOOOF (Fitting Oscillations & One-Over F), opening the possibility to isolate the aperiodic components and investigate them as direct meaningful reflections of the brain's physiological state (Donoghue et al., 2020). Specifically, the aperiodic component does not arise from regular rhythmic brain processes as it reflects continuous, non-rhythmic neural activity defined by two parameters: the offset, representing the overall height or uniform shift of the power spectrum, and the exponent, referring to the steepness of the 1/f decay, which acts as a direct index of the excitation/inhibition (E/I) balance (Donoghue et al., 2020). Preliminary studies using FOOOF showed that aperiodic parameters accurately predict visual working memory performance across different age groups (Donoghue et al., 2020), and are sensitive predictors of general

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[3] When brainwave power is plotted across frequencies, this aperiodic background forms a steep downward slope often referred to as a "1/f-like" distribution, meaning that lower frequencies naturally exhibit exponentially greater power than higher frequencies (Donoghue et al., 2020)

cognitive decline in neurological conditions such as Alzheimer's disease and multiple sclerosis (Kien et al., 2024).

While literature investigated how baseline periodic oscillations and aperiodic features dictate general cognitive readiness and affective responsiveness, their specific role as predictors of behavioral accuracy in discriminating emotion authenticity remains entirely unexplored.

1.3 Social cognition

Social cognition broadly refers to all the mechanisms needed to effectively navigate the human social environment (Frith, 2008). There are a variety of cognitive processes which underlie how we detect and integrate social signals, and how we act in the social context. The main cognitive constructs involved in social skills that have been explored are Theory of Mind, emotional empathy, emotion perception and social behavior (Scarpazza et al., 2025). Emotion perception has been extensively researched, specifically, as among the various social signs informing us about our surrounding facial expression is the most informative to learn about others' emotional states (Frith, 2008), research's endeavors focused on how specific personality traits and cognitive abilities directly impact the ability to recognize facial affect (Scarpazza et al., 2025).

Current literature defines alexithymia as a multi-faceted socio-affective personality trait linked to difficulties identifying and describing feelings, an externally oriented cognitive style, and a reduced inclination to imagination (Rosenberg et al., 2020). These different vulnerabilities are indicative of the multifaceted nature of this construct, which have been formalized into three core dimensions: Difficulties Identifying Feelings (DIF), Difficulties Describing Feelings (DDF) and Externally Oriented Thinking (EOT) (Bagby et al., 1994). A substantial body of research indicates that these deficiencies significantly impact recognition of emotional facial expressions in others (Rosenberg et al., 2020). Behaviorally, alexithymic individuals usually exhibit inefficient affective processing; this trait is associated to atypical visual scanning patterns, more time and more intense emotional stimuli needed for a correct emotional identification, and often struggles at the semantic level, when associating the expression to its corresponding internal emotional state (Grynberg et al., 2012).

As a personality trait, alexithymia is distributed across the healthy population, where individuals vary in their degree of severity (Grynberg et al., 2012). Nonetheless, it is recognized as a transdiagnostic factor frequently co-occurring with psychiatric conditions characterized by poor social skills, such as autism spectrum conditions, eating disorders, and social anxiety disorders (Grynberg et al., 2012). As a matter of fact, psychophysical and behavioral investigations have revealed that emotion recognition deficits traditionally attributed to specific psychiatric and neurodevelopmental diagnoses are predominantly driven by the high prevalence of comorbid alexithymia within these clinical populations (Cook et al., 2013; Grynberg et al., 2012). When accounting for alexithymia scores as a covariate, or when patient groups are strictly matched with neurotypical controls based on this multidimensional trait, the expected group differences in emotion perception frequently vanish, suggesting that the primary clinical diagnosis itself does not inherently cause the perceptual failure (Grynberg et al., 2012).

The emotional dysregulations typical of alexithymia are often interpreted according to two complementary frameworks: *deficit models*, which posits that alexithymia represents a form of emotional hyporeactivity, and *over-responding models*, which suggest that highly alexithymic individuals experience heightened initial arousal to emotional stimuli, which prompts an automatic attentional avoidance when presented with a potentially overwhelming emotion (Mas & Luminet, 2025). An additional framework has been proposed, the *attention-appraisal model*, which argues that emotional processing can be disrupted at distinctive chronological stages, depending on the individual's alexithymia profile reflected by the different facets of alexithymia (Preece et al., 2017). According to this view, the externally oriented thinking (EOT) facet disrupts early involuntary attention allocation, while difficulties identifying and describing feelings (DIF/DDF) hinder the subsequent semantic appraisal of the perceived expression (Preece et al., 2017). Although the specific intersection between alexithymia and authenticity discrimination has been underexplored, it is plausible to speculate that these vulnerabilities in internal evaluation affect higher-order processes, such as distinguishing a genuine expression from a fake one.

At the neural level, alexithymia was found to be associated with automatic hyporesponsiveness across the brain's affective, interoceptive, and mirror neuron networks (Rosenberg et al., 2020).

Transitioning from intrapersonal affective traits to higher-order interpersonal mechanisms, ToM represents another crucial pillar of social cognition. Defined as the human capacity to reason about mental states and to understand how these subjective states drive behaviour (Apperly, 2012), ToM is frequently dichotomized into two distinct facets: Cognitive ToM (CToM) and Affective ToM (AToM) (Stafford et al., 2023). CToM refers to the intellectual ability to evaluate social contexts and situational cues, while AToM refers to mentalizing, the ability to deduce another person’s feelings, emotional preferences, and affective states (Stafford et al., 2023).

As delineated earlier, emotional processing proceeds through distinct stages of perceptual elaboration. Building upon this foundation, ToM operates as a higher-order cognitive process of mental state deduction, enabling the observer to make accurate inferences about complex psychological states (Stafford et al., 2023). This specification is particularly critical when evaluating complex or ambiguous social signals, such as emotional authenticity, which should require an individual to move beyond superficial morphological decoding and actively recruit ToM networks to infer the sender's true underlying intentions (Drolet et al., 2012; Rakoczy, 2022).

At the neural level, ToM is subserved by an extensive "social brain" network consistently recruiting the medial prefrontal cortex (mPFC) and the temporoparietal junction (TPJ), with distinct frontostriatal and orbitofrontal circuitries mediating its cognitive and affective dimensions, respectively (Apperly, 2012; Rakoczy, 2022; Stafford et al., 2023).

The correlation between these specific aspects of social cognition and authenticity discrimination has not been extensively investigated empirically and in general, specific cognitive mechanisms underlying the perception of emotional authenticity remain largely unexplored. However, as briefly presented above, current models of social cognition make it highly plausible to position both alexithymia and Theory of Mind (ToM) as critical variables of interest.

Chapter 2

The Present Study

The present study aims to contribute to the ongoing debate on authenticity perception and the understanding of neural mechanisms involved in processing genuine versus inauthentic facial expressions. As highlighted in the introduction, the recognition of authenticity and its underlying mechanisms are still unclear and under-researched. Previous studies suffered two major limitations: the reliance on static stimuli, which overlook advantages provided by the fluid kinematics of dynamic display, and the frequent use of stimuli that lack true sender veracity, as they were not derived from spontaneous emotional experiences.

This study attempts to incorporate the theoretical and empirical considerations presented in the previous chapter, primarily through the use of an Emotion Authenticity Recognition task based on the PEDFE database (see section 2.2) to test several hypotheses at the behavioral and neurophysiological level.

Specifically:

- H1: Higher accuracy is expected in correctly judging genuine expressions compared to posed expressions. This expectation relies on the 'truth bias' (or authenticity bias) (Mccornack & Parks, 1986), which is the psychological tendency for observers to disproportionately assume that facial expressions are genuine (Zloteanu et al., 2018; Zloteanu & Krumhuber, 2021).
- H2: Based on evidence showing that sensitivity to authenticity is modulated by emotional valence (McLellan et al., 2012) and the perceptual advantages of movement (Namba et al., 2018), we hypothesize that accuracy in discriminating authenticity will

be significantly higher for dynamic expressions of positive valence (happiness) compared to those of negative valence (anger, disgust, and fear).

- H3: Authenticity recognition accuracy is expected to remain stable across different levels of emotional intensity. This expectation is based on findings from the PEDFE dataset, which showed that the accuracy of distinguishing between genuine and posed expressions does not significantly vary as a function of expression intensity (Miolla et al., 2023).
- H4: Higher TAS-20 total scores are expected to negatively predict authenticity discrimination accuracy. This expectation is grounded in evidence showing that alexithymia is associated with social–cognitive alterations, including impairments in emotion processing and recognition (García-Rodríguez et al., 2023; Rosenberg et al., 2020). Exploratory analyses will examine the associations between individual TAS-20 subscale scores and authenticity discrimination accuracy, given prior findings suggesting differential contributions of alexithymia components to emotion-related processing (García-Rodríguez et al., 2023).
- H5: Higher mentalizing abilities, as measured by the Reading the Mind in the Eyes Test (RMET) are expected to positively predict authenticity discrimination accuracy in the EAR task. This expectation pivots on the theoretical premises that RMET effectively captures the capacity to infer complex mental states from subtle cues (Maddaluno et al., 2022) and that evaluating emotional authenticity requires the observer to move beyond superficial morphological decoding to deduce the sender's true intentions (Scarpazza et al., 2025).
- H6: Based on evidence indicating that task-related alpha reactivity depends on baseline amplitude (Güntekin & Başar, 2014), higher resting alpha power is expected to predict better overall accuracy in authenticity discrimination. Regarding the role of other

standard frequency bands, exploratory analyses were conducted on their correlation with authenticity discrimination.

- H7: Beyond standard oscillations, we aim to explore the role of aperiodic parameters (Offset and Exponent) in predicting authenticity recognition. Specifically, we will specifically investigate three electrode clusters over temporal, parietal, and motor areas. This exploratory analysis will assess how the baseline physiological state of the areas underneath the clusters predispose an individual's behavioral capacity to discriminate genuine from posed emotions (Bernstein & Yovel, 2015; Luo et al., 2010; McLellan et al., 2010; Wood et al., 2016).

In addition, exploratory analyses were conducted to assess basic emotion recognition accuracy and its potential relationships with TAS-20 and RMET scores. The primary purpose of these assessments was to confirm that participants were fully capable of recognizing basic facial expressions, ensuring that any findings regarding authenticity discrimination cannot be attributed to a general deficit in emotion recognition. Consequently, these analyses will not be matter of discussion.

The upcoming chapters will examine how these hypotheses were tested, present the resulting findings and finally discuss them in relation to existing research.

Materials and Methods

2.1 Participants

Forty master students of the faculty of forensic psychology at the University of Padova (38 females, 2 males, *M* = 23.07 years, SD = 1.61, range = 21-30) were recruited through a university course participant pool. Participation was voluntary and students received partial course credit for their participation. Through an online survey implemented in Qualtrics, participants were screened for their participation. The inclusion criteria were the following: absence of neurological/psychiatric disorders; normal or corrected-to-normal vision; absence of topical dermatological conditions or allergic reactions over the scalp; no medication taken; no habitual use of drugs or alcohol. Basic demographic information (age, sex, education) was gathered through the same questionnaire. All participants gave written consent before participation. The study was approved by the Ethical Committee for Psychological Research of the University of Padua (Protocol n. 931-b) and conducted in accordance with the Declaration of Helsinki.

2.2 Stimulus material and Procedure

The experimental paradigm consisted of 3 phases: the first phase was performed online and participants were asked to complete self-report questionnaires, implemented in Qualtrics, after an initial section to assess demographic information and inclusion criteria; later, in the research lab, the participants performed a resting-state EEG recording, followed by an Emotional Authenticity Recognition (EAR) task designed to assess participants' ability to discriminate between genuine and posed facial expressions. Finally, participants completed two performance based tasks: the Reading the Mind in the Eys Tests (RMET) and Iowa Gambling Task (IGT).

Participants were asked to complete online the Italian versions of the 20-item Toronto Alexithymia Scale (TAS-20) (Bressi et al., 1996), the Interpersonal Reactivity Index (IRI) (Albiero et al., 2006), the Behavioral Inhibition System - Behavioral Activation System BIS/BAS (Leone et al., 2002), and the Barrat impulsiveness Scale-11 (BIS 11) (Leone et al., 2002). For the purposes of this analysis, only the TAS-20 will be considered for modelling and discussion.

The TAS-20 (Table A1, see Appendix) is a widely used self-report questionnaire measuring three distinct but conceptually connected aspects of the alexithymia construct, enabling a detailed examination of emotional processing deficiencies. Specifically, the instrument includes three subscales: difficulties in identifying feelings, difficulties in describing feelings, and externally oriented thinking (Bagby et al., 1994; Bressi et al., 1996). Participants evaluated each item (e.g., "I am often confused by the sensations I feel in my body") through a five-point Likert scale from 1 (I disagree completely) to 5 (I agree completely). Total scores range from 20 to 100. The mean TAS-20 score for normal sample lies around 44.7 (Bressi et al., 1996). Also, the Italian-validated scale demonstrated good reliability and validity in both clinical and non-clinical populations (Bressi et al., 1996).

For each participant we then scheduled an appointment at the laboratory to complete the other two phases of the study. Upon arrival, participants seated in a dim lit room, and started the second phase of the study: the recording of their EEG activity at rest. Participants received information about EEG montage and the resting state condition. Then, an elastic 128-ch EEG net was applied. During the resting-state EEG recording, participants were instructed to sit comfortably in front of a computer screen, approximately 70 cm from it, and to fixate a centrally presented fixation cross displayed in white on a uniform gray background for 10 minutes. They were asked to remain still and avoid thinking about anything in particular. Such instructions appeared on the screen in front of them and were also presented orally by the experimenter. Once this run was completed, participants proceeded with the EAR.

The emotional authenticity recognition (EAR) task was programmed and presented using Open Sesame (Mathôt et al., 2012). The experimental stimuli were selected from the PEDFE (Miolla et al., 2023), a dataset of 1458 dynamic spontaneous and representing the six universal emotions: anger, disgust, fear, happiness, sadness, and surprise (Miolla et al., 2023). In this study we focused on four emotions: happiness, anger, disgust and fear. The remaining two emotions were excluded for the following reasons: sadness was excluded due to its slower temporal unfolding, which complicates short stimulus presentation (Miolla et al., 2023), and to avoid ambiguity, surprise was excluded due to its frequent perceptual overlap with fear(Jack et al., 2009; Matsumoto & Hwang, 2011). Stimuli of these selected categories were selected from the PEDFE on the basis of their validated behavioral indices. Initially, we identified and selected video clips according to the highest hit rates for emotion recognition and the judgment of the experimenters, choosing the most explicit videos representing each emotion. Subsequently, stimuli were further screened based on their hit rate for genuineness classification (i.e., genuine vs. posed). In order to preserve variability in stimulus ambiguity and ecological validity, stimuli were chosen to span a heterogeneous range of genuineness recognition accuracy, with hit rates ranging approximately from 40% to 100%. Some video clips were temporally adjusted in order to preserve the natural temporal dynamics of the facial expression. Specifically, videos were slightly extended or shortened, ending up with an average duration of 3 seconds. As a result, we collected 200 stimuli divided into 8 conditions: Happiness Genuine (HG), Happiness Simulated (HS), Disgust Genuine (DG), Disgust Simulated (DS), Fear Genuine (FG), Fear Simulated (FS), Anger Genuine (AG) and Anger Simulated (AS). Each clip was presented once during the task and it appeared in a random order.

The EAR task (Figure 2) was presented on a laptop and participants performed it after EEG recording and a short break. Each trial began with the presentation of a centrally displayed fixation cross lasting 1000 ms, followed by the presentation of a dynamic emotional video. Stimulus duration varied according to the length of the video clip. After stimulus offset, participants were presented with a response screen and were asked to recognize the emotion expressed among anger, happiness, disgust, fear (each emotion corresponded to a number to be selected on the keyboard) and to determine whether the emotion expressed was authentic or simulated using the two keys on the keyboard (A-L). Finally, they had to evaluate the intensity of the emotion on a 9 point Likert scale (1 = minimum; 9 = maximum). The questions appeared always in the described order, after each emotional video. In total the EAR consisted of 200 experimental trials and its approximate total duration of the task was of 45 minutes. Prior to the experimental trials, participants completed a brief training session – of one trial – to become familiar with the stimuli and the type of response.

After the EAR task, participants were given two more tests: the Italian versions of the Reading the Mind in the Eyes Test (RMET) and the Iowa Gambling Task (IGT) (Baron-Cohen et al., 2001; Bechara et al., 1994; Maddaluno et al., 2022). The administration sequence was counterbalanced across participants to mitigate fatigue or practice effects. As the analysis of the IGT is beyond the scope of the present study, further discussion and modeling will focus exclusively on the RMET scores.

The RMET Test is a neuropsychological test designed to assess the ability to recognize emotions and mental states in others through observation of the eye region alone. During the test, participants are shown a series of 36 black-and-white photographs depicting only the eye region of different people. For each image, participants must choose the term that best describes the mental state expressed by the person in the photograph by selecting one of four options presented under the image. The four response options consist of one target word (the correct mental state) and three foils (distractors), these terms describe the person's internal disposition or attitude including cognitive states such as 'thoughtful', 'arrogant', 'insistent'. A dictionary of all the mental states presented during the RMET is provided to the participants, who are instructed to refer to it whenever they are unclear about a word's definition. Throughout the test, participants can refer to the glossary at any time. The test's score is calculated by adding up the total number of correct answers given by the participant out of a maximum of 36 items. Each correct answer is coded with a score of 1, while incorrect or omitted answers receive a score of 0. The resulting index is a variable that represents the subject's overall accuracy in the mentalization task. The test was administered in paper-and-pencil format, on the table in the laboratory where the entire experimental procedure took place.

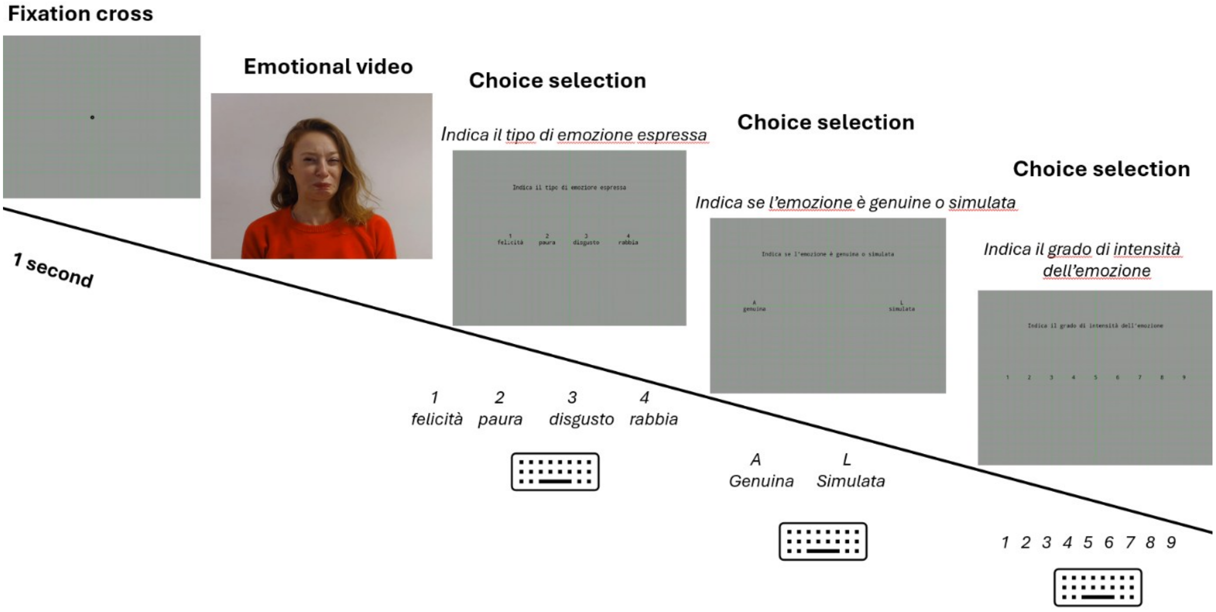

Figure 2. Schematic structure of the EAR task. Each trial started with the presentation of a fixation cross displayed for 1000ms, followed by a dynamic emotional video. After stimulus presentation, participants performed a forced-choice judgment indicating: type of emotion, whether the expression was genuine or simulated and the intensity of the expressed emotion.

2.3 EEG recording and preprocessing

For this study, the resting state condition was recorded using a Geodesic HD-EEG system (EGI® Geodesic System) with a 128-electrode HydroCel Geodesic Sensor Net. In line with EGI system standards, all electrodes were referenced online to the vertex. Impedance was maintained below 60 kΩ for all the electrodes, and the signal sampling rate was 500 Hz. Scalp voltages were amplified through a 24-bit DC amplifier.

The data were processed in MATLAB, using the toolbox EEGLAB (Delorme & Makeig, 2004). We applied the following preprocessing steps: line noise (50 Hz) removal using the Zapline-plus algorithm (Klug & Kloosterman, 2022) and digital filtering using a1 Hz digital high-pass filter. No offline low-pass filter was applied to preserve high-frequency activity, as muscle artifacts were subsequently addressed through Independent Component Analysis (ICA). The continuous EEG was then segmented into 2-sec epochs.

To identify and correct artifacts, we performed a two-step cleaning procedure. First, prior to ICA, epochs containing gross movement artifacts exceeding a maximum-minimum amplitude threshold of ±500 μV were rejected, and the Trial-By-Trial (TBT) EEGLAB plugin (Ben-Shachar, 2018) was utilized to automatically identify bad channels on an epoch-by-epoch basis. Specifically, epochs with more than 10 bad channels were discarded, and channels considered bad in more than 30% of the epochs were marked for later removal. Subsequently, data underwent ICA decomposition using the extended runica algorithm (Bell & Sejnowski, 1995). Independent components underwent visual scrutiny to identify and discard those clearly related to eye-movements, heartbeat and muscular movements (Chaumon et al., 2015).

Following ICA pruning, a second artifact rejection step was applied: remaining epochs exceeding a stricter max-min threshold of ±100 μV were identified, and the TBT plugin was reapplied with the same criteria. Finally, all channels marked as bad across the entire dataset were removed and interpolated using the spherical spline interpolation method (Ferree, 2006; Perrin et al., 1989) and the clean data were re-referenced to the common average reference.

2.4 Statistical Analysis

In the following subsections, the specific analysis steps will be elucidated.

2.4.1 Behavioral Statistical Analysis

The study had a 2 × 4 within-subject factorial design, as all participants were exposed to all levels of the experimental factors: Emotion (Anger, Disgust, Fear, Happiness) and Genuineness (Genuine, Posed). Behavioral dependent variables (DVs) were accuracy in emotion recognition (categorical: correct/incorrect) and accuracy in genuineness discrimination (categorical: correct/incorrect).

Statistical analyses were performed using the R software environment (R Core Team, 2024). Descriptive statistics (mean and standard deviation) were computed to summarize the sample's demographic characteristics, psychological traits (i.e., TAS-20 and RMET scores), and overall behavioral performance. We calculated overall and category-specific percentages for both emotion recognition accuracy and authenticity recognition accuracy, alongside mean perceived intensity ratings across all experimental conditions. To evaluate systematic differences between genuine and posed expressions, paired-samples t-tests were conducted on authenticity recognition accuracy and on perceived intensity ratings, with the latter further analyzed across the distinct emotional categories (Anger, Disgust, Fear, and Happiness).

The TAS-20, its subscales (Difficulty Identifying Feelings, Difficulty Describing Feelings, Externally-Oriented Thinking), and the Reading the Mind in the Eyes Test (RMET) all underwent standardization (z-score transformation) to ensure comparability of effects within the regression models.

To investigate whether emotion recognition and genuineness discrimination were influenced by stimulus characteristics and individual traits, we fitted a series of Generalized Linear Mixed-effects Models (GLMMs) using the lme4 package in R. Because the dependent variables were binary (0 = incorrect, 1 = correct recognition), all models were fitted using a binomial probability distribution with a logit link function. To account for the repeated-measures design and baseline differences across participants, a random intercept for subjects was included in all models. Specifically, regarding Emotion Recognition Accuracy we tested the effect of stimulus features by including Emotion Category (Anger, Disgust, Fear, Happiness), Stimulus Authenticity (Genuine, Posed), and their two-way interaction as fixed factors. Subsequently, a second model explored the role of intensity by testing the interaction between Emotion Category and Perceived Intensity. Finally, to investigate the impact of individual traits, we fitted a third model comprising Emotion Category, the TAS-20 total score, and the RMET score as fixed predictors, without interaction terms.

The same modeling strategy was applied to predict Authenticity Recognition Accuracy. Initially, we tested the influence of stimulus characteristics by entering Emotion Category, Stimulus Authenticity, and their interaction as fixed factors. A separate model then examined the effect of Perceived Intensity and its interaction with Stimulus Authenticity. The impact of individual traits was subsequently evaluated by entering Stimulus Authenticity, the TAS-20 total score, and the RMET score as fixed factors. Finally, to isolate the specific contribution of alexithymia dimensions, we fitted a model with the three TAS-20 subscales (DIF, DDF, EOT), followed by a targeted model aimed at testing the interaction between the EOT subscale and Stimulus Authenticity.

The significance of fixed effects was assessed via Type II Wald chi-square tests (analysis of variance). Where significant interactions or main effects of multi-level factors emerged, post-hoc pairwise comparisons were performed using estimated marginal means. Additionally, slope analysis was conducted through estimated trends to decompose interactions involving continuous predictors (e.g., perceived intensity or personality traits). All post-hoc p-values were adjusted for multiple comparisons using the False Discovery Rate (FDR) method.

2.4.2 Power Spectra Analysis

To estimate the spectral density of RS EEG data, the Welch method (Welch, 1967) as implemented in Brainstorm (Tadel et al., 2011) was used. Spectral analysis was performed by calculating the Power Spectrum Density (PSD) across the standard frequency bands: delta (2-4 Hz), theta (4-7 Hz), alpha (8-12 Hz), beta (13-30 Hz), and gamma (30-45 Hz). This was achieved by partitioning the signals into overlapping windows of fixed duration. For each segment, the Fast Fourier Transform (FFT) was computed, and the resulting power coefficients were averaged across all windows. Finally, based on a visual assessment of the topographical maps, the PSD values were averaged within specific electrode clusters for each frequency range. Specifically, Theta and Gamma power were averaged over a frontal cluster (electrodes 5, 6, 7, 12, 13, 106), while Delta, Alpha, and Beta power were averaged over a parieto-occipital cluster (electrodes 61, 62, 77, 78, 72, 67, 71, 76).

To investigate whether resting-state EEG spectral power predicts the ability to correctly classify emotion genuineness, a GLMM was fitted using the *lme4* package in R. The model utilized a binomial probability distribution with a logit link function. To account for the crossed repeated-measures structure of the data, random intercepts for both participants (subjects) and individual stimuli (items) were included in the model. The continuous spectral power values of the five frequency bands (Delta, Theta, Alpha, Beta, and Gamma) were mean-centered and entered simultaneously into the model as fixed factors. The significance of the fixed effects was evaluated via Type II Wald chi-square tests.

2.4.3 Aperiodic parameter FOOOF

The aperiodic components of EEG signal, which reflect a basic physiological state independent of standard rhythms (e.g., alpha), have been taken into account. To separate the aperiodic (1/f-like) component from the periodic (oscillatory) activity of the EEG signal, the FOOOF (Fitting Oscillations & One-Over-F) algorithm, as implemented in the FieldTrip toolbox (Donoghue et al., 2020) was used. The Power Spectral Density (PSD) of each subject was estimated in the 1–40 Hz frequency range and linearly decomposed into periodic and aperiodic components.

From this modeling process, the *offset* and *exponent* values were extracted for each of the 128 electrodes. The exponent is considered a marker of the balance between excitation and inhibition (E/I balance) in neural circuits. When its value is high (steeper slope), it generally indicates greater inhibition or more synchronized/slower neural activity, while when its value is low (flatter slope), it indicates greater excitation and more pronounced excitability (Donoghue et al., 2020). The offset reflects the overall level of neural activity or the aperiodic "total power". A higher offset indicates higher metabolic activity or average neuronal firing rate (Donoghue et al., 2020).

To test specific functional hypotheses, Offset and Exponent values were averaged across three distinct electrode clusters, defined by their scalp topography. A Parietal cluster, (electrodes 58, 59, 64, 65, 90, 91, 95, 96), selected for its proximity to posterior areas typically involved in visual processing (e.g., FFA); a central cluster (electrodes 36, 37, 41, 42, 87, 93, 103, 104), covering scalp regions often associated with sensorimotor processing and embodied simulation mechanisms (Dijkstra & Post, 2015; Wood et al., 2016); a temporal cluster (electrodes 39, 40, 44, 45, 108, 109, 114, 115), corresponding to the scalp projection of the superior temporal regions (e.g., STS). Prior to statistical modeling, these cluster-averaged values were standardized (Z-scored) across subjects.

To investigate whether these aperiodic features predict the ability to correctly classify emotion genuineness, a series of GLMMs were fitted using the *lme4* package in R. Consistent with the behavioral analyses, the dependent variable (Authenticity Recognition Accuracy) was binary; thus, all models were fitted using a binomial probability distribution with a logit link function. To account for the repeated-measures design, a random intercept for subjects was included in all models. Separate models were constructed for the exponent and the offset within each electrode cluster. Specifically, for each GLMM, the fixed effects included Stimulus Authenticity (Genuine, Posed), the standardized FOOOF parameter of interest (e.g., Parietal Exponent), and their two-way interaction. The significance of the fixed effects was evaluated via Type II Wald chi-square tests. Where significant interactions emerged between the authenticity factor and the aperiodic predictor, slope analyses (estimated trends) were conducted to decompose the interaction, and all post-hoc *p*-values were adjusted using the False Discovery Rate (FDR) method.

Chapter 3

Results

The present chapter reports the results obtained from the behavioral and RS EEG statistical analyses. The first subsection will present the descriptive statistics, followed by a subsection dedicated to the behavioral results, and finally, a subsection focused on RS-EEG components and authenticity recognition.

All model summaries are reported in Appendix A.

3.1 Descriptive Results

Participants reported average levels of alexithymia (TAS-20 Total Score: *M*=46.8, *SD*=9.0) (Bressi et al., 1996), and the performance on the Reading the Mind in the Eyes Test (RMET) showed a mean raw score of 26.7 (*SD* = 3.3), falling within the typical range reported for neurotypical adults (Maddaluno et al., 2022).

Overall emotion recognition accuracy was high (*M*=94.3%, *SD*=3.39). Specifically, Happiness was recognized with the highest accuracy (*M*=99.1%, *SD*=1.81), followed by Disgust (*M*=95.2%, *SD*=4.98), Anger (*M*=91.8%, *SD*=7.43), and Fear (*M*=90.9%, *SD*=6.21).

Furthermore, participants were proficient in discriminating authenticity, correctly categorizing 77.0% (*SD*=12.6) of genuine expressions and 78.2% (*SD*=8.99) of posed ones. A paired-samples t-test revealed no significant difference in authenticity recognition accuracy between genuine and posed stimuli (*t*(39)=−0.37, *p*=.710).

Regarding perceived intensity ratings, a series of paired-samples t-tests were conducted to investigate the differences between genuine and posed expressions across emotional categories. No clear pattern emerged. For Happiness and Fear, genuine expressions were perceived as significantly more intense than their posed counterparts ($t(39)=8.81$, $p<.001$ for Happiness; $t(39)=6.64$, $p<.001$ for Fear). Conversely, posed expressions of Anger were perceived as significantly more intense ($M=5.26$, $SD=1.14$) when compared to genuine ones ($M=4.90$, $SD=1.16$); $t(39)=-3.04$, $p=.004$. Finally, for Disgust, intensity ratings did not significantly differ between the two genuineness conditions ($t(39)=-0.08$, $p=.940$).

3.2 Behavioral Results

Results are presented below according to the specific dependent variable measured: Emotion Recognition Accuracy and Authenticity Recognition Accuracy.

3.2.1 Emotion Recognition Accuracy

A first set of models evaluated the participants' ability to correctly categorize the presented emotions.

*Main effects of Emotion Category and Stimulus Authenticity***.** The analysis of deviance revealed a highly significant main effect of Emotion Category ($\chi^2(3) = 116.16$, $p < .001$) on Emotion Recognition Accuracy. Pairwise comparisons confirmed our hypothesis regarding the hierarchy of recognition: Happiness was identified with the greatest accuracy ($M = 99.1\%$), followed by Disgust ($M = 95.2\%$), whereas Anger ($M = 91.8\%$) and Fear ($M = 90.9\%$) were the most difficult to categorize. Neither the main effect of Stimulus Authenticity ($\chi^2(1) = 1.89$, $p = .169$) nor the interaction between Emotion Category and Stimulus Authenticity ($\chi^2(3) = 2.29$, $p = .514$) reached statistical significance. This suggests that the correct categorization of an emotion is primarily driven by its specific category rather than its genuine or posed nature.

*The role of Perceived Intensity***.** Perceived Intensity also emerged to have a main effect on Emotion Recognition Accuracy ($\chi^2(1) = 39.89$, p < .001, $B = 0.15$). Crucially, a significant interaction between Emotion Category and Perceived Intensity was observed ($\chi^2(3) = 9.37$, $p =$

.024). To further unpack this effect, a slope analysis was performed (Figure 3). Perceived intensity significantly predicted higher accuracy for negative emotions of Anger (*slope*=0.23, 95% *CI* [0.15, 0.32]) and Fear (*slope*=0.18, *CI* [0.10, 0.26]). Conversely, for Disgust (*slope* = 0.01, 95% *CI* [-0.11, 0.13] and Happiness (*slope* = 0.17, 95% *CI* [-0.06, 0.40]) no relationship was found. Post-hoc comparisons of the slopes revealed that the effect of intensity was significantly stronger for Anger compared to Disgust (z=3.04, p=.014). A slight difference was observed between Disgust and Fear (z=−2.39, p=.051). No other significant differences between slopes were found (all p_{adj}>.40).

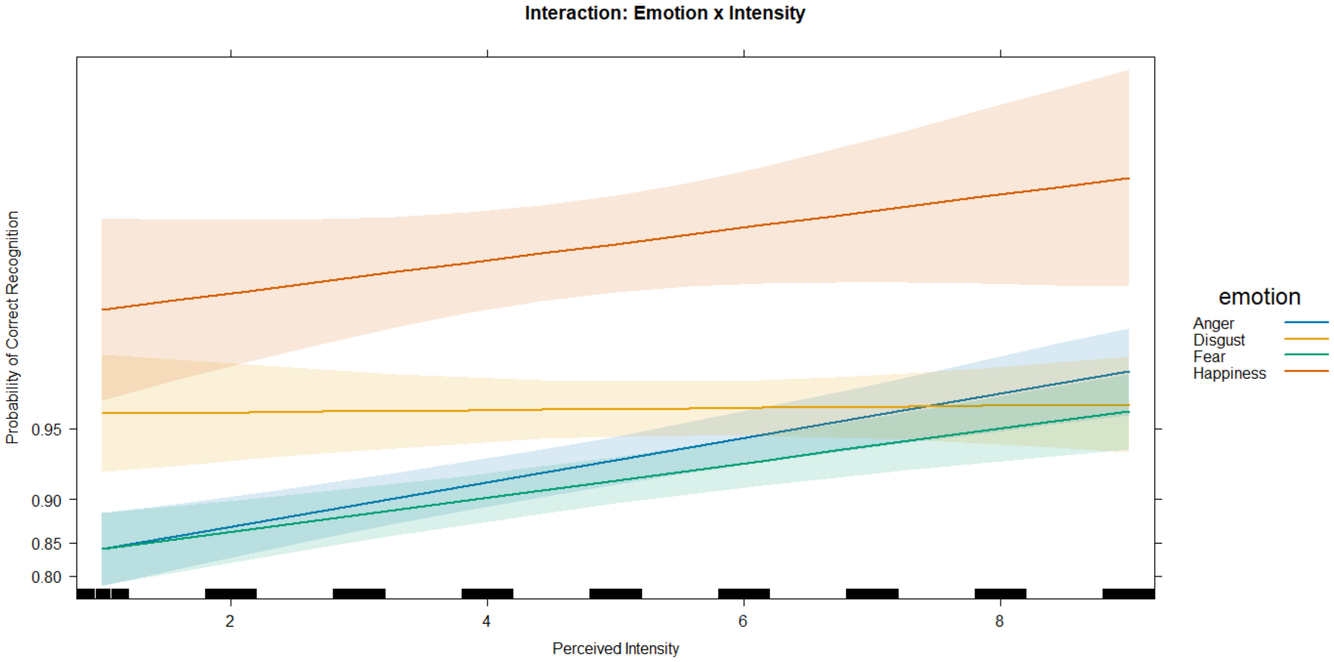

***Figure 3.* Interaction between Perceived Intensity and Emotion Category on Emotional Recognition Accuracy**. The estimated model values for emotion recognition accuracy (y-axis) are reported as a function of each emotion's perceived intensity (x-axis). Shaded bands around each line represent the 95% confidence intervals of the model estimates. A higher perceived intensity generally increases recognition accuracy, its facilitatory effect is significantly weaker for disgust compared to the other emotions.

*Individual Differences***.** A further model evaluated the impact of psychological traits while controlling for Emotion Category. Neither the global TAS-20 score ($\chi^2(1) = 0.79$, $p = .375$) nor the RMET score ($\chi^2(1) = 1.61$, $p = .205$) significantly predicted Emotion Recognition Accuracy.

3.2.2 Authenticity Recognition Accuracy

A second set of models focused on the participants' ability to correctly discriminate whether the displayed emotion was genuine or posed.

Emotion Category modulation. The analysis revealed a highly significant main effect of Emotion Category ($\chi^2(3) = 52.03$, $p < .001$), indicating varying levels of baseline difficulty in authenticity detection across different emotions. The main effect of Stimulus Authenticity was not significant ($\chi^2(1) = 1.63$, $p = .202$). An interaction emerged between Emotion Category and Stimulus Authenticity ($\chi^2(3) = 128.78$, $p < .001$). Simple contrast analysis (Genuine vs. Posed) revealed an emotion-specific pattern (Figure 4). Participants were significantly more accurate at recognizing genuine expressions of Happiness compared to posed ones (contrast = 0.94, $p < .001$). Conversely, a reversed pattern was observed for Anger, where participants were significantly more accurate at identifying posed expressions compared to genuine ones (contrast = -0.93, $p < .001$). No significant differences between genuine and posed expressions were found for Disgust ($p = .245$) and Fear ($p = .537$).

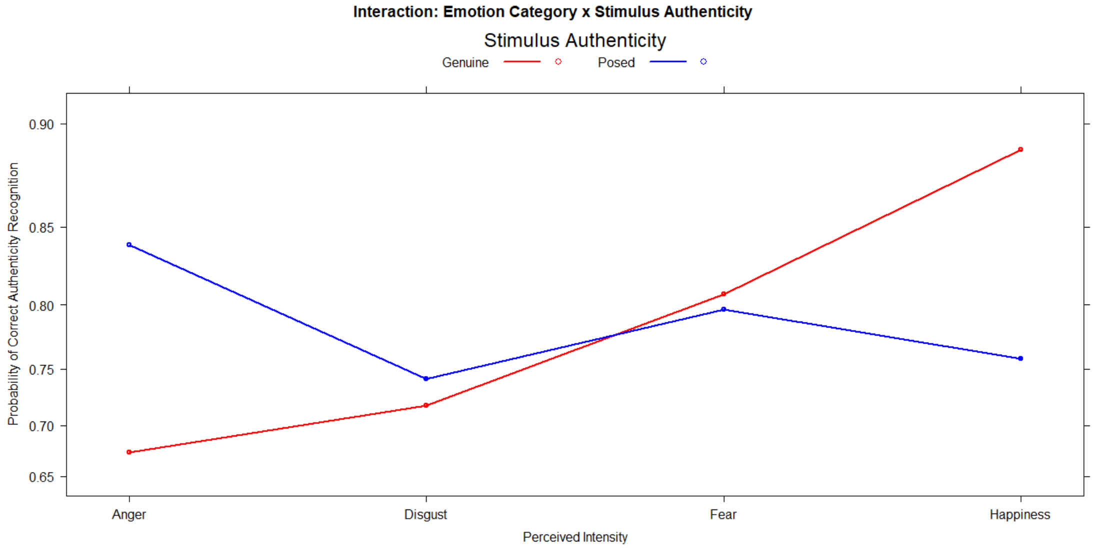

***Figure 4.* Interaction between Emotion Category and Stimulus Authenticity on Authenticity Recognition Accuracy.** The probability of correctly identifying whether an emotion is genuine or posed (y-axis) is reported for each emotion category (x-axis), separated by stimulus type (Genuine in red vs. Posed in blue). Shaded bands around each line represent the 95% confidence intervals of the model estimates. The interaction shows that the advantage of authenticity is emotion-specific: while genuine expressions are more accurately recognized than posed ones for Happiness, the opposite pattern is observed for Anger, where posed expressions are significantly easier to identify.

The role of Perceived Intensity. The analysis of deviance revealed a significant main effect of Perceived Intensity ($\chi^2(1) = 22.37$, $p < .001$). A robust interaction between Stimulus Authenticity and Perceived Intensity ($\chi^2(1) = 25.98$, $p < .001$) was found (Figure 5). Slope analysis demonstrated that for genuine expressions, a higher Perceived Intensity significantly predicted better Authenticity Recognition Accuracy (*slope* = 0.13, 95% CI [0.09, 0.17]). In contrast, for posed expressions, the relationship remained entirely flat (*slope* = -0.004, 95% CI [-0.04, 0.04]). Post-hoc comparisons confirmed that Perceived Intensity greatly facilitated the identification of authenticity exclusively for genuine stimuli ($z = 5.10$, $p < .001$).

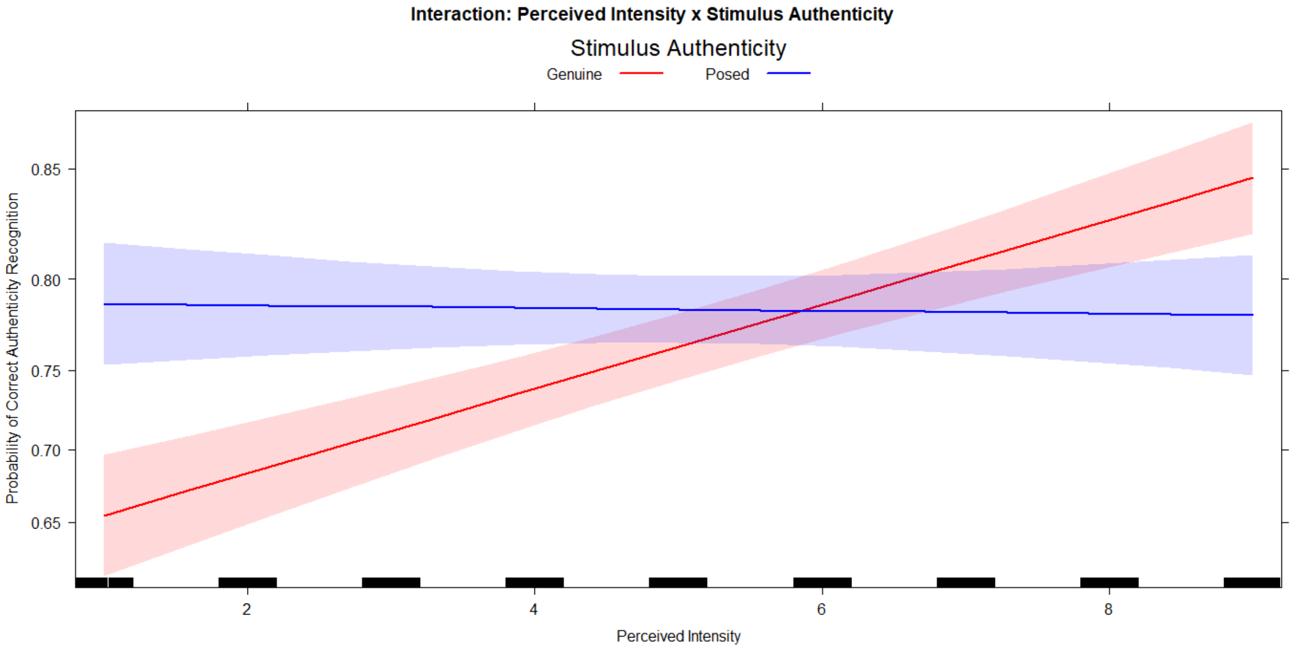

***Figure 5*. Interaction between Perceived Intensity and Stimulus Authenticity on Authenticity Recognition Accuracy.** The plot shows the predicted probability of correctly identifying whether an emotion is genuine or posed, as a function of its perceived intensity, separated by stimulus type (Genuine in red vs. Posed in blue). Shaded bands around each line represent the 95% confidence intervals of the model estimates. The facilitatory effect of perceived intensity on recognition accuracy is significantly stronger for genuine expressions compared to posed ones.

Individual Differences (TAS-20 and RMET). Similarly to emotion categorization, global TAS-20 ($\chi^2(1) = 0.27$, $p = .606$) and RMET scores ($\chi^2(1) = 3.45$, $p = .063$) did not significantly predict Authenticity Recognition Accuracy.

To better explore the nuances of the TAS-20, a specific model including its three subscales as fixed factors was fitted. The analysis of deviance showed that neither the Difficulty

Identifying Feelings (DIF) subscale ($\chi^2(1) = 0.16$, $p = .685$) nor the Difficulty Describing Feelings (DDF) subscale ($\chi^2(1) = 1.09$, $p = .296$) were significant predictors. Conversely, a significant main effect of the Externally Oriented Thinking (EOT) subscale emerged ($\chi^2(1) = 6.13$, $p = .013$), with higher EOT scores generally predicting worse overall authenticity recognition accuracy ($B = -0.04$). To test whether this EOT-related effect was specific to genuine or posed expressions, a follow-up model was constructed, revealing a highly significant interaction between the EOT subscale and Stimulus Authenticity ($\chi^2(1) = 67.59$, $p < .001$).

The slope analysis (Figure 6) showed that the higher the score of the EOT subscale, the worse the authenticity recognition for genuine stimuli (*slope* =−0.14, 95% CI [−0.18,−0.10]), and the better the authenticity recognition for posed stimuli (*slope* =0.05, 95% CI [0.01,0.09]). Post-hoc comparisons confirmed that the effect of EOT differs radically between the two condition of authenticity (*estimate*=−0.19, *SE*=0.02, *z*=−8.22, *p*<.001).

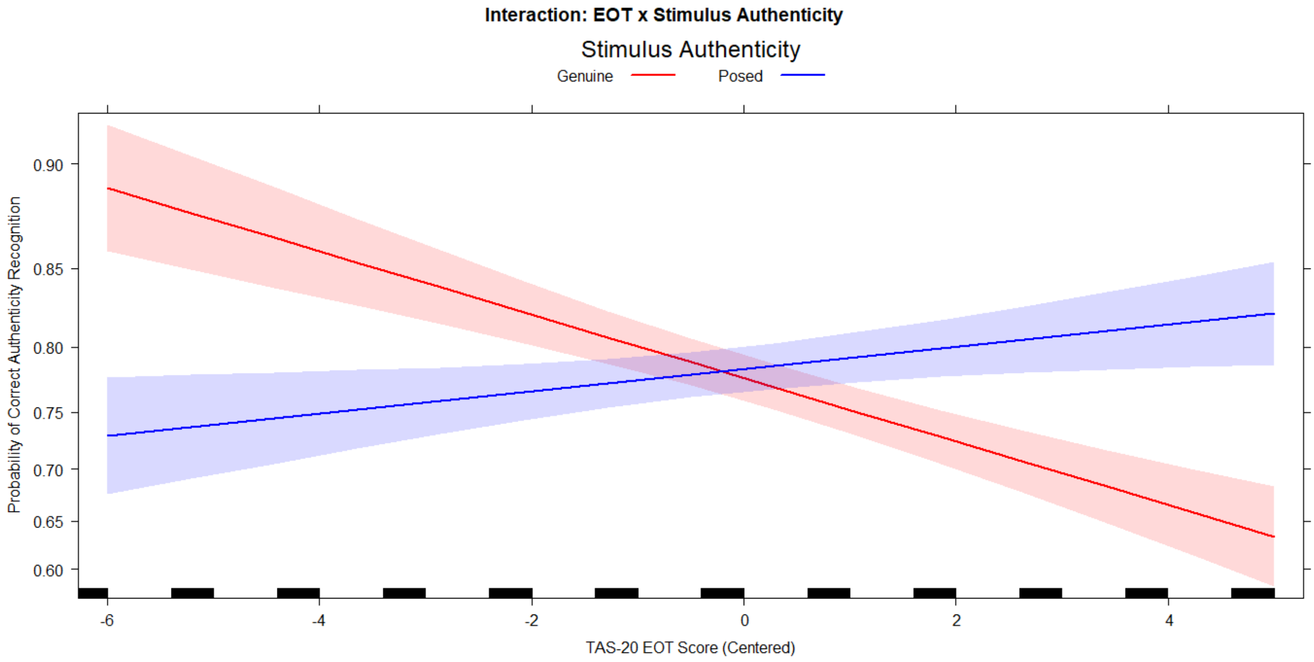

***Figure 6*. Interaction between EOT subscale and Stimulus Authenticity on Authenticity Recognition Accuracy.** The plot shows the predicted probability of correctly identifying whether an emotion is genuine or posed (y-axis), as a function of the EOT scores (x-axis), separated by stimulus type (Genuine in red vs. Posed in blue). Shaded bands around each line represent the 95% confidence intervals of the model estimates. Higher EOT levels are associated with a decrease in the recognition of genuine expressions, whereas a positive trend is observed for posed expressions.

3.3 Neurophysiological Results

To investigate the neural correlates of behavioral performance, we performed a series of GLMMs, to test whether resting-state EEG activity could predict the participants' Authenticity Recognition Accuracy. The analysis was divided into classic periodic oscillations and aperiodic (FOOOF) dynamics.

3.3.1 Power Spectrum Density Results

We assessed the predictive role of standard frequency bands (Delta, Theta, Alpha, Beta, Gamma) on Authenticity Recognition Accuracy. The analysis of variance revealed that none of the included frequency bands (Delta, Theta, Alpha, Beta, Gamma) significantly contributed to the Authenticity Recognition Accuracy (all $p > .05$).

3.3.2 Aperiodic Parameter FOOOF Results

We evaluated the role of aperiodic neural activity. Specifically, the Offset and the Exponent were extracted from three electrode clusters (Parietal, Motor, and Temporal) and entered as continuous predictors of Authenticity Recognition Accuracy.

Parietal Cluster. Regarding the Offset model, the analysis of deviance revealed no significant main effects for the Parietal Offset (χ^2 (1)=0.06, p=.800) and no significant main effect of Stimulus Authenticity (χ^2 (1)=1.53, p=.216). However, a significant interaction between Stimulus Authenticity and Parietal Offset emerged (χ^2 (1)=6.43, p=.011). Simple slope analyses revealed a cross-over pattern (Figure 7, Panel A): the higher the offset power, the lower the accuracy for genuine expressions (*slope*=-0.08), while the higher the accuracy for posed expressions (*slope*=0.06). The difference between the two conditions was significant (p = .011).

The same trend appeared for the Exponent parameter. The analysis of deviance showed no significant main effect of Stimulus Authenticity (χ^2 (1)=1.53, p=.216). and no significant main effect of the Parietal Exponent (χ^2 (1)=0.09, p=.767). A significant interaction between the Exponent and Stimulus Authenticity emerge (χ^2 (1)=6.15, p= .013). The slope analysis (Figure 7, Panel B) confirmed that the higher the exponent, the lower the accuracy for genuine expressions (slope= -0.05, 95%*CI*[-0.18, 0.01]), while the higher the accuracy for posed expressions (slope= 0.08, 95%*CI*[-0.04, 0.15]). The difference between the two conditions was significant (*p* = .013).

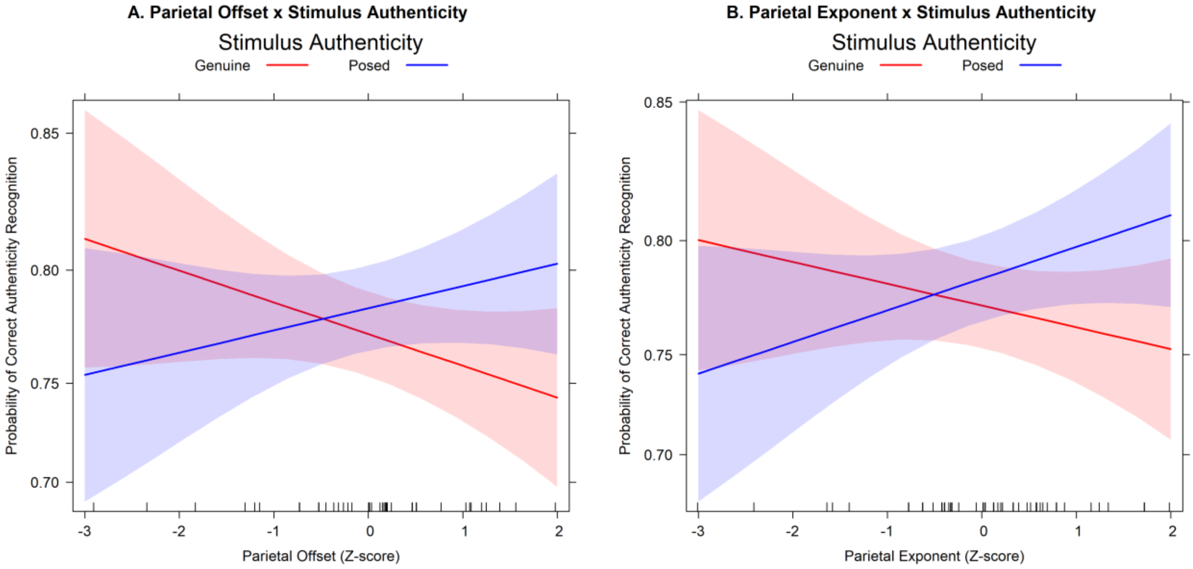

***Figure 7*. Interaction between parietal aperiodic parameters and stimulus authenticity on authenticity recognition accuracy.** The plots display the predicted probability of correct recognition (y-axis) as a function of the Parietal Offset (Panel A) and Parietal Exponent (Panel B), separated by stimulus type (Genuine in red vs. Posed in blue).Shaded bands represent the 95% confidence intervals of the model estimates. **Panel A:** Increase in the offset value, which reflects greater metabolic activity below the parietal cluster, correlates positively with the recognition accuracy of posed emotions and negatively with genuine emotions' recognition accuracy. **Panel B**. As the exponent increases, indicating greater neural inhibition and more synchronized activity, the recognition of posed emotions increases, while the recognition of genuine emotions decreases.

Temporal Cluster. The aperiodic parameters over the temporal cluster showed a different profile. For the Temporal Offset, the analysis of deviance revealed no significant main effect of Stimulus Authenticity (χ^2 (1)=1.54, *p*=.215) and no significant main effect of the Temporal Offset (χ^2 (1)=0.07, *p*=.792) and no significant interaction (χ^2 (1)=0.01, *p*=.893).

Regarding the Temporal Exponent, no significant main effects emerged for Stimulus Authenticity (χ^2(1) = 1.51, *p* = .219) and Temporal Exponent (χ^2(1) = 1.10, *p* = .295). However, a significant interaction between Stimulus Authenticity and the Temporal Exponent emerged. A slope analysis (Figure 8) showed an opposite pattern to the one observed in the parietal cluster: an higher exponent, in the temporal cluster, was associated with an increase in detection accuracy for genuine expressions (slope=0.12, 95%*CI*[0.02,0.22]). Regarding posed expressions, the slope was negative but not different from zero (slope=−0.04, 95%*CI*[−0.14,0.06]). The difference between the two slope resulted statistically significant (*p*=.001).

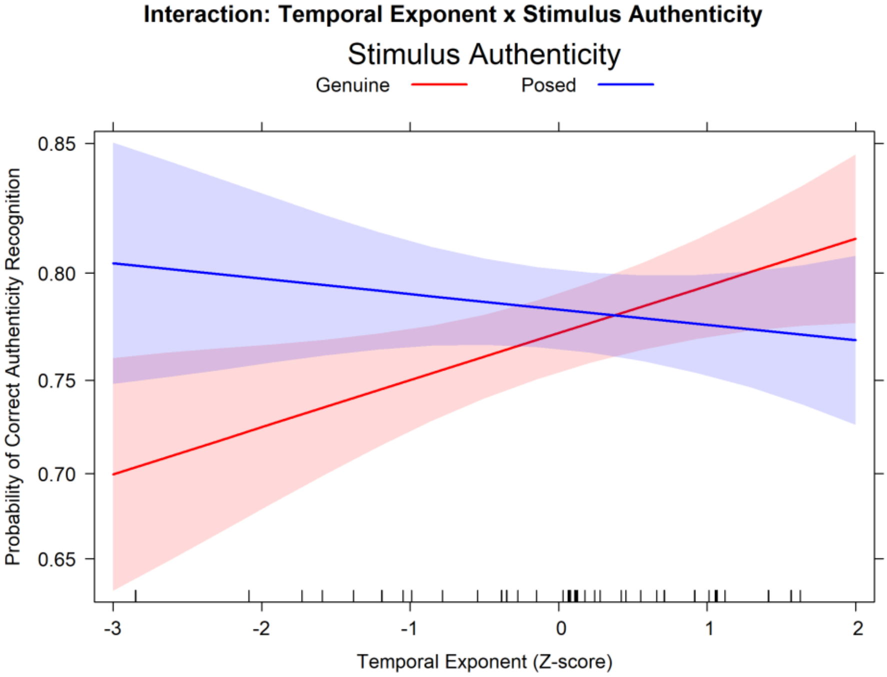

***Figure 8.* Interaction between Temporal Exponent parameter and Stimulus Authenticity on Authenticity Recognition Accuracy.** The plots display the predicted probability of correct recognition (y-axis) as a function of the Temporal Exponent, separated by stimulus type (Genuine in red vs. Posed in blue). Shaded bands represent the 95% confidence intervals of the model estimates. A higher temporal exponent is associated with a significant increase in the accuracy of genuine expression recognition.

Motor Cluster. Finally, regarding the Offset model, the analysis of deviance revealed no significant main effect of Stimulus Authenticity ($\chi^2(1) = 1.54$, $p = .215$), no significant main effect of the Motor Offset ($\chi^2(1) = 0.22$, $p = .636$), and no significant interaction ($\chi^2(1) = 0.29$, $p = .589$). Similarly, the Exponent model showed no significant main effect of Stimulus Authenticity ($\chi^2(1) = 1.53$, $p = .216$), no significant main effect of the Motor Exponent ($\chi^2(1) = 0.77$, $p = .381$), and no significant interaction ($\chi^2(1) = 2.15$, $p = .142$).

Chapter 4

Discussion

This chapter aims to offer a tentative interpretation of the results introduced in the previous chapter. The first subsection will discuss the findings from the behavioral analysis, while the second will focus on the results of the neurophysiological investigations. To conclude, the study's limitations and future perspectives will be discussed.

4.1 Behavioral Findings

4.1.1 Authenticity Recognition Accuracy

The primary objective of this study was to investigate the behavioral predictors of authenticity discrimination. Contrary to our first hypothesis (H1), the behavioral results did not reveal a generalized "truth bias" or a significant overall advantage for recognizing genuine expressions over posed ones. Participants correctly identified the authenticity of genuine stimuli 77.0% of the time and posed stimuli 78.15% of the time, with no significant difference between the two conditions. The absence of a difference in the discrimination accuracy can be attributed to the type of stimuli used in the EAR task and to the demographics of our sample. The “truth-bias” effect has been established among research on emotion perception that heavily relied on static, posed photographs of stereotypical facial configurations. It is plausible to speculate that as the present study employs ecologically valid, dynamic videoclips of truly spontaneous versus truly simulated emotions, participants had access to rich temporal qualities and kinematic information to successfully discriminate the nature of the stimulus, without resorting to cognitive short-cuts. As a matter of fact, previous studies using dynamic stimuli provide strong evidence that dynamic presentation formats significantly enhance an observer's sensitivity to authenticity (Namba et al., 2018; Zloteanu et al., 2018). Moreover, the initial selection of the stimuli, chosen to span a heterogeneous range of genuineness recognition accuracy, from roughly 40% to 100%, must be integrated in the interpretation. By including stimuli known to be ambiguous and difficult to classify, it is possible the visual ambiguity overrode the observer's default "truth bias". Also, it is crucial to contextualize the result within the specific demographic of our sample: young healthy female psychology students. It is plausible to posit that such specific population possesses a higher baseline proficiency in observing and analyzing human behavior due to their background.

Interestingly, subsequent analyses revealed that sensitivity to authenticity is not a unitary phenomenon but is an emotion-specific process. Our second hypothesis (H2) posited that positive valence (Happiness) would have a general advantage over negative valence in the discrimination of authenticity. Beyond a strong main effect of Emotional Category, confirming that valence modulates sensitivity to authenticity, a highly significant interaction between Emotion Category and Stimulus Authenticity emerged, demonstrating that the advantage of authenticity drastically shifts depending on the valence and social function of the emotion being observed. Specifically, distinct patterns emerged for Happiness and Anger. A clear genuine bias emerged for positive affect: Genuine Happiness was significantly easier to recognize than its Posed counterpart. Genuine happiness is known in literature to generally have unique, robust physical markers (e.g., Duchenne smile), which dynamic stimuli provide in abundance, enhancing observer's sensitivity to genuinely felt positive experiences (Namba et al., 2018). This allowed our observers to easily pick up these true affective signals. Moreover, we are exposed to smiles every day; they are the most pervasive facial expressions used to communicate affiliation and cooperative intent (Johnston et al., 2010). Because these signals are socially relevant, on one hand our perceptual systems became attuned to recognizing genuine happiness, on the other hand, humans have also become remarkably adept at simulating them. This makes posed happiness particularly deceptive and easily confounded with its genuine counterpart, often leading to a genuine bias.

Conversely, a reversed pattern was observed for anger: Posed Anger was more accurately recognized than Genuine Anger. This result can be interpreted in light of the kinematics peculiar to posed and genuine anger. As a matter of fact, simulated expressions of anger often comply to the prototypical scowl, displaying exaggerated and intense facial configurations, whereas spontaneous expressions of anger are actually highly variable, unique, and depend heavily on the individual and the specific context (Barrett et al., 2019). Compared to genuine displays of anger, which are usually less intense and more subtle, its posed displays are therefore easier for observers to spot and classify.

No significant differences in authenticity recognition were found for fear and disgust, indicating that participants were equally capable of correctly identify both posed and genuine expressions of these two emotions. From an evolutionary perspective, fear and disgust do not just express an affective message, rather they function to convey potential biological threats directly linked to survival (Adolphs, 2013; Tybur et al., 2013). Because ignoring or missing a sign of danger has, potentially, dangerous consequences, our brains are exceptionally attuned to these signals. Pivoting on this knowledge, our results suggests that observers process both simulated and genuine displays of disgust with equal vigilance. It can be argued that this heightened perceptual attention, coupled with the fact that these survival-related emotions are difficult to simulate due to their complex involuntary muscle activations convincingly (Ekman, 2003; Hess & Kleck, 1990) allowed to easily spot both genuine and posed expressions, flattening the accuracy advantage.

An unexpected finding emerged regarding the role of perceived intensity on authenticity discrimination (H3). While we initially expected authenticity recognition to remain stable across different levels of intensity, the analysis revealed a robust interaction: higher perceived intensity significantly improved the accurate identification of genuine expressions but had no effect on the recognition of posed expressions. To explain this pattern, we can conceptualize perceived intensity as a perceptual amplifier. For Genuine expressions, when intensity increases, it amplifies the natural and fluid temporal signs typical of authentic expressions. Because dynamic presentation allows essential perceptual cues to parse an emotional experience to be decoded (Zloteanu et al., 2018), this amplified, high-quality visual data allows the observers to confidently and accurately categorize the expression as authentic. For posed expressions, one might logically expect that amplifying the facial display would clearly magnify its kinematic irregularities, such as abrupt onsets or a lack of fluidity. These signs would make the expression look like an unnatural display, making it easier to classify it as simulated. However, the present result can be contextualized considering the affect-induction perspective (Zloteanu & Krumhuber, 2021), which emphasizes that deliberate facial expressions act as strategic communicative signals, often intentionally exaggerated into intense stereotypes to successfully exert social influence. One might postulate that the observer is faced with an obviously exaggerated movement, accompanied, however, by an intensity, deliberately employed to affect the observer successfully (Zloteanu et al., 2018), that conflicts with the irregularities exposing the deception. At this point, it is possible to think that the observer is experiencing a perceptual stalemate, in which the exaggerated kinematics prevent the observer's accuracy from dropping, but the convincing "loudness" of the deliberate social signal prevents their accuracy from improving. This could explains the flat line observed between intensity and posed expressions in our behavioral data.

Finally, we investigated how the individual traits of alexithymia and ToM, as measured by the TAS-20 and RMET, predict authenticity discrimination (H4, H5). Both the RMET and the global TAS-20 score failed to predict accuracy. The null result for the RMET likely stems from two interrelated methodological factors. From a psychometric perspective, the RMET scores of our sample (M = 26.7, SD = 3.3) fall within the normative range for healthy adults, exhibiting a “restriction of range”. The absence of participants with socio-cognitive deficits (typically associated with lower scores) limited the variance required for the regression model to yield a robust effect in a sample of 40 subjects. In addition, the test requires participants to deduce complex, static mental states from isolated, black-and-white photographs of the ocular region (Baron-Cohen et al., 2001). Recent findings reviewed the nature of the RMET primarily as a measure of static emotion perception, heavily reliant on crystallized intelligence, vocabulary comprehension, and semantic knowledge (Kittel et al., 2022; Pavlova & Sokolov, 2022).Therefore, it is plausible that this specific ability is simply not transferable to the complex demands of authenticity discrimination. Detecting whether an emotion is genuinely felt or strategically posed, as operationalized in the dynamic EAR task, does not rely on matching a static visual pattern to a semantic label but it requires the continuous evaluation of full-face, dynamic kinematic cues, such as the fluidity, rapid onset, and temporal trajectory of facial movements (Scarpazza et al., 2025). These factors might have played an important role in the results we observed in our experiment.

Also, the global score of the TAS-20 did not significantly predict authenticity discrimination. This result can be interpreted in light of the psychometric characteristics of the sample, as participants reported an overall mean score (M = 46.8, SD = 9.0) that was in line with normative data for the healthy population. Moreover, the construct of alexithymia is operationalized in the TAS-20 through three factors (DIF, DDF, EOT), each of which reflects a distinct difficulty in emotional processing. For instance, a deeper exploration of its subscales showed a significant interaction involving the Externally Oriented Thinking (EOT) subscale, which reflects the tendency to direct their attention toward external details and events rather than subjective feelings and internal affective states (Rosenberg et al., 2020). The analysis highlighted a cross-over effect: higher EOT scores predicted worse accuracy in recognizing genuine expressions but paradoxically predicted better accuracy in identifying posed stimuli. A tentative interpretation of this peculiar pattern stems from the sensorimotor simulation hypothesis (Wood et al., 2016): Evaluating the genuineness of an emotional display requires the observer to implicitly mirror the perceived expression, generating a corresponding internal affective state to physically "feel" its authenticity. High-EOT individuals are theoretically less prone to engage in such process, as they have been found to avoid internal affective processing and exhibit reduced physiological reactivity to emotional stimuli (García-Rodríguez et al., 2023; Grynberg et al., 2012). Thus, on one hand, it can be proposed that they might struggle to simulate and decode the natural fluidity of genuine emotions internally, on the other hand, as they mostly rely on external cues to navigate social interactions, they appear better equipped to spot simulated emotions. Our results support the proposal that without an internal resonance, high EOT individuals are particularly sensitive to the deliberate, stereotyped, mechanical features of posed emotions, thus recognizing them with greater accuracy.

4.2 Neurophysiological Findings

The behavioral investigation on authenticity discrimination was complemented by an analysis of its underlying neurophysiological correlates using high-density EEG recording. We recorded intrinsic baseline activity at rest, therefore focusing on how an individual's baseline physiological state predicts their subsequent behavioral performance.

4.2.1 Power Spectrum Density Findings

Our initial hypothesis (H6) examined the predictive power of standard periodic oscillations (Delta, Theta, Alpha, Beta, and Gamma frequency bands). However, this Power Spectrum Density (PSD) analysis yielded null results, with none of the canonical frequency bands significantly predicting authenticity recognition accuracy. Two main arguments may help contextualize the observed result. First, from a purely topographical perspective, the data-driven use of macro-clusters for PSD extraction may have induced a spatial dilution effect. The processing of complex mental states (mentalizing) and the decoding of ambiguous biological signals recruit focal networks; it is therefore plausible that the use of clusters flattened and masked the essential predictive contribution of these focal nodes. Second, the processing of complex social signals such as emotional authenticity likely goes beyond the simple modulation of local absolute power. The literature has extensively explored the idea that brain areas communicate with one another through synchronization and that neural efficiency in complex socio-perceptual tasks is predominantly expressed through functional connectivity dynamics (Chiarion et al., 2023; Güntekin & Başar, 2014). In light of these methodological considerations, it is plausible that the traditional absolute power analysis employed in our study lacked the sensitivity required to capture the highly integrated and dynamic neural signatures underlying authenticity discrimination, ultimately leading to the observed null results.

4.2.2 Aperiodic parameter FOOOF Findings

Current research reflected on the analytical risks of merging periodic and aperiodic features within standard frequency bands, a shift prompted by findings that the isolated aperiodic signal is not merely noise, but rather a physiologically meaningful metric that significantly predicts cognitive functioning (Donoghue et al., 2020). In our experiment, we explored the aperiodic components analysis (H7), in relation to authenticity discrimination, using the FOOOF (Fitting Oscillations & One-Over F) algorithm to isolate explicitly and parameterize its parameters of interest: the Offset and the Exponent. The Exponent acts as an index of the excitation/inhibition balance in neural circuits, while the Offset reflects the total aperiodic power, serving as an indicator of the overall neuronal firing rate and, consequently, the metabolic investment of the underlying area (Donoghue et al., 2020). Our investigation of the aperiodic components focused on specific topographical distributions: temporal, parietal and motor electrode clusters, which yielded different patterns.

In the temporal cluster our results suggest that higher Exponent predicts better recognition accuracy for genuine expressions. There was no concurrent effect for the Offset parameter. According to current knowledge, higher Exponent reflects greater neural inhibition, resulting in more synchronized and slower neural activity (Donoghue et al., 2020). While our scalp-level recordings preclude precise source localization, the temporal electrode cluster topographically overlies crucial cortical regions of the dynamic face perception network, such as the STS, which is known to be attuned to biological motion and serves as a rapid functional bridge from early visual perception to emotional evaluation (Bernstein & Yovel, 2015; Foley et al., 2012). This synchronization over temporal areas suggests the possible recruitment of highly automated neural circuits dedicated to face perception, and it can therefore be tentatively speculated that the accurate decoding of a genuinely felt emotion relies on highly synchronized neural firing that does not require massive additional metabolic investment.

In the parietal cluster, higher accuracy in recognizing posed emotions was predicted by both a higher Exponent and a higher Offset. While, as mentioned before, elevated exponent indicates that this neural activity is highly synchronized and slower, a high offset represents an increase in total aperiodic power, indicating a higher frequency of neuronal firing and a greater metabolic demand (Donoghue et al., 2020). It is known in neurophysiological literature that there is an inverse relationship between the speed of neural oscillations and the spatial distance of neural communication, with slower, synchronized neural activity responsible for long-range communication across cortical networks (Siegel et al., 2012). Therefore, the topographical distribution of this combined presence of high metabolic investment and slow, synchronized activity suggests the involvement of parietal regions as active integration hub. In light of this scenario, it can be tentatively argued that to successfully unmask a simulated expression these regions are recruiting and integrating multisensory information from distally located networks.

Regarding the motor cluster, our analyses yielded null results, with neither the Exponent nor the Offset significantly predicting the accuracy of authenticity discrimination. The absence of modulation of the aperiodic parameters suggests that, within our sample, the ability to successfully distinguish a genuine expression from a posed one is not driven by a differential metabolic investment (Offset) or by specific excitation/inhibition balance (Exponent) in the areas underlying this electrode cluster. These regions are central to the sensorimotor simulation hypothesis (Wood et al., 2016), consequently, this finding tentatively can be interpreted as evidence that in our experiment authenticity discrimination might not strictly depend on sensorimotor simulation. Importantly, our analysis specifically evaluated the amplitude of metabolic activity and the overall neural synchronization, thus the lack of an effect in these specific indices strictly indicates that the areas underlying this electrode cluster do not differentiate genuine from posed stimuli based on the sheer quantity of recruited neurons or their synchronized firing rate, and it remains entirely possible that motor areas are equally recruited during the observation of both expression types, and that any differential processing relies on functional mechanisms not captured by this aperiodic analysis.

Chapter 5

Conclusion

As reviewed at the beginning of this research, navigating the human social environment requires more than just identifying the emotions of others: to thrive and successfully “read the room” it is crucial to evaluate, perceive, and integrate the subtle nuances conveyed even by the most blunt social signals. The present study aimed to unravel the behavioral and neurophysiological predictors of authenticity discrimination, challenging historical paradigms that relied on static stimuli and oversimplified cognitive models. A clear picture emerges from this investigation: authenticity discrimination is not a universal reflex driven by a general "truth bias" or simple motor mirroring, rather, it appears to be a highly sophisticated, emotion-specific cognitive achievement that requires distinct neural and metabolic strategies.

Behaviorally, our results suggest that the observer’s perceptual system dynamically adapts to the specific social and evolutionary function of the perceived emotion. We do not evaluate the sincerity of a smile in the same way we evaluate an angry scowl, nor do we process survival-critical signals like fear and disgust with the same biases. Moreover, differences in cognitive style appeared to modulate the evaluation of these social signals, as demonstrated by individuals with high externally oriented thinking (EOT), who were found to have an advantage in the recognition of posed emotions. At the neurophysiological level, our investigations highlight that evaluating a genuinely felt emotion relies on automated neural circuits that are metabolically efficient, whereas successfully unmasking a simulated expression demands high metabolic investment and slow, synchronized neural activity indicative of a long distance integration hub.

This project entails notable strengths that advance the current understanding of emotion authenticity discrimination. Firstly, unlike early research relying on static, stereotypical photographs, this study uses dynamic, validated stimuli from the PEDFE database. This allowed the investigation of unfolding temporal kinematics and genuine sender veracity, aligning with modern theories of emotion perception. Furthermore, the integration of behavioral assessments with advanced neurophysiological parameterization is a novelty, providing novel evidence for the role of the excitation/inhibition (E/I) balance in complex socio-perceptual tasks.

However, several limitations of the present study need to be acknowledged. A primary limitation lies in the sample, which consisted entirely of young, healthy, predominantly female (38 out of 40) university students enrolled in a psychology program. As we focused on a healthy population, the lack of broader individual differences may have limited the statistical power needed for the regression models to detect more nuanced socio-cognitive effects. A further methodological limitation pertains to the intrinsic spatial resolution of electroencephalography (EEG). Our investigation relied on scalp-level recordings mapped to broad topographical electrode clusters, which precludes precise cortical source localization. While we can speculate the involvement of underlying anatomical structures, we cannot definitively attribute the observed modulations to specific neural substrates. Moreover, our exclusive reliance on localized resting-state EEG (RS-EEG) analyses, although informative regarding baseline metabolic and neural states, might have obscured the dynamic network processes that likely underlie authenticity detection. As a matter of fact, literature emphasizes that the perception of facial expressions recruits a widely distributed neural network, where specialized regions and visual processing areas must continuously communicate and synchronize.

Based on these findings and methodological considerations, future investigations should overcome the limitations of a homogeneous sample, integrating larger and more demographically diverse cohorts. Also, to properly capture the nature of social perception, subsequent electrophysiological investigations must expand beyond localized power metrics with analyses of functional and effective connectivity. Importantly, although most research on authenticity perception focused on visual, face-decoding tasks, there is evidence for the reliance on multiple modalities to distinguish genuine from posed emotions (Drolet et al., 2012; Walle & Campos, 2014). Therefore, it could be relevant to investigate how the synergistic actions of the face, body muscles, and voice either align to signal a genuinely felt emotion or conflict to reveal a posed display.

Appendix A

Table A1.

Items TAS-20

N	Item	Subscale
1	Sono spesso confuso/a sulle sensazioni che provo nel mio corpo.	**DIF**
2	Trovo difficile trovare le parole giuste per i miei sentimenti.	**DDF**
3	Ho sensazioni fisiche che neppure i medici capiscono.	**DIF**
4	Riesco a descrivere facilmente i miei sentimenti.	**DDF**
5	Preferisco analizzare i problemi piuttosto che descriverli.	**EOT**
6	Quando sono sconvolto/a non so se sono triste, spaventato/a o arrabbiato/a.	**DIF**
7	Sono spesso perplesso/a dalle sensazioni del mio corpo.	**DIF**
8	Preferisco lasciare che le cose accadano piuttosto che capire perché sono accadute.	**EOT**
9	Ho sensazioni che non riesco a identificare.	**DIF**
10	Essere in contatto con le emozioni è essenziale.	**EOT**
11	Trovo difficile descrivere ciò che provo per le persone.	**DDF**
12	La gente mi dice di descrivere di più i miei sentimenti.	**DDF**
13	Non so cosa sta succedendo dentro di me.	**DIF**
14	Spesso non so perché sono arrabbiato/a.	**DIF**
15	Preferisco parlare con la gente delle loro attività quotidiane piuttosto che dei loro sentimenti.	**EOT**
16	Preferisco guardare spettacoli leggeri piuttosto che drammi psicologici.	**EOT**
17	È difficile per me rivelare i miei sentimenti più intimi, anche agli amici più cari.	**DDF**
18	Riesco a sentirmi vicino a qualcuno, anche in momenti di silenzio.	**EOT**
19	Trovo utile esaminare i miei sentimenti per risolvere problemi personali.	**EOT**
20	Cercare significati nascosti nei film o nelle commedie distoglie dal piacere dello spettacolo.	**EOT**

Note: Test downloaded from https://lumsa.it/sites/default/files/UTENTI/u432/TAS-20.pdf as developed by Bressi et al. (1996)

Table A2.

Descriptive Statistics of the Sample and Behavioral Variables

Predictors (Variables)	Mean (or %)	std. Error (SD)
Demographics & Traits		
Age	23.07	1.61
Gender (Female / Male)	38 / 2	–
TAS-20 (Total Score)	46.80	9.02
RMET (Raw Score)	26.70	3.31
Emotion Recognition Accuracy		
Overall	94.27	3.39
Anger	91.85	7.43
Disgust	95.25	4.98
Fear	90.90	6.21
Happiness	99.10	1.81
Authenticity Recognition Accuracy		
Overall	77.58	5.06
Genuine stimuli	77.00	12.60
Posed stimuli	78.15	8.99
Perceived Intensity		
Overall	5.28	0.94
Anger × Genuine	4.90	1.16
Anger × Posed	5.26	1.14
Disgust × Genuine	5.48	0.98
Disgust × Posed	5.48	1.13
Fear × Genuine	5.82	0.87
Fear × Posed	5.07	1.16
Happiness × Genuine	5.83	1.01
Happiness × Posed	4.42	1.23

Table A3.

Effects of Emotion Category on Authenticity Recognition Accuracy

	Accuracy (0/1)				
Predictors	***Odds Ratios***	*std. Error*	***CI***	***Statistic***	***p***
Intercept	3.65	0.20	3.28 – 4.06	23.68	<0.001
Anger	0.57	0.04	0.50 – 0.64	-9.08	<0.001
Disgust	0.70	0.04	0.62 – 0.79	-5.59	<0.001
Fear	1.15	0.08	1.00 – 1.32	2.01	0.044
Genuine Expression	1.01	0.06	0.90 – 1.13	0.17	0.861
Anger × Genuine Expression	2.51	0.24	2.08 – 3.02	9.62	<0.001
Disgust× Genuine Expression	1.11	0.10	0.93 – 1.33	1.19	0.236
Fear × Genuine Expression	0.92	0.09	0.76 – 1.12	-0.81	0.416
Random Effects					
σ^2	3.29				
$\tau_{00\ \mathrm{subject\_nr}}$	0.05				
ICC	0.02				
$N_{\mathrm{subject\_nr}}$	40				
Observations	8000				
Marginal R^2 / Conditional R^2	0.047 / 0.062				

Table A3.1.

Contrasts for Authenticity within each Emotion Category

contrast	*emotion*	*estimate*	*SE*	*df*	*z.ratio*	*p.value*
Genuine - Posed	**Anger**	-0.93	0.11	Inf	-8.49	0.00
Genuine - Posed	**Disgust**	-0.12	0.10	Inf	-1.16	0.25
Genuine - Posed	**Fear**	0.07	0.11	Inf	0.62	0.54
Genuine - Posed	**Happiness**	0.94	0.12	Inf	7.53	0.00

Table A4.

Interaction between Emotion Category and Authenticity on Emotion Recognition Accuracy

	Accuracy (0/1)			
Predictors	***Odds Ratio***	***std. Error***	***Statistic***	***p***
(Intercept)	25.52 (20.39 – 31.92)	2.92	28.34	<0.001
Anger	0.50 (0.42 – 0.60)	0.05	-7.64	<0.001
Disgust	0.91 (0.74 – 1.12)	0.09	-0.90	0.367
Fear	0.44 (0.37 – 0.53)	0.04	-9.13	<0.001
Genuine Expression	0.94 (0.82 – 1.08)	0.07	-0.92	0.355
Anger × Genuine Expression	1.07 (0.90 – 1.28)	0.10	0.79	0.430
Disgust× Genuine Expression	0.88 (0.72 – 1.08)	0.09	-1.24	0.216

Fear × Genuine Expression	0.99 (0.83 – 1.18)	0.09	-0.11	0.916
Random Effects				
σ^2	3.29			
$\tau_{00\ \text{subject\_nr}}$	0.30			
ICC	0.08			
$N_{\text{subject\_nr}}$	40			
Observations	8000			
Marginal R^2 / Conditional R^2	0.209 / 0.274			

Table A5.

Interaction of Emotion Category and Intensity on Emotion Recognition Accuracy

	Accuracy (0/1)			
Predictors	***Odds Ratio***	***std. Error***	***Statistic***	***p***
(Intercept)	12.32 (8.08 – 18.78)	2.65	11.68	<0.001
Anger	0.34 (0.21 – 0.54)	0.08	-4.58	<0.001
Disgust	1.78 (0.97 – 3.28)	0.55	1.87	0.062
Fear	0.36 (0.23 – 0.57)	0.08	-4.37	<0.001
Perceived Intensity	1.16 (1.08 – 1.25)	0.04	3.98	<0.001
Anger × Perceived Intensity	1.09 (0.99 – 1.19)	0.05	1.81	0.070
Disgust × Perceived Intensity	0.87 (0.78 – 0.97)	0.05	-2.48	0.013

Fear × Perceived Intensity	1.03 (0.95 – 1.13)	0.05	0.69	0.489
Random Effects				
σ^2	3.29			
τ_{00} subject_nr	0.36			
ICC	0.10			
N subject_nr	40			
Observations	8000			
Marginal R^2 / Conditional R^2	0.226 / 0.302			

Table A5.1.

Slope Analysis of Intensity across Emotions

Emotion	*Perceived Intensity Trend*	*SE*	*df*	*asymp.LCL*	*asymp.UCL*
Anger	0.23	0.04	Inf	0.15	0.32
Disgust	0.01	0.06	Inf	-0.11	0.13
Fear	0.18	0.04	Inf	0.10	0.26
Happiness	0.17	0.12	Inf	-0.06	0.40

Table A6.

Interaction between Authenticity level and Intensity on Authenticity Recognition Accuracy

	Accuracy (0/1)			
Predictors	***Odds Ratio***	***std. Error***	***Statistic***	***p***
(Intercept)	2.48 (2.09 – 2.95)	0.22	10.35	<0.001

Genuine	0.67 (0.58 – 0.77)	0.05	-5.39	<0.001
Perceived Intensity	1.07 (1.04 – 1.10)	0.02	4.42	<0.001
Genuine × Perceived Intensity	1.07 (1.04 – 1.10)	0.01	5.10	<0.001
Random Effects				
σ^2	3.29			
$\tau_{00\ \mathrm{subject\_nr}}$	0.06			
ICC	0.02			
N $_{\mathrm{subject\_nr}}$	40			
Observations	8000			
Marginal R^2 / Conditional R^2	0.011 / 0.028			

Table A6.1

Simple Slopes of Intensity for Genuine vs. Posed Faces

Stimulus Authenticity	*Perceived Intensity Trend*	*SE*	*df*	*asymp.LCL*	*asymp.UCL*
Genuine	0.13	0.02	Inf	0.10	0.17
Posed	-0.00	0.02	Inf	-0.04	0.04

Table A7.

Effects of TAS-20 and RMET on Emotion Recognition

	Accuracy (0/1)			
Predictors	***Odds Ratio***	***std. Error***	***Statistic***	***p***
(Intercept)	25.45 (20.41 – 31.75)	2.87	28.71	<0.001

Anger	0.50 (0.42 – 0.60)	0.05	-7.59	<0.001
Disgust	0.90 (0.74 – 1.10)	0.09	-1.02	0.306
Fear	0.44 (0.37 – 0.53)	0.04	-9.12	<0.001
Alexithymia (TAS-20)	0.99 (0.97 – 1.01)	0.01	-0.89	0.375
Theory of Mind (RMET)	1.04 (0.98 – 1.10)	0.03	1.27	0.205
Random Effects				
σ^2	3.29			
τ_{00} subject_nr	0.28			
ICC	0.08			
N subject_nr	40			
Observations	8000			
Marginal R^2 / Conditional R^2	0.212 / 0.274			

Table A8.

Effects of TAS-20 and RMET on Authenticity Recognition

	Accuracy (0/1)			
Predictors	***Odds Ratio***	***std. Error***	***Statistic***	***p***
(Intercept)	3.51 (3.22 – 3.82)	0.15	29.05	<0.001
Genuine	0.97 (0.92 – 1.02)	0.03	-1.24	0.215
Alexithymia (TAS-20)	1.00 (0.99 – 1.01)	0.00	-0.52	0.606

Theory of Mind (RMET)	1.02 (1.00 – 1.05)	0.01	1.86	0.063
Random Effects				
σ^2	3.29			
τ_{00} subject_nr	0.05			
ICC	0.01			
N subject_nr	40			
Observations	8000			
Marginal R^2 / Conditional R^2	0.002 / 0.016			

Table A9.

TAS-20 Subscales Predicting Authenticity Recognition

	Accuracy (0/1)			
Predictors	***Odds Ratio***	***std. Error***	***Statistic***	***p***
(Intercept)	3.51 (3.24 – 3.80)	0.14	30.70	<0.001
Difficulty Identifying Feelings (DIF)	1.00 (0.97 – 1.02)	0.01	-0.41	0.685
Difficulty Describing Feelings (DDF)	1.01 (0.99 – 1.03)	0.01	1.05	0.296
Externally Oriented Thinking (EOT)	0.96 (0.93 – 0.99)	0.02	-2.48	0.013
Random Effects				
σ^2	3.29			
τ_{00} subject_nr	0.04			
ICC	0.01			
N subject_nr	40			

Observations	8000
Marginal R^2 / Conditional R^2	0.004 / 0.015

Table A9.1.

Simple Slopes of EOT for Genuine vs. Posed Faces

Stimulus Authenticity	***EOT trend***	***SE***	***df***	***asymp.LCL***	***asymp.UCL***
Genuine	-0.14	0.02	Inf	-0.18	-0.10
Posed	0.05	0.02	Inf	0.01	0.09

Table A10.

PSD Power predicting Authenticity recognition

	Accuracy (0/1)			
Predictors	***Odds Ratio***	***std. Error***	***Statistic***	***p***
(Intercept)	3.73 (2.98 – 4.66)	0.43	11.55	<0.001
alpha s	0.99 (0.95 – 1.04)	0.02	-0.39	0.697
beta s	1.23 (0.54 – 2.81)	0.52	0.48	0.630
delta s	0.98 (0.85 – 1.12)	0.07	-0.35	0.727
gamma s	0.02 (0.00 – 7.11)	0.06	-1.31	0.190
theta s	1.08 (0.86 – 1.35)	0.13	0.65	0.516
Random Effects				

σ^2	3.29
τ_{00} subject_nr	0.05
ICC	0.01
N subject_nr	40
Observations	8000
Marginal R^2 / Conditional R^2	0.001 / 0.015

Table A11.

Analysis of Parietal Aperiodic Parameters on Authenticity Discrimination

	Parietal Offset Model				**Parietal Exponent Model**			
Predictors	***Odds Ratio***	***std. Error***	***Statistic***	***p***	***Odds Ratio***	***std. Error***	***Statistic***	***p***
(Intercept)	3.51 (3.22 – 3.84)	0.16	28.04	<0.001	3.51 (3.22 – 3.84)	0.16	28.04	<0.001
Genuine	0.97 (0.92 – 1.02)	0.03	-1.22	0.222	0.97 (0.92 – 1.02)	0.03	-1.25	0.210
Parietal Offset	0.99 (0.90 – 1.08)	0.04	-0.27	0.787				
Genuine × Parietal Offset	0.93 (0.89 – 0.98)	0.03	-2.54	0.011				
Parietal Exponent					1.01 (0.93 – 1.11)	0.05	0.28	0.781
Genuine× Parietal Exponent					0.93 (0.89 – 0.99)	0.03	-2.48	0.013
Random Effects								
σ^2	3.29				3.29			
τ_{00}	0.05 subject_nr				0.05 subject_nr			
ICC	0.02				0.02			

N	$40_{\text{subject\_nr}}$	$40_{\text{subject\_nr}}$
Observations	8000	8000
Marginal R^2 / Conditional R^2	0.002 / 0.017	0.002 / 0.017

Table A12.

Analysis of Temporal Aperiodic Parameters on Authenticity Discrimination

	Temporal Offset Model				**Temporal Exponent Model**			
Predictors	***Odds Ratio***	***std. Error***	***Statistic***	***p***	***Odds Ratio***	***std. Error***	***Statistic***	***p***
(Intercept)	3.51 (3.21 – 3.83)	0.16	28.06	<0.001	3.51 (3.22 – 3.83)	0.16	28.43	<0.001
Genuine	0.97 (0.92 – 1.02)	0.03	-1.24	0.215	0.97 (0.92 – 1.02)	0.03	-1.17	0.242
Temporal Offset	1.01 (0.93 – 1.10)	0.05	0.27	0.791				
Genuine × Temporal Offset	1.00 (0.95 – 1.05)	0.03	-0.13	0.893				
Temporal Exponent					1.04 (0.96 – 1.14)	0.05	0.97	0.333
Genuine × Temporal Exponent					1.09 (1.03 – 1.15)	0.03	3.15	0.002
Random Effects								
σ^2	3.29				3.29			
τ_{00}	$0.05_{\text{subject\_nr}}$				$0.05_{\text{subject\_nr}}$			
ICC	0.02				0.01			
N	$40_{\text{subject\_nr}}$				$40_{\text{subject\_nr}}$			
Observations	8000				8000			

Marginal R^2 / Conditional R^2	0.000 / 0.016	0.003 / 0.017

Table A13.

Analysis of Motor Aperiodic Parameters on Authenticity Discrimination

	Motor Offset Model				**Motor Exponent Model**			
Predictors	***Odds Ratio***	***std. Error***	***Statistic***	***p***	***Odds Ratio***	***std. Error***	***Statistic***	***p***
(Intercept)	3.51 (3.21 – 3.83)	0.16	28.12	<0.001	3.51 (3.22 – 3.83)	0.16	28.30	<0.001
Genuine	0.97 (0.92 – 1.02)	0.03	-1.23	0.217	0.97 (0.92 – 1.02)	0.03	-1.21	0.226
Motor Offset	1.02 (0.94 – 1.11)	0.05	0.47	0.642				
Genuine × Motor Offset	1.01 (0.96 – 1.07)	0.03	0.54	0.589				
Motor Exponent					1.04 (0.95 – 1.13)	0.05	0.85	0.393
Genuine× Motor Exponent					1.04 (0.99 – 1.10)	0.03	1.47	0.142
Random Effects								
σ^2	3.29				3.29			
τ_{00}	0.05 $_{\text{subject\_nr}}$				0.05 $_{\text{subject\_nr}}$			
ICC	0.02				0.01			
N	40 $_{\text{subject\_nr}}$				40 $_{\text{subject\_nr}}$			
Observations	8000				8000			
Marginal R^2 / Conditional R^2	0.001 / 0.016				0.001 / 0.016			

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