UNIVERSIDAD COMPLUTENSE DE MADRID

FACULTAD DE PSICOLOGÍA

TESIS DOCTORAL

DINÁMICAS NEURONALES DE LA IDENTIDAD DEL YO EN CONTEXTOS SOCIALES Y LINGÜÍSTICOS

NEURAL DYNAMICS OF SELF-IDENTITY IN SOCIAL AND LINGUISTIC CONTEXTS

MEMORIA PARA OPTAR AL GRADO DE DOCTOR

PRESENTADA POR

Miguel Alejandro Rubianes Méndez

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Francisco Muñoz Muñoz

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Abstract

The study of self-identity has generated much research interest in psychology and cognitive neuroscience. From this perspective, a growing body of evidence suggests that self-related stimuli (e.g., faces, names or personal objects) are preferentially processed compared to non-self-related content. This bias is known as the self-reference effect. However, less is known as to the neural and psychological correlates underlying self-related processing. Furthermore, it remains unclear whether self-related information can bias other cognitive processes, particularly language comprehension. Hence, the aim of this thesis is twofold: (i) to investigate the neural and cognitive mechanisms underlying self-referential processing; and (ii) to investigate the interplay between self-referential processing and other cognitive processes, including perception (visual awareness), attention and language comprehension. These aims will be addressed by means of different electrophysiological measures.

This thesis starts by examining a fundamental aspect of self-identity, which concerns to the sense of sameness over time. The event-related potential (ERP) results showed that the N250 was the earliest neural marker distinguishing the self from other identities. The P3 was the most robust index of self-specificity. Crucially, the LPC was the only component that reflects the continuity of the self over time (i.e., the difference between current and past selves). The estimated neural sources for self-continuity showed a distributed brain network. Collectively, these findings support the notion of a sense of self-identity and its continuity over time in the human brain.

The second study aimed to investigate whether syntactic language processing can be affected by self-related visual information under masked conditions. The face identities were presented for 16 ms before the target word. Face-related components showed a self-specific response, as indexed by the N250. Language-related components showed the largest LAN effect, followed by a reduced P600 effect for self-faces. Additionally, alpha power was more suppressed over the left inferior frontal gyrus (IFG) only when self-faces appeared before the critical word. Collectively, these results suggest that identity-related information is rapidly decoded from facial stimuli and may impact core linguistic processes.

The third study aimed to explore the oscillatory correlates and neural signal variability involved in visual self-recognition. Time-frequency analysis indicated that theta-band activity over posterior regions is specifically involved in visual self-recognition. The possible

mechanisms underlying these oscillatory dynamics are discussed. Further, a lower entropy was observed for self-faces than for friend and unknown faces. These findings revealed that self-related processing is characterized by non-random neural patterns over a wide range of temporal scales.

The data presented in this thesis constitute novel evidence for the neural underpinnings underlying self-related processing. Moreover, these findings highlight that self-representation is central to cognitive functioning. The results of this study demonstrate that self-referential information can bias different cognitive processes at different processing stages. The implications of these findings are discussed. Additionally, future directions are outlined.

Resumen

El estudio de la identidad del yo ha suscitado un gran interés en la psicología y la neurociencia cognitiva. Desde esta perspectiva, cada vez hay más pruebas de que la información relacionada con el yo (por ejemplo, caras, nombres u objetos personales) se procesa de forma preferente en comparación con el contenido no relacionado con el yo. Este sesgo se conoce como el efecto de autorreferencia. Sin embargo, se sabe menos sobre los correlatos neuronales y psicológicos que subyacen al procesamiento relacionado con el yo. Además, sigue sin estar claro si la información relacionada con el yo puede sesgar otros procesos cognitivos, en particular la comprensión del lenguaje. Por lo tanto, el objetivo de esta tesis es doble: (i) investigar los mecanismos neurales y cognitivos que subyacen al procesamiento referenciado al yo; y (ii) investigar la interacción entre el procesamiento referenciado al yo y otros procesos cognitivos, incluyendo la percepción (conciencia visual), la atención y la comprensión del lenguaje. Estos objetivos se abordarán mediante diferentes medidas electrofisiológicas.

Esta tesis comienza examinando un aspecto fundamental de la identidad del yo, que se refiere a la sensación de ser la misma persona a lo largo del tiempo. Los resultados de los potenciales evento-relacionados (ERP) mostraron que la N250 era el marcador neural más precoz para distinguir el yo de otras identidades. La P3 fue el índice más robusto de la especificidad del yo. Crucialmente, la LPC fue el único componente que refleja la continuidad del yo en el tiempo (es decir, la diferencia entre el yo actual y el pasado). Las fuentes neuronales estimadas para la continuidad del yo mostraron una red cerebral distribuida. En conjunto, estos resultados apoyan la noción de un sentido de identidad del yo y su continuidad del tiempo en el cerebro humano.

El segundo estudio pretendía investigar si el procesamiento sintáctico del lenguaje puede verse afectado por la información visual relacionada con el yo en condiciones de enmascaramiento. Las identidades de las caras se presentaban 16 ms antes de la palabra objetivo. Los componentes relacionados con las caras mostraron una respuesta específica del yo, indexada por la N250. Los componentes relacionados con el lenguaje mostraron un mayor efecto LAN seguido de un efecto P600 reducido para las caras de uno mismo. Además, la potencia alfa estaba más suprimida en la circunvolución frontal inferior izquierda (IFG) sólo cuando las caras propias aparecían antes de la palabra crítica. En conjunto, estos resultados

sugieren que la información relacionada con la identidad se descodifica rápidamente a partir de los estímulos faciales y puede afectar a los procesos lingüísticos básicos.

El tercer estudio pretendía explorar los correlatos oscilatorios y la variabilidad de las señales neurales implicadas en el autorreconocimiento visual. El análisis de tiempo-frecuencia indicó que la actividad de la banda theta en las regiones posteriores está específicamente implicada en el reconocimiento visual del yo. Se discuten los posibles mecanismos subyacentes a estas dinámicas oscilatorias. Además, se observó una entropía más baja para las caras propias que para las caras de amigos y desconocidos. Estos resultados revelaron que el procesamiento relacionado con el yo se caracteriza por patrones neuronales no aleatorios en una amplia gama de escalas temporales.

Los datos presentados en esta tesis constituyen evidencias novedosas sobre los fundamentos neuronales que subyacen al procesamiento relacionado con el yo. Además, estos hallazgos ponen de relieve que la representación del yo es fundamental para el funcionamiento cognitivo. Los resultados de este estudio demuestran que la información referenciada al yo puede sesgar distintos procesos cognitivos en diferentes etapas del procesamiento. Se discuten las implicaciones de estos resultados. Además, se esbozan futuras direcciones.

CHAPTER 1. INTRODUCTION

Chapter 1. Introduction

What is the sense of self, and how is it represented in the brain? These are fundamental questions concerning human nature. On this view, the question about the self can be traced back to such long-standing disciplines as philosophy or anthropology. While this topic has been a matter of debate over the centuries, the self is often conceived to be central to human experience and cognition (Gallagher & Daly, 2018). Over the past few years, a growing body of research in psychology and cognitive neuroscience has provided new insights into this issue through advanced neuroimaging techniques. Accordingly, the main research question posed from this perspective would be: *What neural dynamics underpin our sense of self?* To address this question, the main goal of this thesis is to study the neural and cognitive processes underlying one's own identity in relation to other identities. To this end, this thesis will focus on the processing of different facial stimuli, as they are robust markers when accessing identity representations in the brain (Estudillo, 2017; Young & Burton, 2018). This first chapter outlines a broad overview of the self, along with the main electrophysiological techniques that will be used in this thesis.

1.1. Conceptualizing the self

From an etymological perspective, the term “self” derives from the Old English words “sylf” or “seolf”, which often referred to one's person or individuality. Similar meanings can be found in other Germanic languages such as German (“selb”), Dutch (“zelf”), or Norwegian (“selv”). This concept is analogous to the Latin term “ego”, which is reflected as “yo” in Spanish, “eu” in Portuguese, “je” in French, or “io” in Italian, to name a few. A first connotation of the term "self" that arises from this perspective reflects a set of individual traits and characteristics associated with one's identity (e.g., personality traits, physical characteristics, beliefs, or values), which are critical to distinguishing one's identity from others' (Heatherton, 2011).

Following a psychological perspective, William James (1842–1910) was one of the first psychologists to elaborate a theoretical account of the self. In his seminal work, *The Principles of Psychology* (1890), he distinguished two conceptions *of the sense of self*: namely, the “Me” concept, which refers to the understanding of ourselves as an object of experience (“I see *me* in the mirror”; self as object); and the “I” concept, which comprises the subjective experience of ourselves as an active agent ("the *Thinker* that does the thinking"; self as agent). Stated differently, while the former ("Me") includes the knowledge of ourselves (e.g., self-concept, personality traits; that is, self-identity), the latter ("I") reflects *"the direct awareness of the process of our thinking as such"* (James, 1890; p. 305).

Therefore, another critical feature related to the term "self" is that it can be understood as part of a *conscious experience* of being me (either as "Me" or "I"), also investigated as phenomenal selfhood or self-consciousness (Northoff, 2016; Woźniak, 2018). Moreover, it has been argued that this subjective experience of *being me* is a perception –or a collection of perceptions– based on encoded predictions during a lifetime (Seth, 2022). This view also entails that the self as object can be approached depending on the type of information it comprises, that is, experiential (phenomenal selfhood) or self-concept representations (e.g., self-knowledge).

Another remarkable feature of the sense of self is related to its *stability and continuity over time* (Morin, 2006; Northoff, 2017; Northoff & Horvart, 2022). These connotations are raised by questioning whether there are aspects of the self ("I" or "Me") that may evolve over time. It is thought that the memorial link between one's past and present is the foundation both of the subjective sense of the self as agent ("I") and of the concrete content assigned to the self ("Me") (Sedikides et al., 2023). Notably, Northoff (2017) has suggested to dissociate between the processing of self-related information corresponding to a *given time*, which is linked to a *synchronic component* (i.e., ever-changing events such as our body or physiology), and the consciousness of oneself *across time*, which is referred to as the *diachronic component* or *self-continuity* (i.e., "I am I" despite physical changes during lifetime). It is argued that this connection between one's past and present self (i.e., self-continuity) is fundamental to effective self-concept development (Sedikides et al., 2023), as well as for the construction of self-referential narratives (Gallagher & Cole, 2011). From this temporal perspective, therefore, the "I" is also involved in unifying past and present experiences of oneself (Sedikides et al., 2023). However, these (synchronic and diachronic) components related to oneself remain poorly understood in the extant literature. Thus, one of the specific objectives of this thesis is to investigate the neural dynamics involved in such self-continuity. This issue will be further examined in *Chapter 3*.

It should be noted that the distinction between self and other is often characterized as a matter of degree in terms of the strength in relation or relevance to the self, rather than a binary classification. Previous studies have shown that this degree of self-relatedness can be addressed by presenting different self-relevant cues, such as one's own face (as the highest relevance), familiar face (as intermediate relevance), and unknown face (as the lowest relevance) (Levorsen et al., 2023; Xu et al., 2017). This attribution reflects a continuum between self-identity and the identity of others, in which the attribution of self-relative people takes place at some point along this continuum (that is, self-relatedness), as they are also part of our own identity (group membership), thereby sharing representations in long-term memory along with emotional content (Ramon & Gobbini, 2018; Yeshurun, 2021).

A growing number of studies in psychology and cognitive neuroscience have highlighted how external information becomes self-related, thus suggesting the critical role of the social environment along with bodily information in shaping the mental state of the self (Qin et al., 2020). Hence, the sense of self can be described as a psychological construct rooted both biologically (Frewen et al., 2020) and socio-culturally (Markus & Kitayama, 2010; Lee et al., 2023), which serves as an integrative mechanism linking internal and external stimuli along with different psychological processes (Sui & Humphreys, 2015), including the subjective or phenomenal experience of oneself (Northoff, 2016). Related to the subjective experience, the human sense of self has the remarkable capacity to become the object of one's own attention. This is usually referred to as *self-awareness*, which entails that only we can be a reflective observer of ourselves, as shown by our inner thoughts or mind-wandering (Morin, 2006).

This perspective of the self is consistent with some early observations reported in cognitive psychology research. Notably, a set of experiments conducted by Rogers and colleagues in the late 1970s highlighted the involvement of self-reference in information processing (Kuiper & Rogers, 1979; Rogers et al., 1977), which is currently known as the *self-reference effect* (e.g., Cunningham & Turk, 2017). Rogers et al. (1977) presented a task in which participants judged whether or not a trait-word stimulus was descriptive of oneself and examined both the latencies of such judgments and subsequent performance on incidental recall of the judged stimuli. They observed that the adjectives that had been encoded in reference to the self (that is, self-referential information) were better recalled (cue question:

does this adjective describe you?) relative to other kinds of tasks, namely, structural (*how long is this adjective?*), phonemic (*is this adjective rhythmic?*) and semantic (*is this adjective meaningful to you?*). Compared to the semantic judgment task. Their results were interpreted based on the richness[1] (or degree of elaboration) of self-reference as an encoding device of personal information, as compared to the semantic judgment task. As Rogers et al. (1977, p. 48) noted: "When self-reference is involved, *it should provide a useful device for encoding or interpreting incoming information by virtue of accessing the extensive past experience abstracted in the self*." From this view, a critical point is that the self operates –a *cognitive representation or (self-)schema*– by which incoming data are interpreted or encoded, involving an interplay between the previous knowledge and the incoming information. This representation is thought to be involved in the information processing related to oneself and others and in keeping track of the extensive volume of self-relevant information encountered throughout one's lifespan. Therefore, the sense of self embodies the abstracted essence of one's ¡ perception and provides a degree of meaning to the incoming information (Kuiper & Rogers, 1979). Additionally, Rogers (1981) extended these cognitive interpretations by suggesting that an *affective component* may also be implicated in the processing of self-relevant information.

According to these earlier formulations, the self can thus be pictured as a *high-level of cognitive organization or superordinate schema* –perhaps the highest– that is deeply involved in the processing of (personal) information and by which all other cognitive processes revolve (Greenwald & Banaji 1989; Markus, 1977; Rogers et al., 1977). Thus, individuals would select and filter relevant information on account of this highly structured self-schema, leading to preferential processing compared to non-self-relevant information. The majority of current neurocognitive models of the sense of self are grounded on these insights (Klein, 2014; Northoff, 2016; Sugiura, 2013; Sui & Humphreys, 2015; Sui & Gu, 2017). Building on these neurocognitive models, this thesis will focus on the study of the neural underpinnings of the self as a cognitive and social phenomenon (i.e., the self as object). It should be noted,

[1] This notion of depth-of-processing or degree-of-elaboration was introduced by Craik & Lockhart (1972) and Craik & Tulving (1975), as these studies used similar incidental recall procedure (presenting structural, phonemic and semantic tasks). Rogers et al. (1977) introduced a self-referential task to this procedure and suggested that self-reference engaged even deeper or more elaborated processing compared to the semantic judgment task.

however, that the sense of first-person subjectivity (i.e., self as agent) will not be addressed in this thesis.

1.2. Self-reference effect and cognitive functioning

Since the experiments by Rogers in the late 1970s, a substantial body of literature has demonstrated how self-referential processing can impact core aspects of cognitive functioning, including perception (Sui et al., 2023), memory (Tanguay et al., 2018), attention (Macrae et al., 2018), and decision-making (Woźniak et al., 2018). Preliminary evidence has also been found between self-reference and emotions (Pereira et al., 2021) and language processing (Fields & Kuperberg, 2016). Collectively, these studies converge that self-relevant incoming information (e.g., self-face or self-name) receives more attention than non-self-relevant information, and such prioritized information could be subsequently retrieved with better performance (Klein, 2014; Qin et al., 2020). In addition, participants respond faster and more accurately than to other-related stimuli (Sui et al., 2023). As introduced above, this bias is known as the *self-reference effect* (Rogers et al., 1977; Symons & Johnson, 1997), which has also been described as *self-related processing* or *self-referential processing*[2] (Northoff, 2016; Sui & Gu, 2017).

As a highly social species, this bias draws on the notion of automatic monitoring of the social environment for self-relevant information. For instance, hearing our own name in a crowded setting can rapidly capture our attention, as illustrated by the so-called *cocktail party effect* (Moray, 1959). Over the past decades, this self-bias has been tested using a wide variety of stimuli, such as one's own face or name (e.g., Alzueta et al., 2019; Kotlewska & Nowicka, 2015), personal objects (e.g., Miyakoshi et al., 2010; Muñoz et al., 2020), or when an arbitrary stimulus (e.g., triangle, square or circle) has been associated with the self (e.g., Sui et al., 2023; Woźniak et al., 2018). These stimuli have proven to be reliable measures of access to the *core-self* brain network, both consciously and unconsciously (Bola et al., 2021; Geng et al., 2012). Notwithstanding, an open question in this regard is *what neural and cognitive processes are*

[2] Although the terms *self-related* and *self-referential processing* can be used interchangeably, both terms can be defined independently. For example, Northoff (2016) indicates that the former refers to describing the processing of a stimulus in relation to the self, highlighting its relational, implicit and automatic properties, whereas the latter refers to describing the representation of a more specific content in relation to the self, operating in an explicit and controlled manner.

involved in self-referential processing. As stated above, this is the main research question that will be addressed in this thesis.

Within this framework, Sui and Humphreys (2015) proposed a neurocognitive account of growing interest based on a wealth of neuroimaging and behavioral findings, referred to as *the integrative self*. More specifically, they stressed that *"the presence of a self-representation does indeed do something for us –notably, it acts as an integrative hub for information processing, helping to bind together different types of information and even different stages of processing"* (p. 719). According to this account, self-representation mediates between external stimuli and psychological processes as an *integrative mechanism*. Thus, self-related information is facilitated due to its increased binding with different psychological processes (perception, memory, attention, and decision-making). This binding between stimuli and psychological processes is driven by an increased functional coupling between brain regions through a spatiotemporal coordination of bottom-up and top-down processes[3] (Humphreys & Sui, 2016; Sui & Gu, 2017).

It should be noted, however, that most research on self-referential processing has focused on cognitive processes related to attention and memory. Concerning memory, Martinelli et al. (2013) have proposed that self-knowledge comprises three functionally independent systems with different levels of abstraction in the brain, namely (i) *episodic autobiographical memories* of one's own life (e.g., concrete and specific items of personal information), (ii) *semantic autobiographical memories* of one's own life (e.g., general knowledge of personal facts), and (iii) *semantic summary representations* of one's personal identity (conceptual self; e.g., self-knowledge of personality traits). This draws on the cognitive account of the *self-memory system* proposed by Conway (2005). Hence, self-representation includes declarative self-referential aspects and implicit features such as reward value and high emotional significance (Northoff & Hayes, 2011).

[3] The attentional system is generally divided in two distinct functional mechanisms: *bottom-up (or exogenous) attention and top-down (or endogenous) attention.* In short, the latter reflects an internally induced process in which information is actively processed based on voluntarily chosen factors, while the former is an externally induced process in which information is more automatically processed due to stimulus properties (e.g., saliency), or when it is unexpected, and may act as a 'circuit breaker' of the former.

Current research on self-referential processing and attention has shown that self-related stimuli are powerful cues for attention, as they can modulate performance in a relatively automatic manner (Humphreys & Sui, 2016). Other authors have also argued that this self-reference is driven by familiarity as a consequence of high exposure to long-term memory (e.g., Bortolon et al., 2018). However, most extant literature has typically used the stimuli at attended locations and were task-relevant. In this regard, an open question in the literature is whether the self-reference effect can capture our attention explicitly or consciously, or rather implicitly or unconsciously. Furthermore, little is known about how self-referential processing can interact with other cognitive processes, especially language processing. This issue will be further examined in *Chapter 4*.

1.3. Neural basis of self-referential processing

From a neurocognitive perspective, different meta-analyses have shown the involvement of the Cortical Midline Structures (CMS) in self-referential processing, including the ventromedial prefrontal cortex (vmPFC), the dorsomedial prefrontal cortex (dmPFC), the anterior and posterior cingulate cortex (aCC, pCC), and the precuneus (PC) (Northoff et al. 2006, 2011; Murray et al., 2015). Recent findings have also found the involvement of the bilateral insula in self-related processing, given its critical role in dealing with internal sensory integration (i.e., interoceptive processing) (Qin et al., 2020) and in detecting salient emotional features (Uddin et al., 2019). It is argued that these brain regions mediate higher-order cognitive processing, attention to external and internal events, attributing reward value, saliency, and valence to self-related content, as depicted in Figure 1.1 (Berkman et al., 2017; Qin et al., 2020; Sui & Gu, 2017). Most importantly, the vmPFC appears to be a remarkable brain region involved in specific internal self-representations, which may impact the processing of external stimuli by coupling across posterior regions, such as the temporoparietal junction (TPJ) (Apps et al., 2015; Frewen et al., 2020; Levorsen et al., 2023; Tsakiris, 2017).

Furthermore, the neural processing of self-referential content has also been associated with the spontaneous brain activity observed in the resting state, as the brain regions of the default-mode network (DMN) largely overlap with those of the CMS (Davey et al., 2016; Kim, 2012; Qin et al., 2016; Raichle et al., 2001). The DMN –comprising mainly the medial prefrontal cortex (mPFC), the inferior parietal lobule (IPL) or TPJ, and the pCC/PC– is engaged when people are internally focused on different tasks such as autobiographical memory retrieval, mind-wandering, projecting the future, and thinking about the perspectives of others (Menon, 2023). In contrast, the DMN decreases its activity during goal-directed and non-self-referential tasks as external attention to the environment is demanded (Raichle, 2015). Consequently, the DMN is a dynamic network combining extrinsic information with prior intrinsic information –an individual's idiosyncratic past memories and knowledge– (Yeshurun et al., 2021).

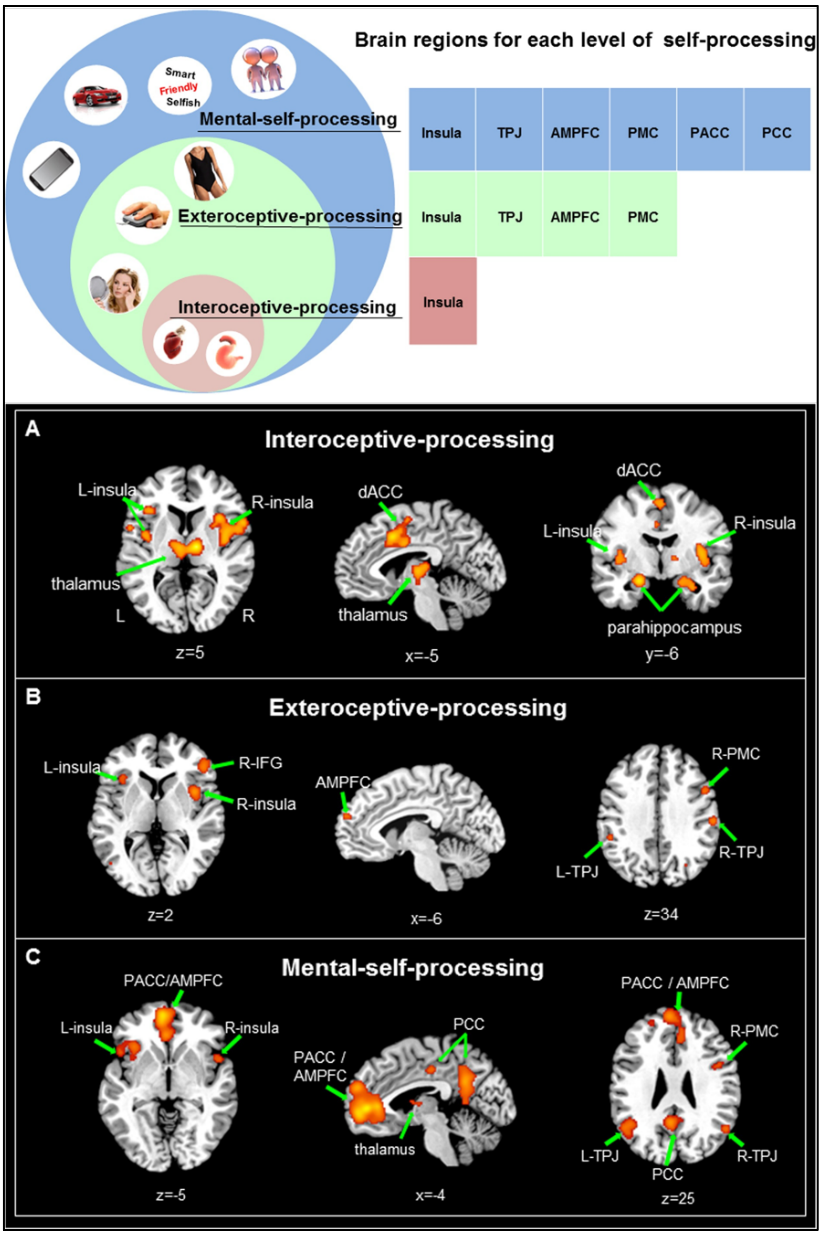

Figure 1.1 Brain regions for each level of self-related processing. Abbreviations: AMPFC: anteromedial prefrontal cortex; dACC: dorsal anterior cingulate cortex; IFG: inferior frontal gyrus; pACC: pregenual anterior cingulate cortex; PCC: posterior cingulate cortex; PMC: premotor cortex; TPJ: temporal parietal junction. Reprinted with permission from Qin et al. (2020). Linking bodily, environmental and mental states in the self-A three-level model based on a meta-analysis. *Neuroscience and biobehavioral reviews, 115*, 77–95. Copyright 2017 by Elsevier.

In a review conducted by Buckner and DiNicola (2019), they observed that such internal processing –involving autobiographical remembering, episodic retrieval, and mentalizing tasks– all overlapped between vmPFC and pCC regions. Neuroimaging studies seem to agree that this dedicated brain system might support the human sense of self. More particularly, different neuroimaging studies have observed common neural activations in the core set of DMN regions –critically, the vmPFC and the pCC/PC– when comparing resting-state activity and self-referential processing (Davey et al., 2016; Frewen et al., 2020; Knyazev et al., 2020). In addition, the activity of this set of regions seems to increase when explicitly thinking about self-related processes (Davey et al., 2016; Knyazev et al., 2020) and when retrieving autobiographical episodes (Roehri et al., 2022). Accordingly, it is argued that the DMN comprises the brain structures involved in self-referential processing (CMS), and its resting-state activity can predict subsequent degrees of self-related processing (Davey et al., 2016; Menon, 2023; Qin et al., 2016; Wolff et al., 2019)

According to this perspective, the self-referential processing is therefore supported through a *core-self* network –primarily involving the coupling between the mPFC/vmPFC and the pCC/PCC– which is embedded within the DMN nodes (Knyazev et al., 2020; Qin et al., 2020; Sui & Gu, 2017). As shown by Figure 1.2, this *core network* closely interacts with other macro-scale brain networks, namely the *frontoparietal* or *executive control network* –which is supported by the dorsolateral prefrontal cortex (dlPFC) and the posterior superior temporal sulcus (pSTS)– and the *salience network* –which is anchored in the insula and subcortical structures– (Uddin et al., 2019). The executive network is associated with cognitive control and executive function (e.g., working memory), and its activation is negatively correlated with DMN activity (Menon & Uddin, 2010; for a recent review, see Menon, 2023). The salience network is considered critical for detecting and filtering (self-)relevant stimuli, thus mediating as a dynamic switch between the DMN and the executive network (Schimmelpfennig et al., 2023).

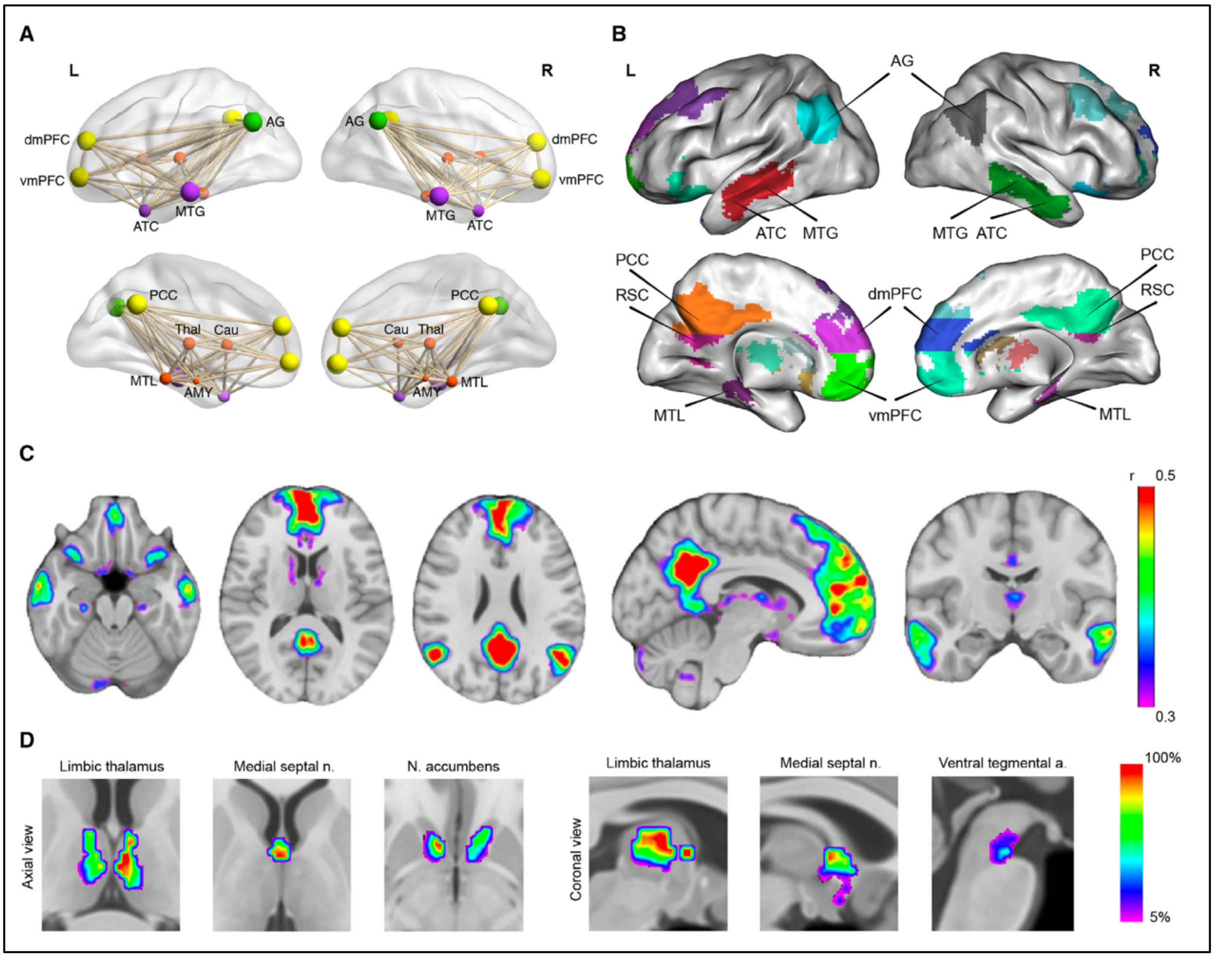

Figure 1.2 (A) Illustration of DMN nodes as a functionally and anatomically interconnected system. (B and C) Cortical nodes of the DMN: posterior cingulate cortex (PCC) and retrosplenial cortex (RSC) in posterior medial parietal cortex; medial PFC (mPFC) with its dorsomedial (dmPFC) and ventromedial (dmPFC) subdivisions; anterior temporal cortex (ATC); middle temporal gyrus (MTG) in lateral temporal cortex; medial temporal lobe (MTL); and angular gyrus (AG) in lateral parietal cortex. (D) Subcortical nodes of the DMN: anterior and mediodorsal thalamic nuclei, medial septal nuclei, and nucleus accumbens. Reprinted with permission from Menon V. (2023). 20 years of the default mode network: A review and synthesis. *Neuron*, *111*(16), 2469–2487. Copyright 2023 by Elsevier.

Following Sui and Gu (2017), the executive network is engaged when sustaining (social) attention to external stimuli in self versus other judgments, whereas the salient network is involved in the processing of reward and salient emotional features. It has also been noted that the joined activation between the core-self network and the salient network may be central in attributing self-relevance to external information (Qin et al., 2020; Sui & Gu, 2017). Thus, the pattern observed between the core-self and executive networks is inversely correlated in the presence of self-related stimuli, similar to the DMN activity (Sui et al., 2013; Wolff et al., 2019). In other words, the core-self brain regions show decreased activity –as well as the DMN– while the executive network has increased activity in the presence of stimuli associated with other people or when self-related information is irrelevant to the task. Thus, the inverse pattern of activity between these two systems relies on the degree of self-relevance of external information (Northoff, 2016; Qin et al., 2020).

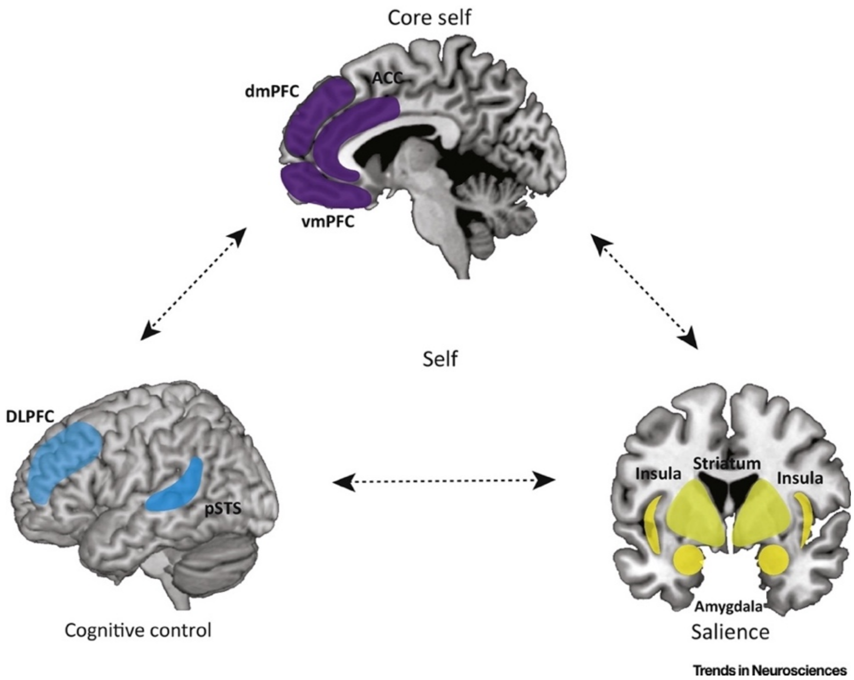

Figure 1.2 A neurocognitive model of the self. From this perspective, the self is implemented in the human brain through a 'core-self' network (e.g., cortical midline structures, such as the medial prefrontal cortex; mPFC) that interacts with the cognitive control network [e.g., dorsolateral (dl)PFC, posterior superior temporal sulcus (pSTS)] and salience/affective network (e.g., insula, amygdala and striatum). The 'core-self' network is crucial for maintaining self-representation. The dlPFC and pSTS are thought to process attention and cognitive control with respect to external stimuli. The insula, striatum, and amygdala are involved in processing salient emotional and reward stimuli. Reprinted with permission from Sui, J., & Gu, X. (2017). Self as object: Emerging trends in self research. *Trends in neurosciences*, *40*(11), 1–11. Copyright 2017 by Elsevier.

Although it will not be the focus of this thesis, it is worth noting that an impairment in the core-self network is linked to atypical mental functioning, ranging from neurodevelopmental disorders such as autism spectrum disorders (Nijhof & Bird, 2019) to mental disorders such as depression (Nejad et al., 2013) or schizophrenia (Borda & Sass, 2015), but to name a few. These studies in clinical populations also emphasize the importance of self-referential processing in cognitive functioning.

1.4. Event-related potentials underlying facial identity processing

Electroencephalography (EEG) is the main technique used in this thesis, as it may provide fine-grained details about the ongoing neural dynamics (in the order of milliseconds, ms). The EEG signal reflects the electrical activity of postsynaptic potentials from large neural populations, namely cortical pyramidal cells that are temporally coordinated and spatially aligned with respect to the scalp (Buzsáki & Vöröslakos, 2023). Nevertheless, different neural sources related to a wide range of events (sensory, cognitive, and motor) are embedded within the EEG raw data, making it difficult to isolate individual cognitive processes and behaviors. In this regard, different analyses can be conducted from the EEG signal, such as the so-called *event-related brain potentials* (ERP) or *time-frequency representations (TFR)*, which will be described in more detail below.

As for the ERP, the electrical brain activity (potentials) can be related to specific events (e.g., when a face is presented) by a simple signal-averaging technique over trials and participants, thus extracting event-driven waveforms while reducing other unrelated activity (e.g., blinks, motor artifacts, noise activity). The resulting averaged waveforms, which are known as *components*, consist of a sequence of positive (P) and negative (N) deflections, often peaking around a given latency after the stimulus onset (e.g., 170 ms or 250 ms) with a given topographic distribution (e.g., occipitotemporal negativity for the N170). Notably, ERP components can vary in polarity, amplitude, latency, or topographic distribution (Luck, 2012).

Of interest, several electrophysiological components have been typically found when presenting self-related information (that is, facial stimuli), as illustrated, for example, by the N170 component (e.g., Geng, et al., 2012). As such, this component –termed by Bentin and collaborators in 1996– is considered to be the earliest negative deflection on posterior scalp regions that can be observed for face perception (peaking around 150 and 200 ms after face onset), being its amplitude larger for faces than inverted faces, distorted faces, animal faces, and other non-face stimuli (e.g., Eimer et al., 2011; Joyce & Rossion, 2005).

Prior research suggests that this component comprises the neural processes involved in the analysis of structural encoding of face configuration, that is, the *first-order relational* *face configuration mechanism*, e.g., two eyes above a nose and above a mouth (Bentin & Deouell, 2000; Eimer, 2011; Schweinberger & Neumann, 2016). This mechanism draws on the notion of the *structural encoder* proposed by Bruce and Young's (1986) model of face perception. In other words, the N170 is thought to reflect facial detection after low-level visual analysis (pictorial encoding). Neural source reconstruction[4] of the N170 component has been linked to the occipital face area (OFA), the fusiform face area (FFA), and the posterior superior temporal sulcus (pSTS) (Bobes et al., 2019; Olivares et al., 2015).

Following the early computations of face perception, the N250 is a subsequent relevant electrophysiological component involved in the ability to *recognize* individual faces (as opposed to *detecting*), peaking around 200 and 300 ms after face onset. It is thought that the neural generator of the N250 component is most likely the anterior part of the FFA (Olivares et al., 2015). Tanaka et al. (2006) have suggested that the N250 indexes two types of face memories, namely the access to self and personally familiar face representations from long-term memory and to a newly acquired face representation that was encoded during the experiment (i.e., participants produce a degree of familiarity with the stranger's face).

According to this view, the N250 latency range may reflect not only the access to *face recognition units* (FRU) but also the number of face repetitions (Bruce & Young, 1986; Schweinberger & Neumann, 2016). These observations have led some authors to propose that the amount of exposure to a stimulus (i.e., familiarity) is a causal factor contributing to the mixed results between the early face-related components (i.e., N170, N250) (Butler et al., 2013; Bortolon et al., 2017). In this regard, there is an open debate as to whether the N170 is also sensitive to identity-related effects (self and familiar faces) or it is specific to the N250 and the late electrophysiological components (Caharel & Rossion, 2021; Olivares et al., 2015; Schweinberger & Neumann, 2016).

Interestingly, the neural sources of the N170 and N250 components (the FFA along with the OFA and the pSTS) are involved in the so-called *core network* of face processing (Haxby et al., 2000). This core network deals with the *visual appearance* of a face, including the *early perception* of facial features (linked to the OFA), *dynamic information* (supported by

[4] In general terms, neural source reconstruction consists of estimating the dominant neural generator based on scalp distribution data. This estimation is commonly referred to as the inverse problem (for an extensive review, Michel & He, 2019).

the pSTS), and *invariant information* (underpinned by the FFA) (Chen et al., 2023; Gobbini & Haxby, 2007; Weiner & Grill-Spector, 2012). Dynamic information includes emotional facial expressions or gaze movements, while invariant information refers to the identity, age, or gender of the face.

On the other hand, the *extended network* is critical for retrieving personal knowledge –mainly comprising the mPFC, pCC/PC, pSTS/TPJ, and the anterior temporal lobule (ATL)– along with emotional content related to oneself and others (Gobbini & Haxby, 2007; Ramon & Gobbini, 2018; Visconti di Oleggio Castello et al., 2021). Again, this extended network exhibits a large overlap with the cortical midline structures (CMS) involved in self-referential processing described by Northoff et al. (2006) and the DMN nodes (e.g., Davey et al., 2016; Frewen et al., 2020). The late face-related components are linked to the activity of this extended network since they reflect the engagement of higher-order cognitive functions, such as the P3 or the late positive complex (LPC) (Azizian & Polich, 2007; Hajcak & Foti, 2020; Polich, 2020). In this regard, both P3 and LPC seem to reflect a step further in allocating attentional resources, including semantic memory, autobiographical information, and episodic memory (Tanguay et al., 2018), as well as affective evaluation processes and detecting the motivational relevance of the stimulus (Cunningham et al., 2005).

1.5. Neural oscillations: time-frequency analysis

Since the first EEG pattern described by Hans Berger in 1929, much research over the past decades has focused on the study of neural oscillations, as they are regarded to reflect different neural and cognitive computations (Cariani & Baker, 2022; Klimesch, 2018). It is generally accepted that human brain rhythms comprise several oscillatory bands, ranging from infra-slow (0.01–0.1 Hz), slow (0.1–1 Hz), fast frequencies (1–100 Hz), to ultrafast frequencies (> 100 Hz) (Buzsáki & Draguhun, 2004; Lakatos et al., 2005; Palva & Palva, 2018). As such, rhythmicity is a core mechanism of neural activity in biological systems, as illustrated by recurrent patterns of sleep-wake cycles, recurrent patterns of breathing, or recurrent patterns of action potentials (Lakatos et al., 2019). It is well established that the cortical synchronous rhythms, which are involved in oscillatory neural activity, can be measured by the EEG signals (Buzsáki & Vöröslakos, 2023; Wang, 2010).

The neural oscillations contained in the EEG waveforms are typically used to examine changes, in terms of power spectra, relative to experimental events. Different frequency bands have been identified: delta (0.1–4 Hz), theta (4–7 Hz), alpha (8–12 Hz), beta (13–30 Hz), and gamma (30+ Hz) (Buzsáki & Draguhun, 2004).

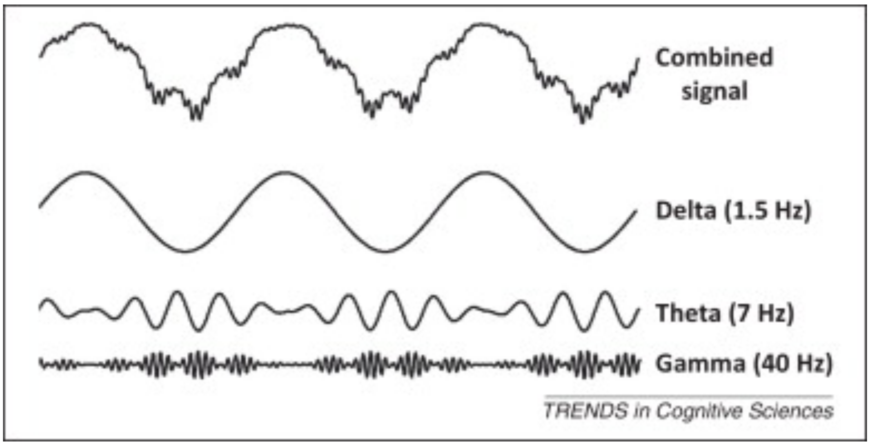

Figure 1.4 Hierarchical phase–amplitude coupling in a hierarchy of oscillations. The top trace depicts a typical EEG signal comprising several oscillatory frequencies. The other three traces are the individual oscillations that are added to create the combined signal. The phase of lower-frequency oscillations determines the amplitude of higher frequencies in a hierarchical fashion. The phase of the delta oscillation is coupled to the amplitude of the theta oscillation such that the theta amplitude is larger during one phase of the delta and smaller during the opposite phase. The phase of the theta oscillation is similarly coupled to the amplitude of the gamma oscillation. Thus, gamma oscillations are comodulated by both delta and theta rhythms. Reprinted with permission from Calderone, D. J., Lakatos, P., Butler, P. D., & Castellanos, F. X. (2014). Entrainment of neural oscillations as a modifiable substrate of attention. *Trends in cognitive sciences, 18*(6), 300–309. Copyright 2014 by Elsevier.

An important principle concerning the architecture of brain oscillations is that the *phase* of lower frequencies (e.g., theta band) modulates the *amplitude* of higher frequencies (e.g., gamma band) (Fries, 2015, 2023; Palva & Palva, 2018). This notion is typically referred to as *nested frequencies* and might be a key principle in brain organization, as depicted in Figure 1.4 (Buzsáki & Draguhn, 2003; Mitra & Raichle, 2015; Klimesch, 2018). It should be noted that this notion relies primarily on the observation of infra-slow (less than 0.1 Hz) spontaneous activity –as measured by blood oxygen level-dependent signals (BOLD) and resting-state functional magnetic resonance imaging (fMRI)– that correlates with functionally defined resting-state networks or intrinsic-connectivity networks (Mitra & Raichle, 2016). Prior studies using full-band electroencephalography (fbEEG) and fMRI have shown that EEG fast oscillations (more than 1 Hz) are correlated with infra-slow fluctuations observed by BOLD signals, probably reflecting the same underlying neural dynamics (Hiltunen et al., 2014; Keinänen et al., 2018; Palva & Palva, 2018). Hence, the amplitude of EEG fast oscillations is nested in the phase of intra-slow fluctuations, suggesting that brain dynamics are governed by spontaneous fluctuations of neural activity at different cortical and subcortical levels (Palva & Palva, 2018; Uddin, 2020).

Furthermore, these oscillatory components are not necessarily *phase-locked* to an event. Nevertheless, event-related changes corresponding to each frequency activity band can be computed by using *time-frequency analysis* with different tools, such as the Fourier or wavelet transform (for a review of different methods, see Keil et al., 2022). Thus, by measuring the amount of power (which is the amplitude squared) in a given frequency, researchers can characterize different neural and cognitive computations in relation to an event of interest[5] (Cariani & Baker, 2022). For instance, a theta power increase in response to an incoming stimulus would reflect an event-related synchronization (ERS), whereas a power decrease would reflect an event-related desynchronization (ERD) (Klimesch, 2018). It is worth noting that, unlike theta modulations, alpha-band activity typically exhibits the opposite pattern as a consequence of task demands. This notion is known as the *functional inhibition hypothesis* (Jensen & Mazaheri, 2010). Following this framework, alpha power decrease or suppression is thought to reflect the allocation of cognitive resources to task-relevant brain regions while task-irrelevant brain regions are inhibited. Hence, whereas alfa-band modulations seem to respond to increased processing (or cortical activation) with a decrease in power, theta-band activity responds to increased processing with an increased in power.

So far, how self-related processing is supported by neural oscillations remains less understood. In this respect, Most EEG studies have focused on measurements provided by ERPs (i.e., P3/LPC), disregarding time-frequency dynamics. Recent studies have found the involvement of different frequency bands for self-related processing (Alzueta et al., 2020;

[5] It is important to note that a combination of both evoked and induced activity is reflected in time-frequency representations. In general terms, the evoked activity is usually *phase-aligned* with the event onset, while the induced activity is typically *time-locked* (but not necessarily phase-locked) to the event onset. In order to distinguish between evoked and induced responses, a conventional approach involves decomposing them linearly (e.g., by averaging the power spectra over trials and participants) (Tallon-Baudry & Bertrand, 1999). With this approach, the induced activity tends to cancel out in the averaged evoked potential.

Haciahmet et al., 2023). For instance, Alzueta et al. (2020) observed an alpha/beta power decrease for self-face recognition in contrast to friend and unknown faces over face-related brain regions. Relatedly, Haciahmet et al. (2023) presented geometric shapes associated with either the self (e.g., square) or a stranger (e.g., circle), and they reported a decrease in beta power and an increase in delta/theta power for self-associated stimulus processing. Hence, it seems of interest to study the evoked oscillatory responses that may subserve self-referential visual processing.

1.6. Neural variability: multiscale entropy analysis

A remarkable feature of the human brain is that it is highly variable and dynamic from moment to moment at every level of the nervous system (Faisal et al., 2008; Shafiei et al., 2023; Yousefi & Keilholz, 2021). In that vein, brain activity can vary along different timescales, such as moment-to-moment with ongoing thoughts and processes (i.e., milliseconds or seconds), on the order of minutes or hours depending on brain state (arousal or task engagement), more slowly over the course of the day (e.g., with circadian rhythms), or over the course of weeks or years (e.g., with extensive experience in a task) (Gratton et al., 2018). Further, there is a relationship between *time* and *spatial scales*. Specifically, the structure of variability at short timescales is thought to reflect local neural population processing, while variability at longer timescales has been linked to large-scale network processing (i.e., more local versus more long-range information processing in the brain) (Basset & Sporns, 2017; Shafiei et al., 2023). For instance, the brain's spontaneous activity can be observed at the level of individual neurons or at the level of large-scale networks (Raichle, 2015; Uddin, 2020).

This neural variability, however, is usually minimized or disregarded –considered as noise– when computing linear analysis of neurophysiological data, as shown by ERP or spectral power signals for EEG. As noted above, these mean-based signals are intended to mitigate the noise contained in the trial-to-trial variability in order to represent the evoked response. Recent evidence suggests that this component of noise may, in fact, correspond to empirically observed modulations of moment-to-moment neural variability during cognitive operations (Kloosterman et al., 2020) and resting state (Grady et al., 2023). Grounded on this notion, non-linear analyses of biological time series, such as *multiscale entropy analysis* (MSE)

(Costa et al., 2002), can quantify the *variability or complexity* contained in a given physiologic time series. As noted by Costa et al. (2002):

> MSE is based on the simple observation that complex physical and biologic systems generally exhibit dynamics that are far from the extrema of perfect regularity and complete randomness. Instead, complex dynamics typically reveal structure on multiple spatial and temporal scales. These multiscale features, ignored by conventional entropy calculations, are explicitly addressed in the MSE algorithm (p. 068102-3).

In broad terms, MSE relies on the estimation of the Sample Entropy[6] (SampEn), which is intended to describe the similarity of two distinct data patterns across time series (Richman & Moorman, 2000). Unlike single-scale methods, MSE is computed at multiple timescales, that is, from *fine* to *coarse* timescales (similar in logic to fast and slow frequencies). This is done by down-sampling the original EEG data by averaging consecutive data points, thus generating a new data point that corresponds to a coarser or higher scale, as shown in Figure 1.3. Accordingly, scale 1 represents the native sampling rate of a given physiologic time series (e.g., 250 Hz or 4 ms sampling interval), while scale 2 represents the native sampling rate divided by 2 (e.g., 125 Hz or 8 ms), and so forth for successive scales.

Interestingly, neural patterns that tend to repeat over time yield *lower entropy*, whereas non-repeating patterns (that is, more irregular signals) are assigned *higher entropy* estimates. Moreover, prior research has suggested that lower or finer timescales are related to local network processing and high-frequency dynamics, while longer or coarser timescales are associated with large-scale network processing and low-frequency dynamics (Basset & Sporns, 2017; Courtiol et al., 2016; Shafiei et al., 2023). Yet, the contribution of frequency-specific content on MSE timescales (from fine to coarse) remains a matter of debate in the current literature (Kosciessa et al., 2020).

One of the main limitations of the traditional MSE is that it requires substantial continuous data (ranging from 10 seconds to minutes) for robust estimation, which makes

[6] The estimation of sample entropy is based on counting how often data patterns of m adjacent data points reoccur in time (e.g., $m = 2$), and counting how often patterns of $m + 1$ data points reoccur within the amplitude range across time in the EEG waveform. For a more detailed review, see Cuortiol et al. 2016.

the conventional method less useful for studying transient neural and cognitive operations but well-suited for characterizing the signal dynamics in resting-state studies (Grandy et al., 2016; Kaur et al., 2019). However, current research in this respect suggests that spontaneous brain activity is characterized by non-random patterns over a wide range of spatiotemporal scales (Deco et al., 2011; Uddin, 2020; Zanin et al., 2020). This evidence suggests that the DMN activity tends to display a more regular neural pattern, that is, less entropy. Intriguingly, increasing studies are showing that several aspects of spontaneous brain activity, including such neural patterns of variability, can be altered in neurological and psychiatric disorders (Bernardi et al., 2023; Hohenfeld et al., 2018).

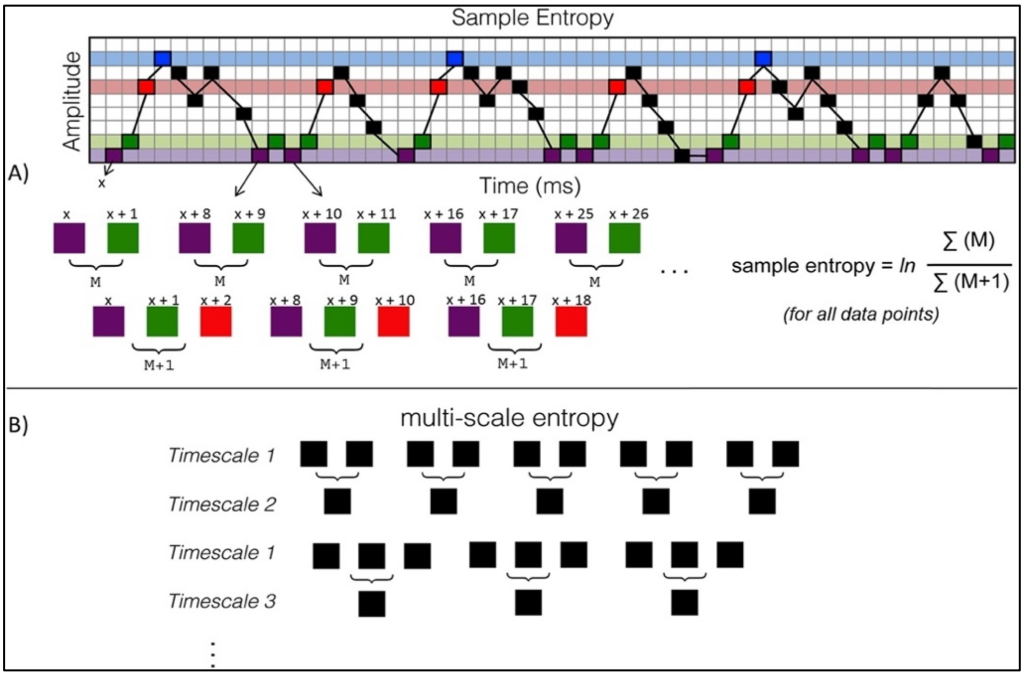

Figure 1.3 Standard multiscale entropy (MSE) estimation procedure. MSE quantifies the temporal irregularity of time series data at multiple timescales by counting how often temporal patterns in the signal reoccur across time in the EEG waveform. (A) The sample entropy measures the probability that two amplitude patterns of sequence length (m = 2) remain similar when the next sample (m + 1) is included in the sequence. Besides, the similarity criterion *r* represents a pre-specified amplitude range (that is, the signal's standard deviation, r = 0.5), denoted by the height of the colored bands, within which data points are considered to match. (B) Down-sampling of the native physiologic time series (from fine to coarse timescales). This is done by averaging the data points that are close to each other in time and repeating the pattern counting operation at each timescale. Reprinted with permission from Grundy, J. G., Anderson, J. A. E., & Bialystok, E. (2017). Bilinguals have more complex EEG brain signals in occipital regions than monolinguals. *NeuroImage, 159*, 280–288. Copyright 2017 by Elsevier.

As shown in Figure 1.4, a modified version of the MSE (mMSE) has been developed by Kloosterman et al. (2020) with the purpose of increasing the suitability of entropy estimates in conventional designs for neuroimaging and electrophysiological studies (e.g., block- or event-designs). There are two main differences with respect to the standard MSE method. First, the entropy estimates can be computed using discontinuous data segments aggregated across trials via a sliding window approach (see Figure 1.4A). Accordingly, MSE estimates across discontinuous segments are comparable in terms of accuracy and precision compared to the MSE estimates from continuous data (Grandy et al., 2016), overcoming the requirement of substantial continuous data for robust estimation. Further, standard MSE is computed across the complete time series at once, so it has no time dimension. Second, the data is coarsened by applying a Butterworth low-pass filter followed by skipping data points (Figure 1.4B) instead of coarsening the data by averaging adjacent data samples. With this approach, the mMSE seems to retain more control over the frequencies present in the coarsened signal (Kloosterman et al., 2020; Kosciessa et al., 2020; Valencia et al., 2009). Besides, the r parameter is computed only once in the standard MSE instead of recomputed for each timescale.

Building on this notion, both linear (e.g., ERP/TFR) and non-linear (mMSE) analyses of neurophysiological activity may yield a deeper understanding of neural and cognitive mechanisms involved in self-related processing, thus providing a more precise picture of the neural dynamics involved in self-identity. Of interest, no studies to date have examined the brain signal variability underlying self-related processing.

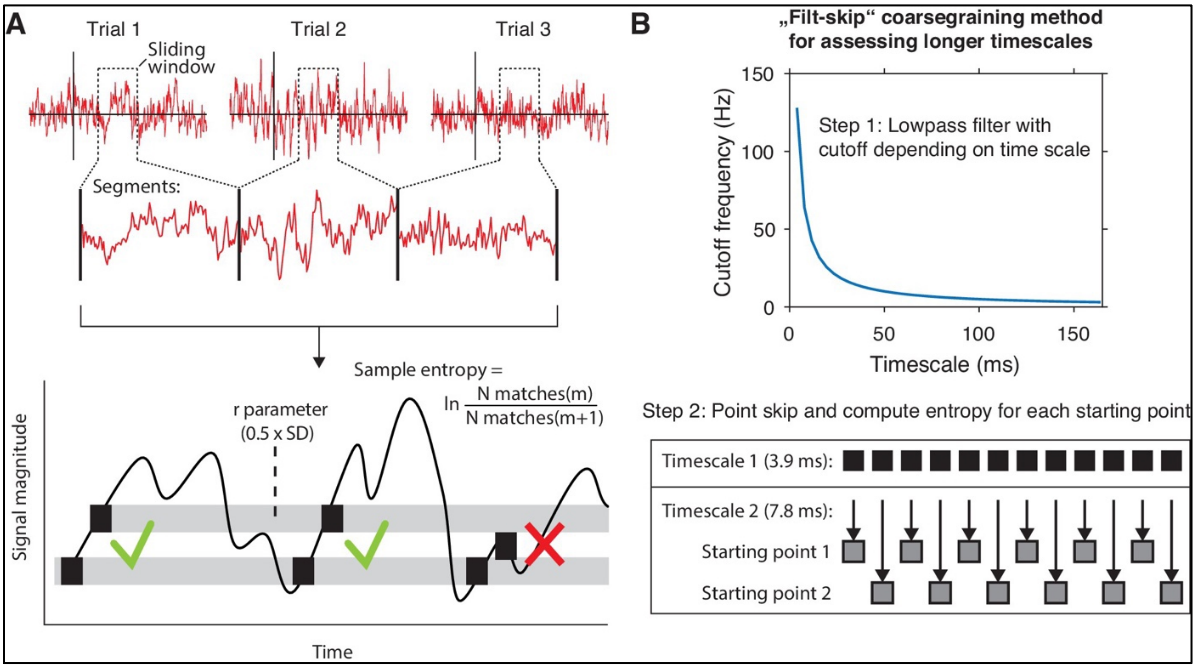

Figure 1.4 Estimation procedure of the modified multiscale entropy (mMSE). (A) Entropy estimates for discontinuous segments across trials. Data segments centered on a specific time point are selected (upper row) and concatenated (middle row) before computing the standard sample entropy (lower row). (B) The coarse-graining procedure is used to estimate entropy on longer timescales. This is done by using low-pass filtering followed by point-skipping. Filter cutoff frequency is determined by dividing the data sampling rate by the timescale of interest. Reprinted from Kloosterman, N. A., Kosciessa, J. Q., Lindenberger, U., Fahrenfort, J. J., & Garrett, D. D. (2020). Boosts in brain signal variability track liberal shifts in decision bias. *eLife*, *9*, e54201. Copyright 2020 Creative Commons Attribution License.

CHAPTER 2. OBJECTIVES AND HYPOTHESES

Chapter 2. Objectives and hypotheses

Taking into account the literature reviewed in the previous chapter, several research questions remain unsettled regarding the neural and cognitive processing of self-referential processing. Among these: (i) How and when do self-reference processes occur in the brain?; (ii) to what extent is the self-reference effect driven by its self-specificity, or instead, by other factors such as familiarity?; (iii) can the self-reference effect capture our attention without explicit awareness?; (iv) what is the relationship between self-referential processing and other cognitive computations, such as language processing?.

The *general objectives* of this thesis are as follows: (i) to study the neural and cognitive mechanisms underlying self-referential processing; and (ii) to examine the interplay between self-referential processing and other cognitive processes, such as perception (i.e., visual awareness), attention and language processing. Different electrophysiological approaches will be used to investigate the neural underpinnings of self-referential processing, including event-related brain potentials (ERP), time-frequency representations (TFR), neural source reconstructions, and multiscale entropy analysis (MSE).

Accordingly, three studies have been performed following their respective *specific objectives* and *hypotheses*. The *first study* (*Chapter 3*) aimed to investigate the neural dynamics of self-identity as a function of time (i.e., self-continuity). To this end, participants were presented with photos from different *identities* (self, friend and unknown) at different *life stages* (adulthood as *current*, adolescence and childhood as *past*). Moreover, in order to assess the consistency of self-reference with different attentional demands, participants had to perform a recognition task with the same stimuli but with two different blocks (or tasks). In one block, they had to judge the *identity* of facial stimuli (irrespective of their age). In another block, they had to judge the *life stage* of facial stimuli (regardless of the identity). Based on previous studies (e.g., Alzueta et al., 2019; Kotlewska & Nowicka, 2015), it was expected to observe that (i) the N170 would be sensitive to facial structural changes, while the N250 may distinguish self from other facial identities; (ii) larger late positivities to the self-faces compared to other identities, as reflected by the P3 and LPC components; (ii) these long-lasting positivities would also be sensitive to the changes of self across life stages, yielding larger amplitudes to current self-faces; (iv) the ERP effects for self-faces compared to other faces would be task-independent; (vi) regarding source analysis, it was expected that anterior regions (e.g., medial prefrontal cortex) would reflect the representation of self-referential information regardless of life stages, while posterior regions (e.g., posterior cingulate cortex or precuneus) would exhibit a larger sensitivity to self-identity across life stages.

The *second study* (*Chapter 4*) aimed to investigate the possible interaction between the self-reference effect and language speech processing and whether the former can occur without explicit awareness. Specifically, this study examined whether syntactic speech processing can be affected by self-reference under masked conditions (i.e., the participants were unaware of the self-referential context). Participants listened to sentences that could contain morphosyntactic anomalies while the face identity (self, friend or unknown faces) was presented for 16 milliseconds preceding the critical word. Thus, self-related stimuli were visually masked with scrambled faces and were task-irrelevant. This design allows testing the low-level attentional capture of self-reference and whether it can influence real-time language processing. As hypotheses for this study, and based on previous works (e.g., Jiménez-Ortega et al., 2017; Rubianes et al., 2021), it was expected to find: (i) that the amplitude of the N250 component, instead of the N170 component, would be larger for self-faces compared to familiar faces; (ii) that both LAN (left anterior negativity) and P600 linguistic components would be influenced by self and friend faces, thus boosting or constraining the cognitive resources during linguistic operations; (iii) a larger alpha suppression for self and personally familiar faces over task-relevant brain regions.

The *third study* (*Chapter 5*) aimed to investigate the oscillatory correlates and entropy estimates underlying self-referential processing. To this end, participants were presented with different face identities, and the task demands comprised the same identity recognition task as in the *first study* (i.e., self, friend and unknown). Based on prior research (e.g., Alzueta et al., 2020; Haciahmet et al., 2023), it was expected to observe increased power in delta/theta bands and decreased power in alpha/beta bands for self-faces, as compared to friend and unknown faces.

Collectively, it is expected that the outcomes from these objectives will improve our understanding from a neurocognitive perspective of one of the most fundamental questions about human nature: How is the sense of self represented in the brain? In this regard, the results obtained in this thesis will provide new insights into the role of the self in human cognition. It is also expected that the findings obtained in this thesis will provide a more precise picture of the neural substrates of face perception.

CHAPTER 3.
NEURAL DYNAMICS OF SELF-IDENTITY AS A FUNCTION OF TIME

Chapter 3. Neural dynamics of self-identity as a function of time

Highlights:

- This study aimed to investigate the neural dynamics underlying self-identity processing and its continuity over time.
- The N170 was only sensitive to changes in the global face configuration when comparing adulthood with other life stages.
- The N250 was the earliest neural marker discriminating the self from other identities and may be related to a preferential access in long-term memory to recognize one's face.
- The P3 was the most robust index of self-specificity, reflecting stimulus categorization and presumably adding an emotional value.
- The LPC was the only component that reflects the continuity of the self over time (i.e., the difference between the current and the past selves).
- The main neural sources estimated were face-specific regions (fusiform gyrus), autobiographical memory regions (medial prefrontal cortex, parahippocampus, and posterior cingulate cortex/precuneus), along with executive regions (dorsolateral prefrontal and anterior temporal cortices).

This chapter is based on the following published articles:

- Rubianes, M., Muñoz, F., Casado, P., Hernández-Gutiérrez, D., Jiménez-Ortega, L., Fondevila, S., Sánchez, J., Martínez-de-Quel, O., & Martín-Loeches, M. (2021). Am I the same person across my life span? An event-related brain potentials study of the temporal perspective in self-identity. *Psychophysiology, 58*(1), e13692. https://doi.org/10.1111/psyp.13692
- Muñoz, F., Rubianes, M., Jiménez-Ortega, L., Fondevila, S., Hernández-Gutiérrez, D., Sánchez-García, J., Martínez-de-Quel, Ó., Casado, P., & Martín-Loeches, M. (2022). Spatio-temporal brain dynamics of self-identity: an EEG source analysis of the current and past self. *Brain structure & function, 227*(6), 2167–2179. https://doi.org/10.1007/s00429-022-02515-9

3.1. Introduction

A remarkable feature of the self is how it can maintain a notion of essential sameness over time in the face of physical or psychological changes. For instance, when thinking about past personal events (e.g., my first day of class at the university) or looking at photographs from the past (e.g., when I was a child), people can effortlessly recognize themselves regardless of ever-changing events (e.g., physical appearance, physiological processes, or individual beliefs). This notion of the self is often conceived as a *diachronic component* or *self-continuity*, which is linked to the awareness of the continuity of oneself across time (i.e., “I am the same person as I was before”) (Northoff, 2017). It has been suggested that self-continuity serves as a core-self component that remains consistent over time, being involved in unifying past and present experiences of oneself (Northoff, 2017; Northoff & Horvart, 2022; Sedikides et al., 2023). By contrast, the sense of self at a particular moment in time is typically regarded as a *synchronic component* (in relation to time) (Carruthers, 2006; Doering et al., 2012). Most neuroimaging and electrophysiological studies on self-recognition have focused on a specific moment in time (i.e., current), while the neural underpinnings of self-continuity as a function of time remain less studied in the literature (Morin, 2006; Northoff, 2017; Sedikides et al., 2023).

This chapter begins by reviewing neuroimaging and electrophysiological studies of self-recognition irrespective of time perspective. Subsequently, it is outlined research that examines both factors in conjunction before describing the aim and design of the study.

3.1.1. How and when does self-related processing occur in the brain?

Visual self-recognition is typically regarded as a reliable marker of self-awareness, as a face conveys a unique physical representation of facial features that are attached to each identity (Suddendorf & Butler, 2013; Young & Burton, 2018; Tsakiris, 2017). It is well established that self-related stimuli (e.g., one’s own face) can capture more cognitive resources than non-self-related stimuli (Cunningham & Turk, 2017), as they are powerful cues for attention and decision-making (Sui & Humphreys, 2015; Sui & Rothstein, 2019). Previous research has suggested that self-face recognition may also occur automatically or even when self-recognition is irrelevant to the task (e.g., Bola et al., 2021; Geng et al., 2012). Hence, this effect appears to be task-independent compared to other faces (Humphreys & Sui, 2016; Sui &

Rothstein, 2019). As introduced in Chapter 1, this phenomenon is known as the *self-reference effect* (SRE; Rogers et al., 1977; for a review, see Cunningham & Turk, 2017).

An open question in this regard is how and when self-preferential access occurs in the brain. Previous studies focusing on self-face recognition and using event-related brain potentials (ERP) have described an early dissociation between self and other identities, as shown by the N170 component. Particularly, a larger N170 has been reported for self-faces compared to other faces (Geng et al., 2012; Keyes et al., 2010). Since other studies have failed to report this early dissociation, the subsequent N250 component has been suggested as a specific neural marker of visual self-face recognition, differentiating between self, familiar and unknown faces (Alzueta et al., 2019; Miyakoshi et al., 2008; Tanaka et al., 2006; Woźniak et al., 2018). It should be noted that the N170 component is often linked to the structural encoding of faces (Eimer, 2011), whereas the subsequent N250 component is thought to reflect the access to stored representations of self and familiar faces in long-term memory (Olivares et al., 2015; Schweinberger & Neumann, 2016; Tanaka et al., 2006). Within this debate, it remains inconclusive to what extent these early face-related components may reflect self-face recognition relative to familiar and unfamiliar faces.

Following the time course on face perception, the late electrophysiological components, such as the P3 and the late positive complex (LPC), are typically involved in self-face recognition. Indeed, the P3, which is thought to reflect the engagement of higher-order cognitive functions (Johnson, 1986; Polich, 2020), has been proposed as the most robust index for self-referential processing (Knyazev, 2013). The LPC appears to reflect a further step in cognitive resource allocation (Azizan & Polich, 2007; Hajcak & Foti, 2020), probably enhanced by the detection of emotional properties and stimulus relevance (Cunningham & Turk, 2017; Xu et al., 2017) as well as by the attribution of meaningful information associated with a person, which includes personal semantics (i.e., semantic memory, autobiographical facts, self-knowledge, and episodic memory) (Renoult et al., 2016; Tanguay et al., 2018). Although the involvement of the P3 in self-referential processing is well established, the function of the LPC remains unsettled and may play a key role due to the significance of self-related content.

A large body of neuroimaging evidence has shown how face processing is underpinned by distributed neural systems comprising both core and extended face-processing systems (Gobbini & Haxby, 2007; Haxby et al., 2000). As part of the core system, a first set of brain regions, the inferior occipital gyrus, the lateral fusiform gyrus (FG), and the posterior part of the superior temporal sulcus (pSTS), are involved in the early visual processing of faces, which includes the processing of dynamic (e.g., facial expressions) and invariant features of faces (i.e., face identity). The extended system, which comprises a broad range of brain structures (e.g., anterior temporal lobule [ATL], anterior/posterior cingulate cortex [aCC/pCC], precuneus [PC] or temporoparietal junction [TPJ]), is engaged in further processing, retrieving different aspects of person-related information (e.g., biographical knowledge, mental states, etc.) along with emotional content (Góngora et al., 2019; Ramon & Gobbini, 2018; Visconti di Oleggio Castello et al., 2017, 2021). In a study conducted by Bobes et al. (2019), they performed a source reconstruction of the ERPs, and participants were presented with familiar and unfamiliar faces. In their study, they found the recruitment of face-responsive brain regions (critically, the FG) along with person-knowledge brain regions for personally familiar faces (mainly, the PC and temporal and frontal structures) as early as 150-210 ms after stimulus onset. What remains less clear, however, is what and how these brain regions of both core and extended face-processing systems reflect the processes involved in self-face processing (Olivares et al., 2015; Qin et al., 2020).

3.1.2. Self and time perspective

Self-continuity requires the ability to effectively discriminate between the current and the past selves, unifying temporally discrete self-related instances into a coherent whole. This subjective sense of sameness over time is crucial when accessing self-knowledge (Klein, 2014). Neuroimaging studies have suggested that access to both current and past self-representations is supported by different neural networks (Murray et al., 2015; Northoff, 2017). More specifically, posterior brain regions (i.e., pCC/PC) appear to be crucial for monitoring the self into an autobiographical memory across the lifespan, whereas anterior brain regions (primarily, the ventromedial/dorsomedial prefrontal cortex [vm/dmPFC]) support the current representation of self-related content (e.g., D'Argembeau et al., 2008; 2010). These brain regions are part of the so-called *Cortical Midline Structures* (CMS), which are a set of brain structures actively involved in self-related processing (Northoff et al., 2006; Qin et al., 2020).

Previous research in social psychology has proposed that people tend to distance themselves from their past self, as it can be regarded as “another person” due to personal changes (both physically and psychologically) across the lifespan, thus adopting a third-person perspective when recalling past traits or behaviors that differ with the current self-concept (Libby & Eibach, 2002; Proning & Ross, 2006). This notion of a certain distance due to personal changes could be reflected in a lower amplitude in the late ERP components for the past self, as compared to the current self. Previous research remains inconclusive as to whether the past self and the past close relative are processed similarly (D’Argembeau et al., 2008; Kotlewska & Nowicka, 2015). A similarity in this sense would suggest that personal knowledge is accessed by both self-related and his/her close relatives when contrasted with a stranger (Cloutier et al., 2011; Ramon & Gobbini, 2018). Given the specificity and relevance of the self in brain processing, it can be hypothesized that the past self should be differentiated from the past close relative at some point in the neural processing.

Not many electrophysiological studies have addressed self-face recognition over time. For example, Butler et al. (2013) studied the neural dynamics related to self-recognition across the lifespan using photographs of dizygotic twins in order to control familiarity. They grouped the stimuli into 5-15 (as more-distant past), 16-25 (less-distant past), and 26-45 (current self) years of age. Their main results indicated that the self and the twin faces share very similar featural (P1), configurational (N170), and matching processes (P3), but it was specific for the self in the latter components (N400). Remarkably, the N400 amplitude was larger for both the current and less-distant past self, as compared to a more-distant past self. They interpreted this result as a consequence of retrieving personal mnemonic information. Moreover, no difference was found between the current and the less-distant past. Kotlewska & Nowicka (2015) examined this issue with different stimuli, namely the current ‘adulthood’ self, past ‘childhood’ self, current familiar ‘close-other’, current adult famous, and current adult unknown faces. It is noteworthy that they reported no differences in the P3 component associated with the current and past selves, suggesting similarly engaged attentional resources, as well as similar levels of personal knowledge between the current and past selves. These results contrast with the study by Butler et al. (2013) outlined above.

3.1.3. The present study

Overall, while a body of evidence has largely explored self-face recognition regardless of a time perspective, less is known about the time course of self-representation at both lower and higher levels of processing (early and late ERP components, respectively). To this end, this study aimed to investigate the neural mechanisms underlying the effect of the temporal perspective (life stages) on the core-self (self-awareness, "I am I" despite physical changes) by examining different ERP measures and data-driven neural sources. The source-level estimations were reconstructed using a beamforming approach along with cluster-based permutation tests (for a recent review, see Westner et al., 2022). Briefly, this data-driven approach computes a 3D voxel-level model representing a given source location (without selecting *a priori* regions of interest) while suppressing the contribution from nearer sources and noise contained in the data (Veen et al., 1997; for more details, see methods).

To this end, participants were presented with a recognition task in which they had to focus on different aspects of the stimuli in two separate blocks: (i) identity recognition (self, close friend -as a control for familiarity-, unknown), and (ii) life stage recognition (adulthood -current-, adolescence, and childhood). This design enabled us to compare the results consistency in both task demands. Accordingly, the stimuli were the same in both blocks: three photographs corresponding to each identity and each life stage (3 x 3 x 3 = 27 photographs in total).

Based on the literature reviewed above, it was expected to found: (i) larger late positivities to the self, compared to the others, whilst close friend exhibiting an intermediate position or similar to the unknown condition (Miyakoshi et al., 2008; 2010; Xu et al., 2017); (ii) ERP modulations would be enhanced for the self across life stages, in particular, related to current self-faces (Apps, et al., 2012; Butler et al., 2013); (iii) the past self should be differentiated from the past close relative at some point in the neural processing; (iv) regarding early face processing, the N170/VPP modulations would be sensitive to facial structural changes, while the N250 may be more responsive to facial identity and some degree of familiarity (e.g., Olivares et al., 2015); (v) along the different ERP components, the effect of self-face processing compared to other faces would be relatively task-independent (Humphreys & Sui, 2016), despite asking participants to focus on different aspects of the stimuli in the different blocks; (vi) as for source-level analysis, it was expected that anterior regions (e.g., medial prefrontal cortex) would reflect self-referential content irrespective of life stages, whereas posterior regions (e.g., PC/pCC) would exhibit a larger sensitivity to self-identity across life stages.

3.2. Methods

3.2.1. Participants

The study included twenty undergraduate and graduate students (M = 23.85; SD = 3.93 years). Ten participants were males, and the other ten participants were females. All participants had normal or corrected-to-normal vision and no history of neurological or cognitive disorders. According to the Edinburgh Handedness Inventory, they were right-handed with a mean handedness score of +86 (range: +63 to +100) (Oldfield, 1971). Participants provided informed consent prior to the experiment. The study was carried out in accordance with the Declaration of Helsinki from the World Medical Association and was approved by the Ethics Committee of the Faculty at Psychology of the Complutense University.

3.2.2. Stimuli and procedure

A set of photographs obtained from the participants was included as material for the study. Prior to the experiment, participants were asked to provide a set of high-quality digitalized photographs of themselves and their closest friends (of the same gender) at each life stage (adulthood, adolescence, and childhood). All participants reported having had a close friendship since childhood. All images displayed a direct gaze and a neutral emotional expression. In order to normalize these stimuli, the set of materials was processed in Adobe Photoshop (CSG); more specifically, the faces were resized by establishing a constant spacing between pupils of 145 pixels (in width); in addition, the same luminance and a black background were applied, and each stimulus was framed within 450 x 600 pixels.

Participants were presented with three different images corresponding to each identity and each life stage (a total of twenty-seven photographs per participant). To improve the signal-to-noise ratio, each stimulus was repeated ten times by randomizing the order of the pictures. The stimuli were matched according to their age and gender. At the conclusion of the experiment, all participants stated that the identity of the unknown person was completely unfamiliar to them. Thus, the unknown condition for each participant was collected from the stimuli of the best friend of an unrelated participant.

Presentation® software (Neurobehavioral Systems, Inc.) was used to conduct the experiment. In an isolated room, participants were seated around 70 cm in front of a monitor (1024 x 768 pixels, LCD screen). As shown in Figure 3.1, each trial started on a fixation cross with a black background for 1000 milliseconds (ms). After a blank of 200 ms, the facial stimulus was randomly presented for 1000 ms, followed by another blank of 200 ms. Thereafter, the response window appeared for 1000 ms. By pressing one of the three buttons available (index, middle, and ring fingers), participants provided their responses. This sequence of buttons was counterbalanced between experiments (right-handed or left-handed). To minimize motor artifacts during stimulus presentation and also considering the fact that previous research has found a shorter reaction time for self-face recognition (e.g., Geng et al., 2012), participants had to hold their responses until the time window appeared.

The experiment was performed in two blocks: (i) in the identity block, participants were instructed to judge the identity of each face (self, friend, and unknown); (ii) in the life stage block, they were instructed to judge the age of each face (adult, adolescent, and child). The block order was counterbalanced between participants. A total of 540 stimuli were shown to the participants (27 photographs x 10 presentations x 2 blocks).

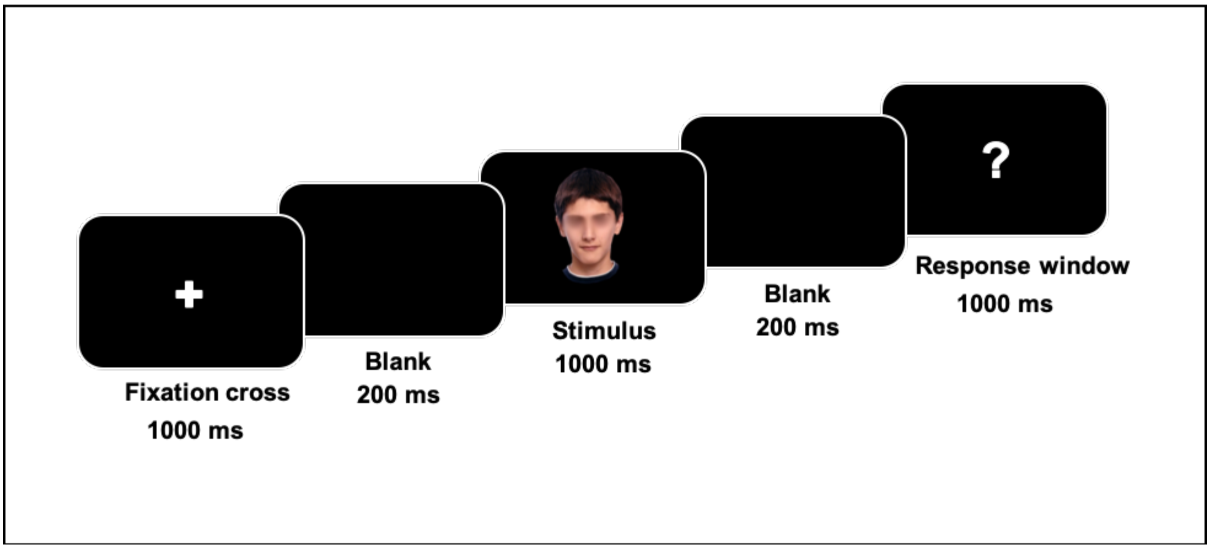

Figure 3.1 Schematic representation of the procedure.

3.2.3. EEG recordings and analysis

Continuous EEG was recorded using 59 scalp electrodes (Brain Products; Gilching, Germany) in accordance with the international 10-20 system. A BrainAmp DC amplifier (Brain Products) with a sampling rate of 250 Hz and a band-pass of 0.01 to 100 Hz was used to record EEG data. All scalp electrodes and the left mastoid were referenced to the right mastoid during EEG recordings; subsequently, they were re-referenced off-line to the mean of the right and left mastoids. The location of the ground electrode was AFz. All electrode impedances were kept below five kΩ. With two vertical (VEOG) and two horizontal (HEOG) electrodes situated above and below the left eye and on the outer canthus of both eyes, respectively, eye movements and blinks were observed.

Brain Vision Analyzer® (Brain Products) and EEGLAB v14.1 (Delorme et al., 2011) as a toolbox of Matlab (R2017b; MathWorks, Natick, MA, USA) were used to analyze EEG data. The raw data were first segmented and filtered with a band-pass from 0.1 to 40 Hz, and subsequently segmented into 1200 ms epochs (beginning 200 ms before the stimulus onset). Baseline corrections were applied from -200 to 0 ms. Incorrect and omitted trials, as well as trials with transient noise, were excluded from the analyses. Independent component analysis (ICA) was used to correct common artifacts (e.g., eye movements or muscle activity) (Bell & Sejnowski, 1995). After identifying the artifacted ICAs, they were excluded from the EEG data. All EEG preprocessing steps are in agreement with the guidelines described by Keil et al. (2014).

The mean of the segments for each condition after artifact rejection was as follows: self (86.55 $\pm$ 3.23), friend (86.00 $\pm$ 4.45), unknown (87.15 $\pm$ 2.97), adulthood (84.00 $\pm$ 5.93), adolescence (81.45 $\pm$ 8.21), and childhood (84.25 $\pm$ 6.13). The average rejection rate of segments throughout all epochs across participants was 21.67% for the identity block and 23.12% for the life stage block. There was a significant difference between the identity (M = 259.7) and life stage blocks (M = 249.7) when comparing the overall segments ($t_{(19)} = 2.574$; $p < .05$). As for the ERP measurement, separate averages were performed for each condition.

Time windows were conducted based on visual inspection of the ERP effects and in consonance with previous studies (e.g., Butler et al., 2013; Gosling & Eimer; Kotlewska & Nowicka, 2015; Nemrodov et al., 2016; Woźniak et al., 2018). In consonance with previous studies (e.g., Butler et al., 2013; Kotlewska & Nowicka, 2015) and based on visual inspection of the ERP effects (Figures 3.2 and 3.3), time windows were conducted as follows: N170 (150–

200 ms), N250 (250–300 ms), P3 (300–400 ms), LPC (450–600 ms). Likewise, the mean amplitudes for both N170 and N250 components were measured at bilateral occipito-temporal sites (PO7 and PO8), according to previous research (Gosling & Eimer, 2011; Nemrodov et al., 2016). The mean amplitudes for P3 and LPC components were measured in specific clusters of electrodes or regions of interest (ROI): namely, anterior (AF3, AF4, Fz, F1, F2, F3, F4), central (FCz, FC1, FC2, FC3, FC4, Cz, C1, C2, C3, C4), and posterior (CPz, CP1, CP2, CP3, CP4, Pz, P1, P2, P3, P4). The clustering was carried out based on the visual inspection of the topographic distribution of the ERP differences (as shown in Figure 3.3) and following previous ERP studies that found a frontocentral distribution for late differences, even though these late components typically exhibit a centro-parietal distribution (e.g., Geng et al., 2012; Sui et al., 2006; Woźniak et al., 2018).

A repeated-measures analysis of variance (ANOVA) was used to assess ERP amplitudes. The factorial design for the N170 and the N250 components was 2 x 3 x 3 (Block x Identity x Life Stage). For the P3 and LPC components, the design was 2 x 3 x 3 x 3 (Block x Identity x Life stage x Topographic distribution). The alpha level for all analyses was set at 0.05. When the sphericity assumption was violated, the Greenhouse and Geisser (1959) method was applied. The mean and 95% Confidence Intervals (CI) were described. The partial eta squared (η_p^2) is reported as a measure of statistical power. Post-hoc tests were corrected using the Bonferroni method. The data included in the statistical analyses can be found in the Open Science Framework (OSF) online repository (https://osf.io/9hfd5/).

3.2.4. Source reconstruction

Regarding source analysis, a scalar beamformer approach was used to compute the neural sources obtained from the preprocessed EEG data. This analysis was conducted in Fieldtrip, an open-source Matlab toolbox (Oostenveld et al., 2011). The lead field matrix (or forward model) was generated using an EEG head model template (Boundary Element Method, BEM) and divided into a 5-mm-spaced grid. The lead field matrix followed the coordinate system from the Montreal Neurological Institute (MNI) atlas. The algorithm used was the *linearly constrained minimum variance* (LCMV, Van Veen et al., 1997), which computes an adaptative spatial filter to the ERP data. Thus, the covariance of all conditions was computed and then employed as a common spatial filter for each time window. Hence, the source reconstruction for each condition is projected using this common filter. According to the ERP results, the time windows of interest were as follows: 150–200 ms (N170), 250–300 ms (N250), and 300–600 ms (P3 and LPC). In order to increase the accuracy of the source analysis and given that the stimuli were presented twice, all conditions between the two blocks were collapsed (doubling the trial-to-condition ratio); consequently, the block factor was excluded from this analysis.

3.2.5. Cluster-based permutation tests

Non-parametric statistics and cluster-based permutation tests were conducted to test the 3D spatial distribution of source power generated by the LCMV method (Maris & Oostenveld, 2007). Using the Monte-Carlo approach, the significance probability is determined under the permutation distribution. This statistical test was used to compare, by means of a t-test, the different experimental conditions and their corresponding interactions (e.g., self vs. friend, self vs. unknown and friend vs. unknown).

As for the source-level statistics, each grid point or sample was contrasted using a t-value, and then a set of samples constituted a particular cluster (whose t-values were larger than a certain threshold of .016, as the alpha was corrected by the number of comparisons). Moreover, selected samples were clustered in connected sets on the basis of temporal and spatial adjacency. Thereafter, the permutation distribution was generated by randomly reassigning the conditions among all participants a given number of times (8000 times). For each permutation, the cluster candidate with the highest sum of values was compared to the permutation distribution. Significant differences were determined if the estimated p-value for the largest cluster-level statistic was smaller than the critical alpha level. As shown in Figures 3.6 and 3.7, the output of source-level statistics was interpolated onto an anatomical high-resolution MRI template (based on MNI coordinates) with a posterior statistical threshold mask (p-corrected = .01, $t > 2.56$).

After interpolating onto an anatomical MRI template (based on MNI coordinates), the output of source-level statistics, and statistical t-maps were depicted with a posterior statistical threshold mask (p-corrected = .01, $t > 2.56$). The atlases used to map the peak t-values were both MRIcron (Rorden & Brett, 2000) and Neurosynth (Yarkoni et al., 2011).

3.3. Behavioral results

The participants' behavioral results in terms of percentage were as follows (mean ± SD): misclassifications (0.87% ± 1.23 for identity; 7.25% ± 6.31% for life stages), hit rates (99.03% ± 1.25% for identity; 92.5% ± 6.28% for life stages), and omissions (0.09% ± 0.16% for identity; and 0.24% ± 0.28% for life stages). A significant difference in misclassifications between tasks was found ($t_{(19)}$ = 4.713; p = .001). Reaction times were considered uninformative, as participants had to wait until the response interval appeared after the facial stimulus presentation.

3.4. Event-related potentials results

The average waveforms for both Identity and Life Stage effects are shown in Figures 3.2 and 3.3. The mean differences and the 95% confidence intervals (CI) of the effect sizes for both Identity and Life stage effects can be observed in Figure 3.4. The interaction effects are depicted in Figure 3.5. Accordingly, different modulations of the ERP across conditions were found by visual inspection of the ERP (Figures 3.2 and 3.3) together with the topographic maps (Figure 3.3). In addition, it appears that the largest differences between conditions along the later components follow a frontocentral distribution, as depicted in Figure 3.3.

Factors (df)	**N170-F(η_p^2)**		**N250-F(η_p^2)**		**P3-F(η_p^2)**	**LPC-F(η_p^2)**
	PO7	**PO8**	**PO7**	**PO8**		
Block (1,19)	1.193	1.138	.379	.067	3.086	5.001*
	.059	.57	.02	.01	.14	.21
Identity (2,38)	.020	.475	3.535*	10.83***	15.78***	43.440***
	.001	.625	.16	.36	.45	.70
Life Stage (2,38)	7.469**	6.260**	8.595**	18.13***	17.86***	9.112**
	.282	.248	.31	.49	.48	.324
Block x Identity	.121	1.306	.535	1.801	1.589	.262
(2,38)	.006	.064	.03	.09	.08	(.01)
Block x Life Stage	2.863	.367	.097	.173	.18	1.234
(2,38)	.131	.019	.01	.01	.01	.06
Identity x Life	1.304	.109	.476	1.877	2.367	4.026**
Stage (4,76)	.064	.006	.02	.09	.11	.18
Block x Identity x	.866	.047	1.348	.221	.681	2.006
*Life Stage (*4,76)	.044	.002	.07	.01	.03	.010

Table 3.1 Statistical analysis of Identity and Life stage effects corresponding to each ERP component. Note: df, degrees of freedom; n.s., not significant; F, F values; η_p^2, partial eta square; * p < .05; ** p < .01; *** p < .001.

The repeated-measures ANOVA for the N170 amplitude revealed no significant differences for the main effects of both Block and Identity. As shown in Table 3.1, a significant difference was found for the main effect of Life stage, showing a higher size effect at PO7 than at PO8. Pairwise comparisons revealed that the N170 amplitude for adulthood was significantly larger with respect to adolescence and childhood at PO7, while no differences were found when comparing the amplitudes between adolescence and childhood. Moreover, the following interactions were non-significant, namely: Block x Identity, Block x Life Stage, Identity x Life stage, and Block x Identity x Life Stage.

The repeated-measures analysis for the N250 amplitude was non-significant for the main and interaction effects involving Block as a factor. Yet, a significant effect was found for Identity, with the size effect being higher at PO8 than at PO7. Follow-up comparisons at PO8 indicated that the amplitude for the self was significantly larger compared to the friend and the unknown, while the contrast between friend and unknown faces was non-significant. In addition, a significant main effect for Life stage, which was associated with a higher size effect at PO8 than at PO7. Pairwise comparisons at PO8 showed a significantly larger amplitude to adulthood relative to adolescence and childhood, along with a larger amplitude to adolescence compared to childhood. However, no significant effects were found for the interaction between Identity and Life Stage.

The ANOVA for the P3 component was not significant for the main and interaction effects involving the Block factor. Yet, a significant effect was found for Identity. In particular, the amplitude for the self was significantly larger than for the friend ($p = .012$) and for the unknown ($p < .001$). The contrast between friend and unknown conditions was also statistically significant ($p = .020$). In addition, a significant effect was found for Life Stage, showing that the amplitudes for adulthood and adolescence were significantly larger compared to childhood ($p < .001$; $p = .002$, respectively), while the contrast between adulthood and adolescence was non-significant ($p = .186$). Regarding the topographical effects, a significant effect was found for the interaction between Identity x ROI ($F_{(2, 38)} = 3.502$, $p = .036$, $\eta_p^2 = .146$), indicating that the largest differences between all identity conditions were more noticeable in the central region (all ps ≤ .012), followed by the anterior and posterior regions, respectively (all ps ≤ .042; all ps ≤ .043). Furthermore, a significant interaction was found between Life stage x ROI ($F_{(2, 38)}$ = 16.927, p ≤ .001, η_p^2 = .47). Follow-up comparisons showed that the mean difference between adulthood and childhood as well as the contrast between adolescence and childhood were more remarkable in the anterior region (all ps ≤ .001), followed by the central region (all ps ≤ .002), while the posterior region was not significant (all ps > .1). Likewise, the P3 amplitude for adolescence was significantly larger than for childhood only in the anterior region (p = .048). No further significant interaction effects, including the ROI factor, were found.

As for the LPC component, the repeated-measures analysis showed a main effect involving the Block factor (see Table 3.1), indicating that the amplitude for the life stages block was significantly larger than the identity block (Δ = .79 V, 95% CI [0.05, 1.52], p = .038). No further significant effects related to the Block factor were found. Furthermore, a significant effect was observed for the Identity factor, showing that the amplitude for the self was significantly larger compared to friend (p < .001) and unknown (p < .001), while the contrast between friend and unknown did not reach statistical significance (p = .066). Moreover, a significant effect was found for Life stage, with the amplitude for adulthood significantly larger compared to adolescence (p = .008) and childhood (p = .007), while the contrast between adolescence and childhood was non-significant (p = .171).

A significant interaction effect was found between Identity x ROI for the LPC component ($F_{(2, 38)}$ = 6.393; p = .004, η_p^2 = .25). In particular, the amplitude for the self was significantly larger than the friend along the anterior, central and posterior regions (all ps < .001), as well as than the unknown (all ps < .001). However, the only ROI that was able to distinguish the contrast between friend and unknown was the anterior region (p = .036), in contrast to the central and posterior regions (p = .068; p = .273, respectively). In addition, the interaction between Life stage x ROI was significant ($F_{(2, 38)}$ = 3.649, p = .033, η_p^2 = .16). The mean amplitude for adulthood was larger than adolescence in the anterior region (p = .029) and most remarkable in the central region (p = .003), while it did not reach statistical significance in the posterior region (p = .053). Likewise, the contrast between adulthood and childhood was more noticeable in the anterior and central regions (p = .003; p = .006, respectively), whilst it did not reach statistical significance in the posterior region (p = .051). The LPC amplitude for adolescence was significantly larger than for childhood in the anterior region (p = .029), and it was non-significant in the central and posterior regions (p = .205; p = .792, respectively). No further significant interaction effects involving the ROI factor were found.

Relevant to the aims of this study, the two-way interaction between Identity x Life Stage revealed a significant effect on the LPC amplitude, as shown in Table 3.1. On one side, comparing the self across time (Figure 3.5A), the amplitude for adulthood was larger compared to adolescence (p = .004) and childhood (p = .003), but no difference was observed between adolescence and childhood (p = .089). Similarly, when comparing the friend across time, the amplitude for adulthood was significantly larger compared to childhood (p = .019). On the other hand, when comparing all identities at each life stage (Figure 3.5B), the self was significantly larger than the friend at each life stage (all ps < .001), as well as compared to the unknown (all ps < .001). Finally, no differences were observed between friend and unknown faces at any life stage (all ps ≥ .082).

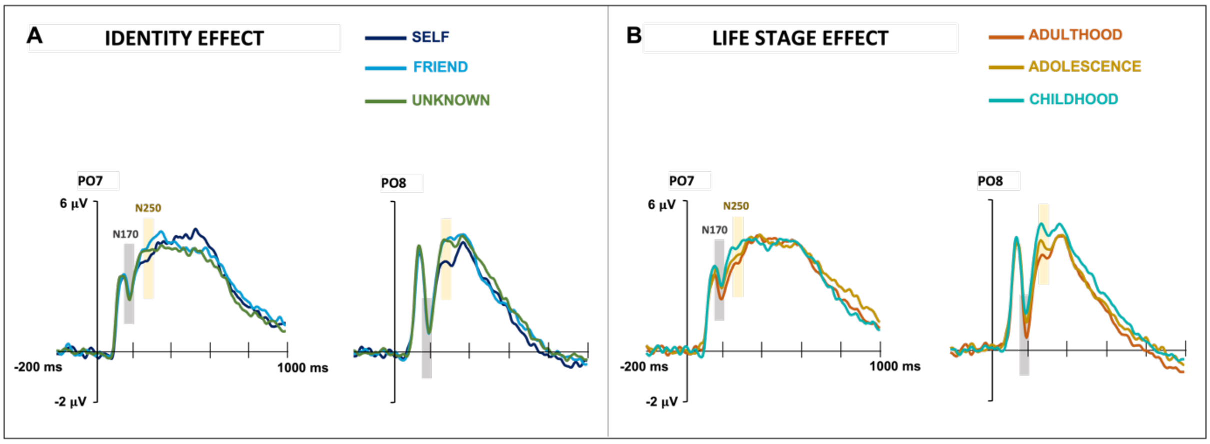

Figure 3.2 Grand average waveforms displaying both N170 and N250 components for the identity (A) and life stage (B) effects.

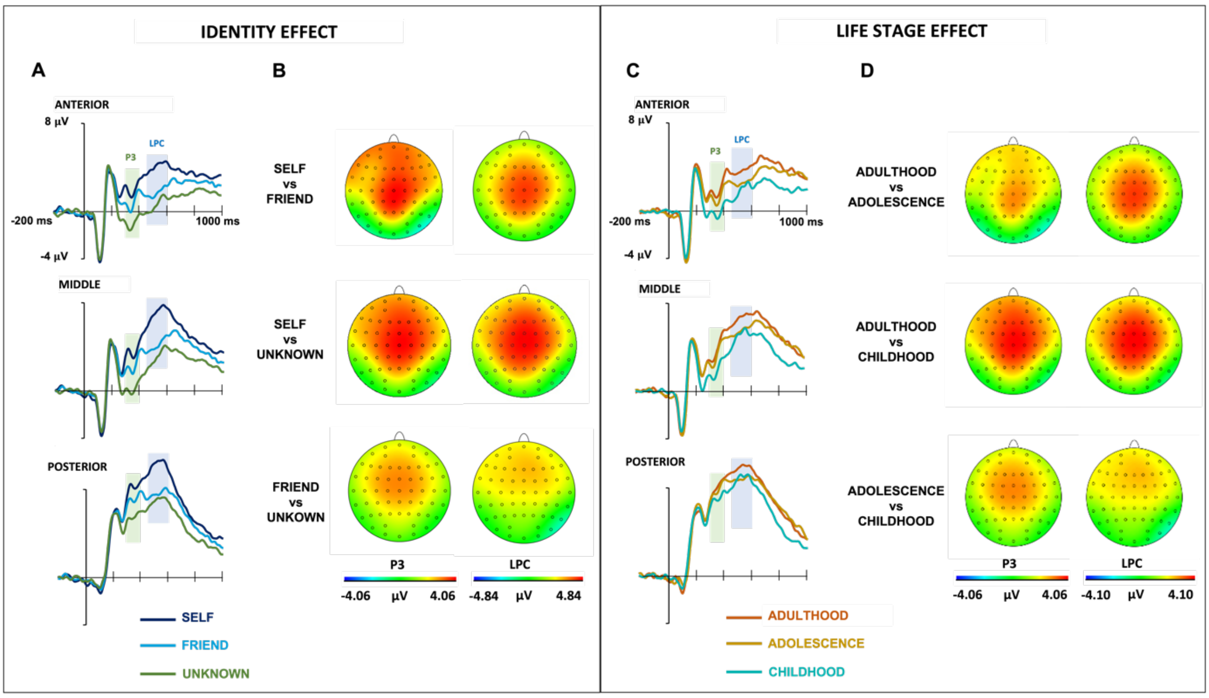

Figure 3.3 Grand average waveforms displaying both P3 and LPC components for the effects of identity (A) and life stage (C).Topographical distributions depicting the difference waves for the identity (B) and life stage (D) effects.

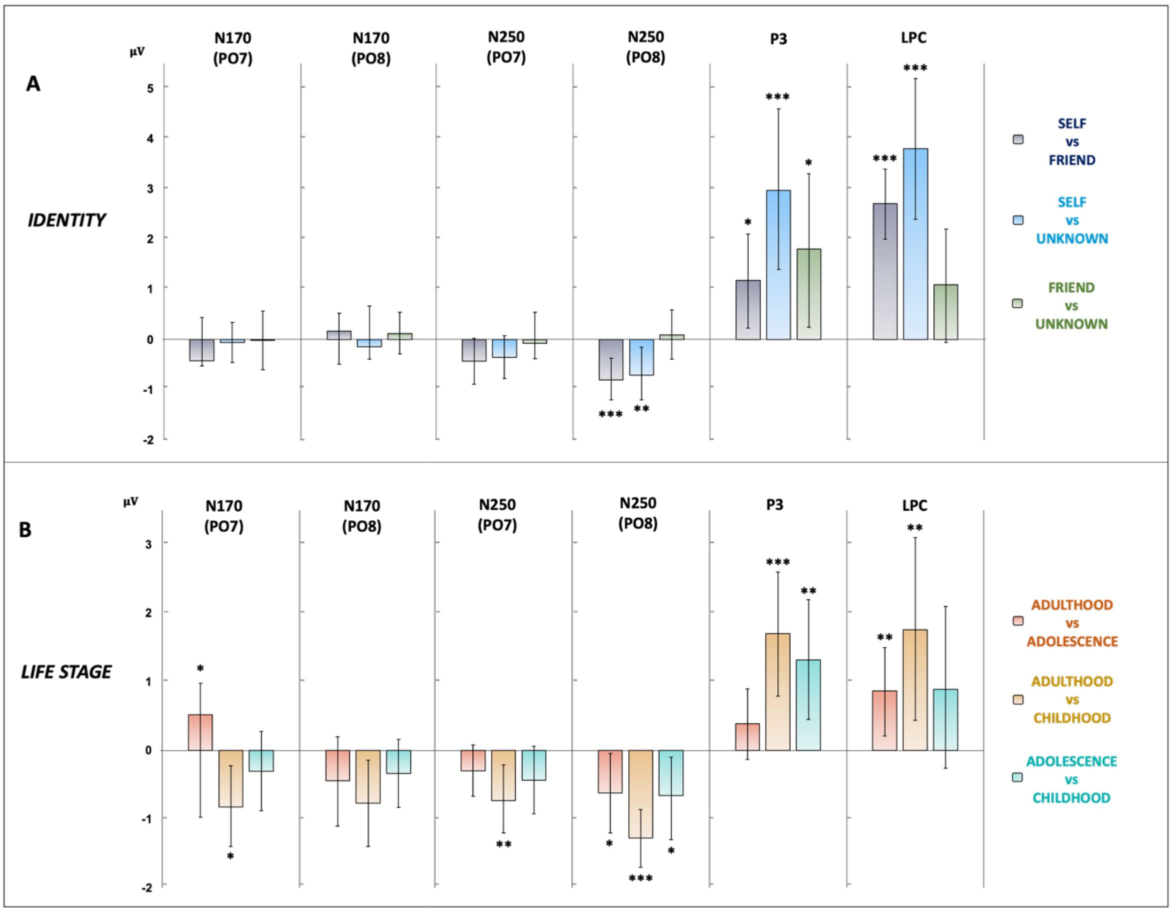

Figure 3.4 ERP bar graphs displaying mean differences and error bars (representing confidence intervals of the effect sizes) for the identity (A) and life stage effects (B).

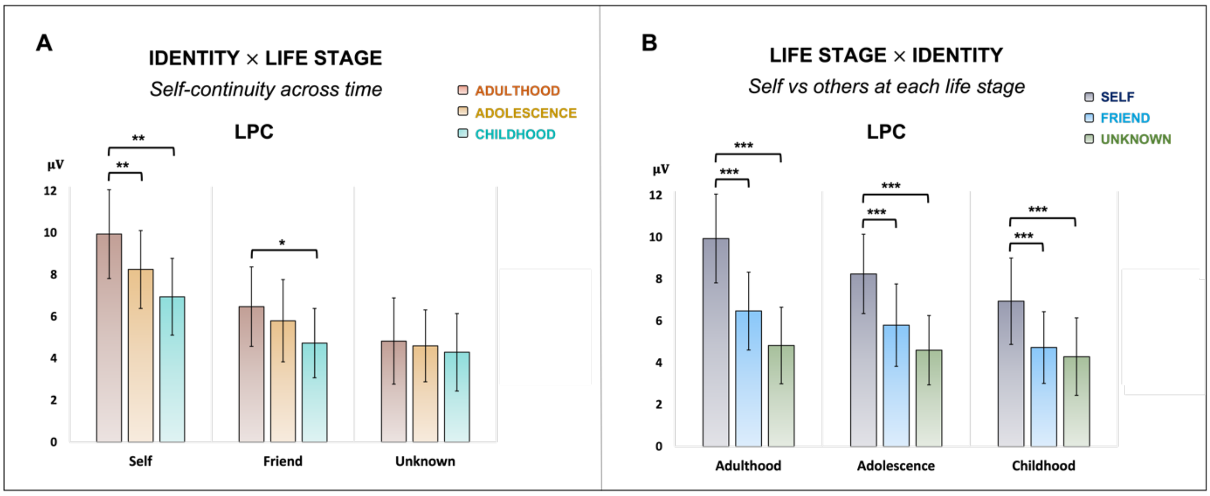

Figure 3.5 ERP bar graphs displaying mean and error bars for the two-way interaction between identity and life stage. The left panel (A) shows the continuity of each identity across time. The right panel (B) depicts the contrast between identities at each life stage. Note that the ROIs were collapsed with the data.

3.5. Source reconstruction results

During the 150–200 ms time window, the cluster-permutation tests showed non-significant differences between all conditions during this time window. For a detailed description of the p-values of the clusters, see Table A1 in the Appendices section.

As for the 250–300 ms time window, the analysis yielded a significant effect for the contrast between self and friend (p = .036). This effect was localized in the dorsolateral and dorsomedial prefrontal cortex (dlPFC/dmPFC), anterior temporal lobule (ATL), and anterior cingulate cortex (ACC), as shown in Figure 6. A significant effect was also found between self and unknown (p = .008) over the medial prefrontal cortex (mPFC) and temporoparietal junction (TPJ). No significant effect was observed for the contrast between friend and unknown faces. For the main effect of the Life stage, the cluster-permutation tests showed a significant effect for the contrast between adulthood and childhood (p = .004). This effect was observed in the precentral gyrus, the inferior frontal gyrus (IFG; pars opercularis), and the inferior temporal gyrus. A significant effect was found for the interaction between Identity x Life Stage. When comparing the self across time, the analysis showed significant differences for the contrast between adulthood and childhood (p = .002) over the dlPFC and fusiform gyrus (FG), as well as for the contrast between adolescence and childhood (p = .027) over the middle and inferior temporal gyrus (MTG/ITG). Similarly, when comparing the friend across time, the cluster-permutation tests yielded significant differences for the contrast between adulthood and childhood (p = .044) over the cuneus, as well as for the contrast between adolescence and childhood (p = .033) over the precentral gyrus and posterior cingulate cortex (PCC). The MNI coordinates associated with the peak t-value for each significant contrast can be found in Table 3.2.

Contrasts	**Regions**	**H**	**MNI coordinates**			**Peak *t*-values**
			x	**y**	**Z**	
Identity						
Self > Friend	Dorsomedial Prefrontal Cortex	R	16	32	50	3.25
	Dorsolateral Prefrontal Cortex	R	42	36	34	3.13
	Anterior Cingulate Cortex	L	16	18	40	3.02
	Anterior Temporal Lobule	R	44	16	-30	3.01
	Dorsolateral Prefrontal Cortex	L	-32	46	34	2.98
Self > Unknown	Medial Prefrontal Cortex	L	-2	62	-10	3.79
	Temporoparietal Junction	L	-34	-42	38	3.66
Life Stage						
Adulthood > Childhood	Precentral gyrus	R	50	12	34	3.25
	Inferior Frontal Gyrus	R	52	30	-6	2.85
	Posterior Inferior Temporal Gyrus	L	-60	-34	-16	3.03
Identity x Life Stage						
Self(Adult > Child)	Dorsolateral Prefrontal Cortex	L	50	18	42	3.05
	Fusiform Gyrus	R	24	-7	-44	2.92
	Fusiform Gyrus	L	-36	-20	-32	2.88
Self (Adol > Child)	Middle Temporal Gyrus	R	64	-34	-4	3.59
	Inferior Temporal Gyrus	R	66	-36	-18	3.50
	Fusiform Gyrus	R	30	-8	-36	3.35
Friend (Adult > Child)	Cuneus	L	-6	-86	10	3.41
Friend (Adol > Child)	Precentral gyrus	R	52	2	34	3.46
	Posterior Cingulate Cortex	L	-2	-46	28	3.03

Table 3.2 Source reconstruction results at the 250-300 ms time window. MNI coordinates and their peak *t*-values ($p < .01$) corresponding to the estimated brain regions. Abbreviations: Adult: adulthood; Adol: adolescence; Child: childhood; MNI: Montreal Neurological Institute.

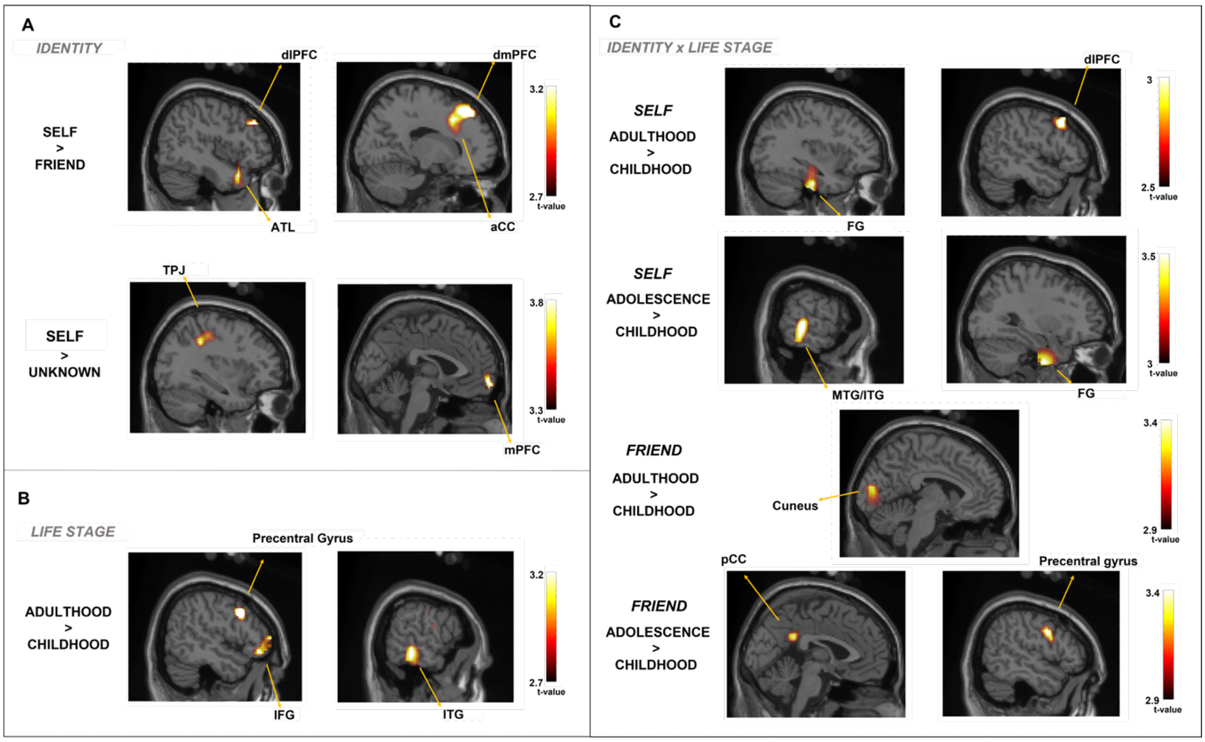

Figure 3.6 Source reconstruction of the statistical t-maps or univariate contrasts at the 250-300 ms time window, displaying the effects of identity (A), life stage (B), and between identity and life stage (C). Reported brain regions that exceed the statistical threshold of $p < .01$. *Abbreviations:* ACC: anterior cingulate cortex; ATL: anterior temporal lobule; dlPFC: dorsolateral prefrontal cortex; dmPFC: dorsomedial prefrontal cortex; FG: fusiform gyrus; IFG: inferior frontal gyrus; ITG: inferior temporal gyrus; MTG: middle temporal gyrus; PCC: posterior cingulate cortex; TPJ: temporoparietal junction.

In relation to source reconstruction during the 300–600 ms window, the cluster-permutation tests showed significant differences for the Identity effect. In particular, significant effects were found for the contrasts between self and friend (p = .026) and self and unknown (p = .017). These effects were observed over the mPFC, as shown in Figure 3.7. However, the analysis showed non-significant differences for the contrast between friend and unknown faces. Regarding the Identity x Life stage interaction, significant effects were observed when comparing the self across time. The analysis revealed significant effects for the contrast between adulthood and adolescence (p = .002) over the precuneus/posterior cingulate cortex (PC/PCC), parahippocampal gyrus (pHC), and FG, as well as for the contrast between adulthood and childhood (p =.038) over the dlPFC and MTG. However, the contrast between adolescence and childhood was non-significant (p = .7). The MNI coordinates associated with the peak t-value for each significant contrast can be observed in Table 3.3.

Contrasts	Regions	H	MNI coordinates x	y	z	Peak *t*-values
Identity						
Self > Friend	Medial Prefrontal Cortex-L	L	-2	52	20	2.89
Self > Unknown	Medial Prefrontal Cortex-L	L	-8	66	14	3.25
Identity x Life Stage						
Self (Adult > Adol)	Precuneus/Posterior Cingulate Cortex	R	21	-44	0	5.32
	Parahippocampal Gyrus-R	R	20	-38	-6	5.08
	Fusiform Gyrus-R	R	28	-40	-12	4.21
Self (Adult > Child)	Dorsolateral Prefrontal Cortex-R	R	40	20	34	3.72
	Middle Temporal Gyrus-R	R	42	74	8	3.48

Table 3.3 Source reconstruction results at the 300-600 ms time window. MNI coordinates and their peak *t*-values (*p* < .01) corresponding to the estimated brain regions. Abbreviations: Adult: adulthood; Adol: adolescence; Child: childhood; MNI: Montreal Neurological Institute.

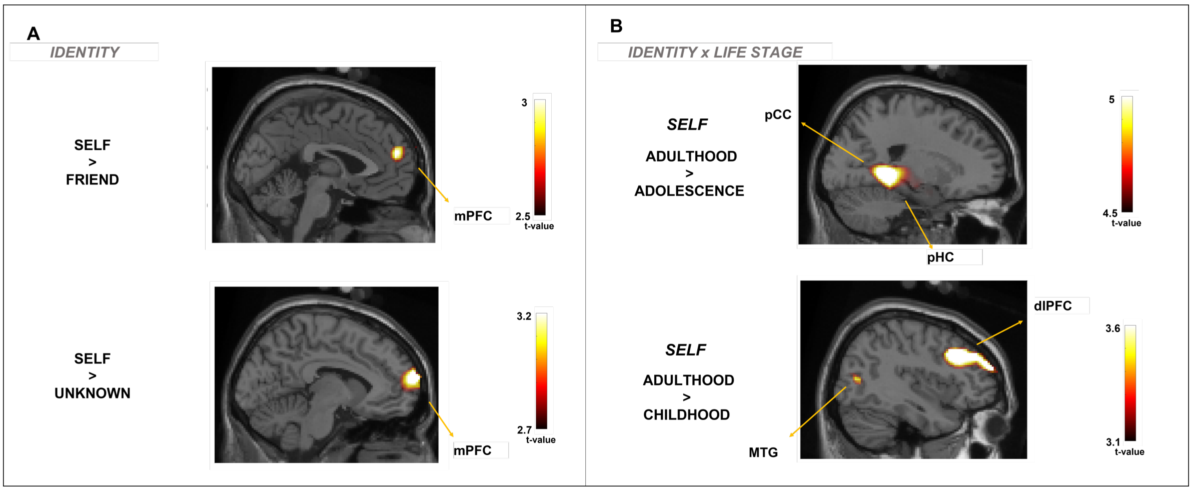

Figure 3.7 Source plots of the statistical t-maps for univariate contrasts at the 300-600 ms time window, showing the significant effects of identity (A) and the interaction between identity and life stage (B). Reported brain regions significantly activated at a statistical threshold of *p* < .01 Abbreviations: dlPFC: dorsolateral prefrontal cortex; FG: fusiform gyrus; IFG: inferior frontal gyrus; mPFC: medial prefrontal cortex; MTG: middle temporal gyrus; pHC: parahippocampal cortex; PCC: posterior cingulate cortex.

3.6. Discussion

This study aimed to investigate the spatiotemporal neural dynamics underlying self-identity processing and its continuity over time. As far as the time course of self-identity processing goes, the data from this study indicate that self-preferential processing (compared to other identities) begins as early as 250 ms, as shown by the N250 component. This preferential processing seems to be continued by long-lasting positivities (i.e., P3 and LPC), although the P3 component was the most robust neural marker for differentiating the self from other identities, irrespective of temporal perspective. As for the interaction between identity and life stage, self-identity processing appears to be sensitive to the temporal dimension of life stages (with larger amplitudes for current self compared to past selves), particularly reflected by the LPC component. It seems that such temporal perspective can also be extended to friend face processing (current vs more-distant past friend). These findings may be due to person-related knowledge and self-relevant information linked to the self and personally familiar faces (Anzelloti & Young, 2020; Ramon & Gobbini, 2018; Tanguay et al., 2018). Regarding the relationship between the past self and past close friend, the data of this study indicated similarities at certain stages of information processing (i.e., N250 and P3 components), while differences were observed at later stages (i.e., LPC) not reported so far.

Furthermore, this study explored the estimated power of neural sources driven by the ERP results. No significant neural sources emerged during the 150–200 ms time window. Source reconstruction results were found in the middle (250–300 ms) and late (300–600 ms) time windows. During 250–300 ms, an increment in source power was found in temporal (ATL), midline and frontal structures (dm/dlPFC and aCC) for the contrast between self and friend conditions. Moreover, the mPFC and TPJ showed an increment of power for the contrast between self and unknown faces. At later latencies (300–600 ms), the mPFC appeared to be more engaged when distinguishing self-faces from other identities, regardless of temporal perspective. Most notably, the interaction between identity and life stages indicated a distributed network of brain regions involved in self-continuity processing during the middle and late time windows, comprising temporal and frontal cortices (dlPFC, MTG and FG) when comparing adulthood and childhood (current vs. more-distant past self), medial and temporal cortices (pCC and pHC) for adulthood in comparison with adolescence (current vs.

less-distant past self), and middle and inferior temporal cortices (MTG/ITG and FG) when comparing adolescence and childhood (less-distant past vs more-distant past self). Collectively, the brain regions reported here are in general agreement with both core/extended face-processing systems (Gobbini & Haxby, 2007; Haxby et al., 2000; Visconti di Oleggio Castello et al., 2021) and neural models of the self (e.g., Murray et al., 2015; Sui & Gu, 2017; Qin et al., 2020). The main results obtained in this study will be further discussed in the following paragraphs.

3.6.1. Behavioral findings

The behavioral results showed that the participants had a substantially better performance for identity recognition than for life stage recognition. Furthermore, more misclassification rates occurred during the judgments of the life stages of the unknown condition. These data may indicate a potential difference between blocks in terms of cognitive demands, yielding larger difficulty in the life stage block. Increasing the interval between ages would probably facilitate its discrimination, thus decreasing misclassification, but intermediate ages would increase difficulty. Another factor that could explain the better performance in recognizing identity concerns familiarity with the presented stimuli. Familiarity with a close friend's face and, particularly, with one's own face would make them more easily recognizable in an identity task. Furthermore, in line with prior studies (Apps et al., 2012; Kotlewska & Nowicka, 2015), a better performance was found with stimuli from the present than to the past.

3.6.2. On the time course of self-identity processing: ERP evidence

The results of this study support that the N170 is insensitive to the effect of face familiarity. This is in line with previous works (Alzueta et al., 2019; Butler et al., 2013; Kotlewska & Nowicka, 2015; Miyakoshi et al., 2008, 2010; Sui et al., 2006; Tanaka et al., 2006; Xu et al., 2017). In turn, this pattern is consistent with the proposal that the N170 reflects an automatic mechanism detecting the global configuration of a face in a recognition task rather than recognizing the identity of a face (Olivares et al., 2015; Schweinberger & Neumann, 2016). Previous studies have described an own-age bias, that is, adults recognize adult faces more accurately than children's faces, whereas children recognize children's faces more accurately than adult faces (Harrison & Hole, 2009; Hills & Lewis, 2011). This might be consistent with our findings on the N170 related to the discrimination of global perception properties between current “adulthood” faces and younger faces (i.e., “adolescence” and “childhood” faces).

At later latencies, the N250 was the earliest neural response to discriminate self-faces from other faces. This finding is in consonance with previous works (Miyakoshi et al., 2008; Scott et al., 2005; Tanaka et al., 2006; Woźniak et al., 2018, and supports the idea that the N250 is involved in the access of self-face recognition units from long term memory. This access to personal knowledge enables the primary function of self-awareness and categorization (recognition of oneself). Likewise, the lower amplitude found for self-faces at this stage of the processing could indicate the facilitation of attentional resources for self-recognition (Olivares et al., 2015; Schweinberger & Neumann, 2016). However, the N250 did not reflect the self as a function of time, as life stage and identity did not interact during this window.

After 250 ms of stimulus onset, self-related processing elicited a long-lasting positivity, that is, both P3 and LPC. These components were able to discriminate between the self and other identities, and this was so regardless of task demands. The P3 has been proposed as a robust and specific index for self-referential processing, reflecting the mobilization of attentional resources to a task-relevant target event. These results are in line with previous research (Keyes et al., 2010; Knyazev, 2013; Miyakoshi et al., 2010; Sui et al., 2006; Xu et al., 2017). Studies on the neural underpinnings of self-relevant processing have suggested that the larger the long-lasting positivity, the more important the self-related content (Anaki & Bentin, 2009; Chen et al., 2011; Muñoz et al., 2020; Tacikowski & Nowicka, 2010; Xu et al., 2017). In other words, larger amplitudes in later components might reflect the increased allocation of attention and more elaborate processing, presumably due to the meaningfulness of self-relevant information.

The P3 may reflect the categorization of the stimulus, involving larger facilitation due to self-preferential access in face recognition units from long-term memory, as well as emotional saliency characteristics. The larger LPC amplitude could reflect a step further in the cognitive re-evaluation process, engaging more allocation of attentional resources as a result of deeper attribution of personal meaning and relevance associated with self-related information. Therefore, self-referential processing includes a certain degree of personal knowledge involving episodic memory (e.g., specific autobiographical events), semantic memory knowledge (e.g., facts about oneself), the first-person perspective of the self (Gillihan & Farah, 2005), as well as top-down attentional control (Humphreys & Sui, 2016).

It should be noted that the results presented here provide evidence of a high degree of consistency involving self-related effects in both explicit and implicit attentional contexts. Given that no statistical differences were found as a function of each block, it seems that the preferential processing of self-related information could emerge regardless of whether the task demands are implicit or explicit. This is in consonance with previous studies that have examined the relationship between targeted or explicit processing versus automatic or implicit processing related to self-face recognition (Geng et al., 2012; Sui et al., 2006). Accordingly, these findings on self-face recognition could reflect the activation of a core self-representation, which is probably operating as an integrative hub that increases coupling across different stages of self-related processing (i.e., perception, memory, attention, and decision-making), along with emotion and reward (Berkman et al., 2017; Sui & Humphreys, 2015).

3.6.3. On the time course of self-identity processing: source-level results

This study did not find any significant neural sources during the early time window (150–200 ms). The lack of significance reported here may suggest that early face detection and initial structural coding involved similar patterns of neural source power when comparing face identities. However, this result contrasts with prior studies showing the involvement of person-related information and face-sensitive brain areas for familiar face processing during this time window (Bobes et al., 2019; Olivares et al., 2013).

During middle latencies (250–300 ms), the data showed a different recruitment of neural sources depending on the degree of self-relevance during middle latencies. Specifically, a broad set of neural sources (ATL, aCC and dm/dlPFC) was involved for the contrast between self and friend faces, whereas a more restricted set of neural sources (TPJ and mPFC) was engaged for the comparison between self and unknown faces. Such distinct patterns of neural sources may reflect more cognitive processes when discriminating the self from friend faces than from unknown faces, as reflected by a greater activity from executive areas (dlPFC) and person knowledge retrieval (ATL). Further, this distributed network may underlie the N250 modulations observed in this study, which is consistent with the view that access to long-term memory takes place during this early time window (Olivares et al., 2015; Schweinberger & Neumann, 2016). Moreover, it could be argued that salient (dmPFC) and executive cortices (dlPFC) are intertwined with such semantic areas (ATL), engaging task-relevant processes (Menon, 2023; Sui & Gu, 2017). Interestingly, the mPFC and part of the aCC are thought to reflect mental states of the self and others (including thoughts, knowledge and feelings), that is, social cognition (Adolphs, 2009; Amodo & Frith, 2006; Frith & Frith, 2012).

On the other hand, both mPFC and TPJ, which are key nodes of the default mode network activity (Fox et al., 2005; Raichle, 2015; Yeshurun et al., 2021), seem to be more engaged when comparing self-related and non-self-related content. This result is in general agreement with the notion that larger self-related activity also engages larger DMN activity, thus reflecting internal orientation and self-referential processes (e.g., Davey et al., 2016; Knyazev et al., 2020). In addition, it has been suggested that the TPJ is more engaged when integrating information from different sensory inputs, thus generating a sense of ownership over one's body (Apps et al., 2012; Tsakiris, 2017).

Of relevance, this study observed that the mPFC is a key brain region when it comes to distinguishing self and other identities at later latencies, regardless of life stages (300–600 ms). This finding is in accordance with a wealth of neuroimaging studies (e.g., Apps et al., 2012; D'Argembeau et al., 2008, 2010; Levorsen et al., 2023; Murray et al., 2015) and neurocognitive models of the self (e.g., Sui & Gu, 2017; Qin et al., 2020). Moreover, evidence from neuropsychological data demonstrated that impairment of the mPFC (along with the insula) leads to the disruption of self-biased responses (Sui et al., 2015). Hence, the mPFC is crucial for accessing core self-representations. In this regard, Levorsen et al. (2023) have also observed that the mPFC is a key region for self-concept, that is, the knowledge that people hold about the kind of person they are (physical attributes, traits, preferences, values, or beliefs).

3.6.4. Self-identity and temporal perspective: ERP evidence

The LPC was the only component involved in the temporal perspective of the self. As far as self-continuity across time is concerned (Figure 3.5A), there was a larger self-specificity response for the current compared to the more distant past self, in line with previous works

(Apps et al., 2012; Butler et al., 2013; D'Argembeau et al., 2008). Interestingly, a similar response was also observed for the friend condition (Butler et al., 2013). The lack of significant differences between past selves (both adolescence and childhood) may be related to similar levels of attentional resources engaged during categorization and recognition, as suggested by previous research (Kotlewska & Nowicka, 2015). This could also be in line with the notion of the stability of identity, which is arranged after adolescence (McAdams, 2013). Remarkably, a novel finding of this study is that the LPC could reflect the difference between self-identity and other identities across all life stages in both blocks (as shown in Figure 3.5b). This distinctive pattern of the LPC may indicate the allocation of specific personal relevance for the self across life stages, differentiating the current self from past selves (both adolescence and childhood).

The personal relevance attributed to the processes reflected in the LPC may be related to deeper information for oneself compared to others in the memory system, as well as their interaction with the affective value of the stimuli. In that vein, previous research using linguistic material has observed that both self-relevant content and emotional information can interact during the LPC (Fields & Kuperberg, 2012, 2016). As for the memory system, there is also evidence that indicates that the LPC, from a distant temporal perspective of current self-representation, is more sensitive to semantic memory rather than episodic memory (Renoult et al., 2016; Tanguay et al., 2018). Accordingly, it appears that personal knowledge is associated with either semantic or episodic memory, depending to some extent on time perspective, albeit further research should explore this notion more exhaustively. Of interest, this study has found a certain degree of self-continuity across time. Despite physical changes over time, self-awareness maintains a unique sense of self irrespective of life stages, thus preserving a coherent identity over time. This is what Northoff (2017) refers to as the sense of continuity of a person across time as the *diachronic identity* (which is similar to the *minimal self*, Gallagher, 2000). Therefore, the results reported here support the view of self-continuity as the temporal core of personal identity (Northoff, 2017).

3.6.5. Self-identity and temporal perspective: source-level results

This study has observed a different pattern of neural sources when processing self-identity at different life stages. Particularly, both core and extended face regions seem to underlie the visual perception of self-continuity starting from 250 ms. As such, temporal (FG) and executive regions (dlPFC) seem to be engaged when comparing the current self and more-distant past self (childhood), while only temporal regions (ITG/MTG and FG) were observed for the current self and less-distant past self (adolescence). In this regard, Murray et al. (2015) observed the involvement of frontal (mPFC) and occipitotemporal regions (FG and other visual regions) when maintaining self-vs-other memory-matched perceptual representation from a socially oriented perspective. Notably, D'Argembeau et al. (2008, 2010) suggested that accessing autobiographical memory is supported by frontal and posterior regions, entailing face-related regions along with memory-related regions. These regions are known to be engaged in response to retrieving personal knowledge (Ramon & Gobbini, 2018; Visconti di Oleggio Castello et al., 2017, 2021). Consistent with this notion, this study found the involvement of visual-related regions (cuneus) for friend faces when comparing current and more-distant past faces and memory-related regions (posterior cingulate cortex) when comparing less-distant past and more-distant past faces. Previous research has also observed the activation of the posterior cingulate cortex in response to familiar visual stimuli, as they convey higher emotional content and person-related knowledge compared to unfamiliar stimuli (Anzelloti & Young, 2020; Gobbini & Haxby, 2007; Ramon & Gobbini, 2018). Critically, such patterns were not observed for unknown faces.

During later latencies (300–600 ms), a similar pattern of temporal (the posterior part of the MTG) and executive regions (dlPFC) was observed when contrasting self-faces in the current and more distant past. The involvement of the dlPFC during middle and later latencies may reflect a higher allocation of top-down modulations for maintaining an updated representation of self-identity (Sui & Rothstein, 2019). Furthermore, this study found an involvement of core face areas (FG) along with extended face-related regions (pHC, pCC and PC) when processing current self-faces compared to less-distant past faces. These findings suggest that both core and extended face-processing systems reflect the processing of self-identity across life stages. Additionally, these neural sources account for the pattern observed for the LPC on the temporal perspective of the self, as these posterior regions are crucial when accessing autobiographical memory of meaningful self-related content.

3.6.6. Limitations

One limitation of this study is related to the sample size, which might affect the statistical power. The process of collecting the participants, who were required to submit multiple high-quality images (their own faces and a close friend's face at different life stages, with neutral expressions and direct gaze), was not a simple task. Nevertheless, the statistical results were accompanied by the power score (partial eta squared) and 95% confidence intervals. A second limitation comes from the fact that the participants carried out a recognition task with the same facial stimuli in two blocks (identity and life stages recognition). Hence, it could be the case that identity processes (e.g., self-relevance) were implicitly taking place during the life stages block, whereas life stage processes (e.g., recognition of children's faces) implicitly occurred during the identity block. Yet, in this work, both blocks were examined together, and no particular interaction of the demands of each block was found. Although both explicit and implicit processes related to identity and life stages processes have not been dissociated in the results, it can be assumed that these effects are dissipated throughout the sample since the block presentation order was randomized.

Regarding source analysis, another limitation concerns collapsing the same stimulus presented twice (identity and life stages recognition tasks) in order to simplify statistical analysis and enhance the signal-to-noise ratio (beamforming techniques are more precise when including more data). Thus, both explicit and implicit processes presumably did not bias the source-level results, as they were collapsed.

3.6.7. Concluding remarks

This study provides new evidence on spatiotemporal neural dynamics underlying self-related processing and its continuity over time. The ERP analysis showed that the N250 reflects the earliest neural marker for self-preferential access over other identities, most likely due to the facilitation of attentional resources for the access of one's face from long-term memory. Subsequently, the P3 was the robust index of self-representation, and it might reflect the categorization of the stimulus (self-awareness) and emotional saliency processing. The LPC probably reflects a step further in self-referential processing, thus expanding the personal significance associated with the self. Remarkably, the LPC was the only component that reflected the temporal perspective of the self, distinguishing the self-identity and its continuity across time, besides discriminating the self-identity from other identities across all life stages. These findings would suggest that the processes reflected by the LPC play a crucial role, presumably engaging larger self-relevant information. These data were complemented by the observation of core and extended face-processing regions underlying self-identity processing during different latencies, as revealed by the ERP source analysis. Notably, the sense of self-continuity seems to be supported by a set of distributed brain regions, presumably related to the executive (dlPFC), memory (pCC, paraHC and MTG) and perceptual processes (FG).

CHAPTER 4.
ON THE INTERPLAY BETWEEN SELF-REFERENCE AND LANGUAGE PROCESSING: NEUROPSYCHOLOGY EVIDENCE

Chapter 4. On the interplay between self-reference and language processing: neurophysiological evidence

Highlights:

- This chapter investigates whether syntactic speech processing can be affected by self-related information conveyed by facial identity under masked conditions.
- Face-related components showed a self-specific response, as reflected by the N250 component.
- Language-related components showed the largest LAN effect followed by a reduced P600 effect was observed for self-faces, while a larger LAN with no reduction of the P600 was found for friend faces compared to unknown faces.
- These ERP results indicated that self-related content is rapidly decoded from masked facial stimuli and may impact cognitive processing during early syntactic processes.
- Source reconstruction from alpha-band activity indicated that the left IFG is more engaged by self-faces during early syntactic computations, probably reflecting increased semantic demands.
- The findings presented here support an interactive view between self-reference and language processes, both at early and later stages of processing.

This chapter is based on the following manuscript:

- Rubianes, M., Drijvers, L., Muñoz, F., Jiménez-Ortega, L., Almeida-Rivera, T., Sánchez-García, J., Fondevila, S., Casado, P., & Martín-Loeches, M. (2024). The self-reference effect can modulate language syntactic processing even without explicit awareness: An EEG study. *Journal of Cognitive Neuroscience*, 1-15.

4.1. Introduction

Current research suggests that self-related stimuli can rapidly capture our attention, as demonstrated by the self-reference effect. In this regard, an increasing body of evidence is showing how self-related information is prioritized during different stages of processing, thus biasing different cognitive processes, such as perception (Sui et al., 2015), memory (Tanguay et al., 2018), attention (Macrae et al., 2018) or decision-making (Sui et al., 2023). However, whether this self-bias may be extended to language processing remains scarcely treated in the literature. To this end, this study investigated the possible interaction between self-reference and language processing. This chapter begins by reviewing ERP research on psycholinguistics with a focus on the processing of (extra-)linguistic variables. Subsequently, the motivation and design of the study are outlined.

4.1.1. Extralinguistic processes affecting language comprehension

Language processing requires the integration of different subprocesses to effectively comprehend utterances, including acoustic-phonological, syntactic, and semantic processes (Jackendoff & Audring, 2020). An outstanding question in psycholinguistic research is how and when the language processing system integrates different sources of extralinguistic and linguistic information (Hagoort, 2017; Münster & Knoeferle, 2018). As for the temporal course of language processing, three ERP components have been primarily studied in the extant literature: left anterior negativity (LAN), N400, and P600.

These components are typically obtained when comparing incorrect, violating or unexpected material (i.e., words) with the correct one. When an incorrectness is found, the brain circuits underlying the type of process that has been violated (e.g., syntactic, semantic) are presumably boosted, yielding visible electrical fluctuations (ERP components). Electrophysiological responses to correct material are then used as control and subtracted in order to isolate these specific language-related fluctuations (e.g., Urbach & Kutas, 2018). In this regard, sentences with syntactic anomalies (e.g., gender or number violations), compared to syntactically correct sentences, typically elicit a LAN around 300–500 ms after the critical word onset (Maran et al., 2022). The LAN component is thought to reflect the early detection of a morphosyntactic mismatch, and its amplitude is usually linked to the difficulty of morphosyntactic integration based on the agreement relations for structure-building

(Friederici, 2017) or verbal working memory operations (Kolk et al., 2003; Martín-Loeches et al., 2005). The LAN is probably originated in the left inferior frontal gyrus (IFG; Brodmann Area [BA] 44) and the posterior superior/middle temporal gyrus (STG/MTG) (Friederici et al., 2000; Herrmann et al., 2009). It is thought that this brain network underlies syntactic processing (Friederici, 2017; Matchin & Hickok, 2020). In turn, the N400 component, which is a negative fluctuation peaking around 400 ms, is generally considered an index of semantic processing, as its amplitude is sensitive to a wide range of semantic manipulations in a given context (Kutas & Federmeier, 2011; for an alternative view on language-related components, see Bornkessel-Schlesewsky & Schlesewsky, 2019). The semantic processing brain network is supported by different subregions of the left IFG (BA 45/47), the angular gyrus (AG), the anterior temporal lobe (ATL), and the STG/MTG (Friederici, 2017; Hagoort, 2017). Subsequently, the P600, a positive component starting around 500 ms stimulus onset, is typically linked to a later stage of reanalysis/repair processes of the sentence structure by integrating different linguistic and non-linguistic inputs (Brouwer et al., 2017; Molinaro et al., 2011; for an alternative view, see Sassenhagen & Fiebach, 2019). It has been suggested that the P600 is probably originated in the superior temporal sulcus (STS) and the posterior part of the STG (Friederici, 2017).

Whereas increasing studies are showing how social and emotional cues afforded by the visual context are rapidly integrated into sentence-level semantic processing, as indicated by N400 effects for the speaker's facial information (Hernández-Gutiérrez et al., 2021; Maquate et al., 2022), it remains unclear whether first-pass syntactic processing may also be sensitive to such extralinguistic information. Of interest, the LAN and the P600 for (morpho)syntactic anomalies have been linked to social and emotional effects elicited by speaker’s identity (Xu et al., 2021), mood (Verhees et al., 2015), social presence (Hinchcliffe, 2020), or emotional words both masked (Jiménez-Ortega et al., 2017, 2021) and unmasked (Espuny et al., 2018; Martín-Loeches et al., 2012). These data support the view that semantic, syntactic, and contextual inputs interact with each other during the early stages of linguistic processing (e.g., McClelland et al., 1989; Pulvermüller et al., 2009). Notwithstanding, other studies have indicated that the LAN is unaffected by emotional content (e.g., Fraga et al., 2017; Padrón et al., 2020) or by other processes summoning attentional resources or increasing arousal (Hohlfeld et al., 2019), thus favoring the traditional view of *encapsulated* syntactic processing. As such, this traditional view regards syntax as a module blind to other cognitive processes (e.g., Ferreira & Clifton, 1986; Hauser et al., 2002).

Within this framework, it appears of interest to study whether the LAN component may be affected by the self-reference effect, especially considering the fact that some ERP fluctuations related to this effect (e.g., N250 component) overlap or even precede the linguistic component. On the interplay between language processing and self-related content, previous research has shown that self-relevant scenarios can modulate language processing while participants read two-sentence social vignettes that could contain different emotional valence (e.g., "A man knocks on *Sandra's/your* hotel room door. *She/You* see(s) that he has a *gift/tray/gun* in his hand"), regardless of syntactic or semantic violations (Fields & Kuperberg, 2012, 2016). For instance, Fields and Kuperberg (2016) reported an interaction between self-relevance and emotion. More specifically, they observed a larger late positive component (LPC) to emotional words versus neutral words in the self-relevant scenarios. This evidence suggests that self-reference and emotional processing may interact during written language processing.

In addition to ERP components, neural oscillations can provide valuable insights into the neural dynamics underlying a broad range of cognitive operations (Meyer, 2018). It is worth noting that alpha-band activity (8–13 Hz) has been proposed to be involved in neural information processing (Klimesch, 2018). Remarkably, it has been proposed that alpha modulations may reflect a primary inhibitory function, allocating cognitive resources to task-relevant brain regions while blocking off task-irrelevant regions (Jensen & Mazaheri, 2010). In line with this, Drijvers et al. (2018a, 2018b) observed that alpha activity was more suppressed over task-relevant brain regions (inferior frontal gyrus along with motor and visual cortices) when visual semantic information (i.e., iconic gestures) mismatched the speech, probably reflecting a larger engagement of these brain regions for the task. Notably, Alzueta et al. (2020) have found that alpha and beta power decreased when perceiving self-faces relative to familiar and unknown faces. Hence, it could be expected to observe a larger alpha suppression over task-relevant brain regions (i.e., extended language network) conveyed by self and personally familiar faces.

4.1.2. The present study

Although increasing studies are highlighting the role of social and emotional information on language comprehension, whether syntactic processes may be sensitive to self-related content remains unexplored, especially when it comes to the early stages of syntactic parsing (reflected by the LAN component). Hence, this study investigated whether syntactic processing –including morphosyntactic anomalies– can be affected by self-reference under masked conditions. The self-related stimuli were manipulated through face identity (i.e., self, friend and unknown faces). Facial identities were masked as personally familiar faces convey substantial social and emotional content and can draw attention to salient information even automatically (Ramon & Gobbini, 2018; Humphreys & Sui, 2015). This way, the unnaturalistic conscious perception of the proper face in a communicative context was avoided while testing the effects of these processes. This paradigm was adapted from previous work (Hernández-Gutiérrez et al., 2021; Jiménez-Ortega et al., 2021; Rubianes et al., 2021).

It is hypothesized that the LAN and P600 components would be modulated as a function of masked self-related information (self <> friend <> unknown faces). On this view, there appear to be two possibilities. In one, a larger LAN followed by a reduced P600 would reflect that early syntactic parsing is modulated by self and familiar faces. For instance, this biphasic pattern has been previously reported when emotion-laden words influenced morphosyntactic mismatches (e.g., Espuny et al., 2018; Jiménez-Ortega et al., 2017). A second possibility is that the LAN may be reduced or even vanish due to a capture of cognitive resources by self-related information. This result would also be compatible with prior evidence for social and emotional information (e.g., Hinchcliffe, 2020; Martín-Loeches et al., 2012). On the contrary, if syntactic processing is modular and encapsulated from other cognitive processes, it is not expected to find an effect on either the LAN or the P600 components by self-reference. As for alpha modulations, it is expected to find a larger alpha suppression driven by self and personally familiar faces over task-relevant brain regions, that is, language-related brain regions such as the inferior frontal gyrus or the temporal lobe (Hagoort, 2017; Matchin & Hickok, 2020).

Following the research questions outlined in Chapter 2, the design of this study also addresses the neural correlates of face identity processing when perceptual awareness levels are substantially reduced, irrespective of task demands. In this regard, increasing evidence is showing that the self-reference effect could be automatically elicited without explicit awareness and when displayed as a task-irrelevant distractor (Bola et al., 2021; Wójcik et al., 2018). Moreover, it is still debated to what extent personally familiar faces could also benefit from this prioritized processing or whether it is self-specific, as both self and familiar faces can activate pre-established representations in long-term memory (LTM). Therefore, consistent with previous studies on both subliminal and supraliminal face processing (e.g., Alzueta et al., 2019; Bola et al., 2021), it is expected that the N250 component, instead of the N170 component, would be larger for self-faces compared to other identities (e.g., Alzueta et al., 2019; Bola et al., 2021).

4.2. Methods

4.2.1. Participants

Thirty-six participants (twenty-four women and twelve men) with normal or corrected-to-normal vision and no history of neurological or cognitive impairments were included (mean age = 23.24 $\pm$ 4.78). According to the Edinburgh Handedness Inventory (Oldfield, 1971), all were right-handed (mean +88, range +72 to +100). The study was carried out in accordance with the Helsinki Declaration of the World Medical Association (1964) and was approved by the Ethics Committee of the Faculty of Psychology at the Complutense University of Madrid. Thirty-six participants were recorded so that all stimuli were counterbalanced: sentence structure (three), voice type (two), correctness (two), and face identity (three) (3 x 2 x 2 x 3 = 36). Besides, no participants were excluded from the sample.

4.2.2. Stimuli and procedure

The study consisted of a 3 x 2 design in which Face Identity (self, close friend, and unknown) and Correctness (correct and incorrect sentences) were manipulated.

The auditory linguistic material comprised two hundred forty Spanish sentences validated from previous works (Hernández-Gutiérrez et al., 2021, 2022). The set of sentences has three different structures according to the critical word (number or gender agreement, marked in bold): [Determiner]-[Noun]-[**Adjective**]-[Verb]-[Preposition]-[Noun] (n = 300); (ii) [Determiner]-[Noun]-[Verb]-[Determiner]-[**Noun**]-[Adjective] (n = 90); (iii) [Determiner]-[Noun]-[Verb]-[Preposition]-[Determiner]-[**Noun**]-[Preposition]-[Determiner]-[Noun] (n = 90). The length of critical words ranged from two to five syllables, and linguistic features such as word frequency, concreteness, imageability, familiarity, and emotional content were controlled across conditions. The sentences were spoken with neutral prosody by four different voices, two for each gender. Some examples of sentences presented in this study can be found in Table 5.1.

Structure 1 (*n* = 300)	Correct	1. a. El pañuelo$_{\text{Masc/Sing}}$ **bordado**$_{\textbf{Masc/}\text{Sing}}$ era de mi abuela.
[Det]-[N]-[**Adj**]-[V]-[Prep]-[N]		1. a. The **embroided**$_{\textbf{Masc/}\text{Sing}}$ cushion$_{\text{Masc/Sing}}$ belonged to my grandmother.
	Incorrect	1. b. El pañuelo$_{\text{Masc/Sing}}$ **bordada**$_{\textbf{Fem/}\text{/Sing}}$ era de mi abuela.
		1. b. The **embroided**$_{\textbf{Fem/}\text{Sing}}$ cushion$_{\text{Masc/Sing}}$ belonged to my grandmother.
Structure 2 (*n* = 45)	Correct	2. a. Los turistas habían fotografiado los$_{\text{Masc/Plur}}$ **glaciares**$_{\text{Masc/}\textbf{Plur}}$ árticos.
[Det]-[N]-[V]-[Determiner]-[**N**]-[Adj]		2. a. The tourists had photographed the$_{\text{Masc/Plur}}$ arctic **glaciers**$_{\text{Masc/}\textbf{Plur.}}$
	Incorrect	2. b. Los turistas habían fotografiado los$_{\text{Masc/Plur}}$ **glaciar**$_{\text{Masc/}\textbf{Sing}}$ árticos.
		2. b. The tourists had photographed the $_{\text{Masc/Plur}}$ arctic **glacier**$_{\text{Masc/}\textbf{Sing.}}$
Structure 3 (*n* = 45): [Det]-[N]-[V]-[Prep]-[Det]-[**N**]-[Prep]-[Det]-[N]	Correct	3. a. Las hojas son recogidas durante el$_{\text{Masc/Sing}}$ **otoño**$_{\text{Masc/}\textbf{Sing}}$ por los barrenderos.
		3. a. The leaves are picked by the sweepers during the$_{\text{Masc/Sing}}$ **autumn**$_{\text{Masc/}\textbf{Sing.}}$
	Incorrect	3. b. Las hojas son recogidas durante el$_{\text{Masc/Sing}}$ **otoños**$_{\text{Masc/}\textbf{Plur}}$ por los barrenderos.
		3. b. The leaves are picked by the sweepers during the$_{\text{Masc/Sing}}$ **autumns**$_{\text{Masc/}\textbf{Plur.}}$

Table 5.1 Examples of sentences presented in the study. Critical words are highlighted in bold. Note that the noun-adjective order in Spanish is reversed compared to English.

In addition to presenting spoken utterances, scrambled faces were displayed to the participants. The scrambled version was generated in Adobe Photoshop© using a 30 × 40 matrix. This stimulus keeps low-level facial features intact (pictorial encoding) without being able to identify the facial features (structural encoding). The facial stimulus corresponding to each identity was presented for 16 ms, masked by the scrambled face. Prior to the EEG experiment, participants were asked to provide a set of three different photographs corresponding to themselves and a close friend. These photographs showed a direct gaze along with a neutral emotional facial expression. The unknown condition was obtained from the photographs of the close friend provided by other participants. All participants stated at the conclusion of the experiment that they did not know the identity of the unknown person. The same procedure was used as in Chapter 3. In addition, all facial stimuli were normalized in several parameters (black background, grayscale, contrast, resolution, facial proportions, and luminance). Participants were presented with a total of two hundred forty sentences (half of them incorrect) along with nine masked faces (including three different photos for each identity). The number of trials for each experimental condition (3 face identity x 2 correctness = 6 conditions) was forty (240 sentences / 6 = 40 trials).

4.2.3. Procedure

As depicted in Figure 4.1, the scrambled stimulus appeared in the center of the screen at the beginning of each trial, and 500 ms later, the audio presentation began. The face identity was presented for 16 ms before the target word, and then the scrambled stimulus was shown again until the end of the sentence. Thereafter, the alternatives (correct or incorrect) were presented for 1500 ms. Participants were informed that they would hear sentences while viewing a visual stimulus at the center of the screen, and that they would have to judge the correctness of each sentence by selecting one of two buttons on a response box. Both the presentation of the alternatives (on each side of the screen) and the response hand were counterbalanced across participants.

After the EEG recording, participants completed a visibility task to test the visual awareness of the masked faces. This task is a subjective measure of visibility (Ramsøy & Overgaard, 2004), and it has been conducted in previous works using masked adjectives (Jiménez-Ortega et al., 2017, 2021). Hence, the visibility task performed in this study comprised 40 trials that were identical to the EEG trial procedure, but participants were instructed to respond if they observed anything beyond the visual (scrambled) stimulus by describing what they saw to the experimenter. According to the participants' declarations, none was aware of the face's identity. Only sixteen participants reported detecting the shape of a face, but they could not recognize its identity. In fact, all participants were amazed when they were told that their own facial stimuli and those of their friends had been presented during the EEG experiment.

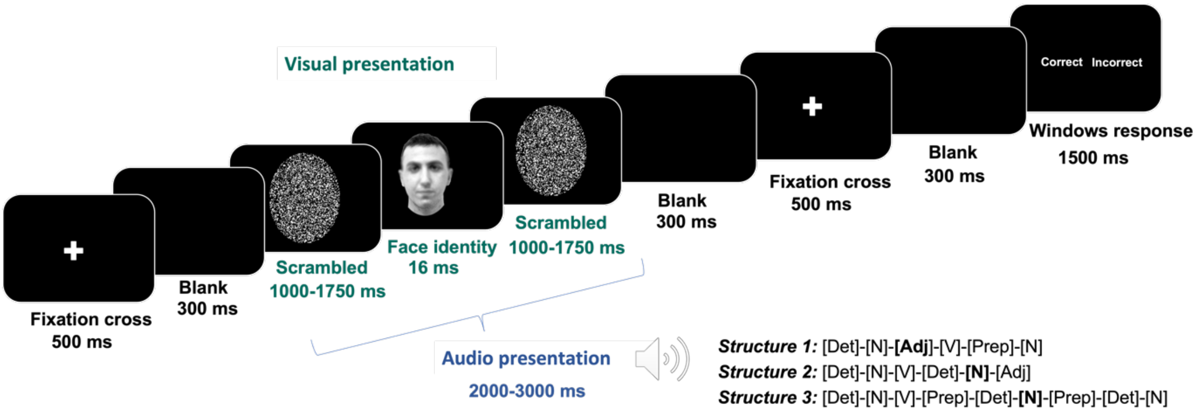

Figure 4.1 Schematic representation of the procedure. The face identity (self, friend, and unknown) was masked by the scrambled stimulus. Three different sentence structures were presented acoustically.

4.2.4. EEG recordings and analysis

Continuous EEG was recorded using 59 scalp electrodes (EasyCap; Brain Products, Gilching, Germany) in accordance with the international 10–20 system. EEG data were registered with a BrainAmp amplifier at a sampling rate of 250 Hz with a band-pass of 0.01 to 100 Hz. During the EEG recording, all scalp electrodes plus the left mastoid were referenced to the right mastoid, and subsequently re-referenced off-line to the average of the right and left mastoids. All electrode impedances were kept under five kΩ. The ground electrode was situated at Afz. Two vertical (VEOG) and two horizontal (HEOG) electrodes were used to record eye movements.

EEG data were preprocessed using the Brain Vision Analyzer® software (Brain Products). The raw data were filtered off-line with a band-pass of 0.1–30 Hz and then segmented into 1200 ms epochs, starting 216 ms before the onset of the critical word. Since the trigger was locked to the onset of the critical word, the baseline correction was moved to -16 ms, so that the effect of interest is time-locked to the face presentation. Thus, the baseline correction was applied from -216 to -16 ms. Both incorrect and omitted responses were excluded from the analyses. Typical artifacts were corrected through infomax independent component analysis (ICA; Bell & Sejnowski, 1995). Trials exceeding a threshold of 100 microvolts in any of the channels were semi-automatically rejected. For each condition, the mean and the standard deviation of segments were as follows: correct sentences for the self (29.89 $\pm$ 1.44), friend (31.75 $\pm$ 1.48), and unknown faces (30.11 $\pm$ 1.94), and incorrect sentences for the self (26 $\pm$ 1.94), friend (28.78 $\pm$ 1.84), and unknown faces (29.14 $\pm$ 2.06). Finally, separate averages were conducted for each condition for the ERP analysis.

For further analysis, including time-frequency and source analyses, the preprocessed EEG data were exported to Fieldtrip (Oostenveld et al., 2011), an open-source toolbox in Matlab (R2021b, MathWorks, Natick, MA, USA).

4.2.5. Time-frequency and source reconstruction

To calculate the oscillatory dynamics contained in the EEG signals, time-frequency representations (TFRs) of spectral power at frequencies between 2 and 30 Hz (steps of 1 Hz) were computed, albeit this study only focused on testing alfa-band activity (8–12 Hz). The time window was performed from -216 ms to 1200 ms (4 ms steps) using a Hanning window of 354 ms (Mitra & Pesaran, 1999). Subsequently, the average power spectrum across conditions and channels was calculated.

To reconstruct the neural sources of the effects observed in the TFR, a spatial beamforming filtering technique was conducted, namely, dynamic imaging of coherent sources (DICS; Gross et al., 2001). This algorithm uses a spatial filter from the cross-spectral density (CSD) matrix to estimate coherent brain regions for each condition. Similar to other beamforming techniques (such as LCMV for ERPs, as shown in Chapter 3), it provides the neural source power over time based on a common spatial filter that contains the covariance of all conditions to project the data through. The source power for each point or sample is thus computed based on a three-dimensional brain grid. This lead field matrix was generated by using an EEG head model template (Boundary Element Method, BEM) with a 5-mm-spaced grid. The coordinate system employed was that of the Montreal Neurological Institute (MNI).

According to the oscillatory activity observed in the alpha band, and with previous studies (e.g., Drijvers et a., 2018), the CSD matrix was calculated at 10 Hz using a time window from 0 to 1000 ms, in agreement with previous studies. The output of source-level statistics was interpolated onto a high-resolution anatomical MNI brain template (as shown in Figure 4.4). No significant effects emerged in other frequency bands.

4.2.6. Cluster-based permutation tests

To statistically test the effects observed in the data, non-parametric statistics and cluster-based permutation tests were performed (Maris & Oostenveld, 2007). As similarly described in Chapter 3, the significance probability is formed from the permutation distribution using the Monte-Carlo method and the cluster-based test statistic. Briefly, the permutation distribution was generated by randomly reassigning the values of each condition a given number of times (8000 times). If the *p*-value for each cluster was smaller than the critical alpha level (.05), the two experimental conditions were considered significantly different. This statistical test was used to examine the differences between experimental conditions in the design of the study: 3 Face Identity (self, friend, and unknown) x 2 Correctness (correct and incorrect).

The main effects for face-related components were computed by selecting *ad-hoc* time windows and including all channels. Based on the visual inspection and previous research (Alzueta et al., 2019; Miyakoshi et al., 2010; Rubianes et al., 2021), the time windows were defined as follows: 100–200 ms (N170 component), 200–300 ms (N250 component), and 300–450 ms (late positive complex). Furthermore, the data were re-referenced off-line to the average of all scalp channels to specifically analyze the N170 component, since the linked mastoids reference could have attenuated the amplitude of this component (Joyce & Rossion, 2005).

The interaction effects in language-related components were approached by calculating the difference between incorrect and correct sentences for each condition, and then each pair of conditions was contrasted (e.g., self [incorrect-correct] vs friend [incorrect-correct]). The critical alpha value was corrected due to multiple comparisons (.05/3 = .016). All channels and the whole-time window were included in this analysis. The magnitude of the effects observed in the data was estimated by using Cohen's d (Cohen, 1988). The mean difference was calculated from the average of all channels during the latencies reported by the cluster-based permutation tests. A report containing more details of all comparisons (maximum of the cluster-level statistics, effect size, and the mean difference) can be found in Table B1 in the Appendices section.

4.3. Results

4.3.1. Behavioral results

A repeated-measures ANOVA was conducted to test both the reaction times and response accuracy, including Face Identity and Correctness as factors. The accuracy was measured as the percentage of successfully detecting whether a sentence was syntactically correct or incorrect (see Table 5.2). The ANOVA showed a significant main effect for Correctness ($F_{(1,35)}$ = 29.172; p < .001; η_p^2 = .455), indicating that participants were more accurate for correct sentences compared to incorrect sentences (Δ= 5.185 ± 0.960 %; p < .001). Yet, the main effect of identity ($F_{(2,70)}$ = 1.139; p = .326; η_p^2 = .032) as well as the interaction effect between of Face Identity and Correctness ($F_{(2,70)}$ = .541; p < .585; η_p^2 = .015) were not significant. Similarly, the ANOVA for reaction times revealed a significant main effect of Correctness ($F_{(1,35)}$ = 15.301; *p* < .001; η_p^2 = .304), showing that participants responded faster to incorrect sentences than to correct ones (Δ = -0.025 ± 0.006 ms; *p* < .001). Again, there were no significant effects for the main effect of Face Identity nor the interaction between Face Identity and Correctness ($F_{(2,70)}$ = 3.201; *p* = .063; η_p^2 = .084; $F_{(2,70)}$ = .157; *p* = .855; η_p^2 = .004, respectively).

	Self (SD)		**Friend (SD)**		**Unknown (SD)**	
	Correct	**Incorrect**	**Correct**	**Incorrect**	**Correct**	**Incorrect**
Accuracy (%)	94.93 (7.01)	89.10 (10.18)	95.83 (4.43)	90.56 (9.51)	94.86 (6.73)	90.42 (8.81)
Reaction times (ms)	379 (18)	356 (15)	389 (19)	364 (17)	396 (21)	368 (17)

Table 5.2 Mean and standard deviation corresponding to the accuracy and reaction times of participants' responses.

4.3.2. Face-related components

Regarding the main effects of Face Identity, the cluster permutation tests showed no differences for the N170 component (as described in Table B1 in the Appendices section). By contrast, analysis for the N250 component indicated a significant difference for self-faces compared to friend (p = .008; Δ = -0.293 mV; d = .29) and to unknown faces (p = .038; Δ = -0.169 mV; d = .19), whereas the difference between friend and unknown faces did not reach statistical significance (p = .057; Δ = .156 mV; d = .18). As shown in Figure 4.2, these significant differences were more pronounced over parieto-occipital sites (approximately between 220 and 280 ms). The analysis for the P3 component revealed a significant difference for self-faces compared to unknown faces at frontal sites around 330–430 ms (p = .025; Δ = 0.225 mV; d = .20), while it was non-significant compared to friend-faces (p = .699; Δ = -0.088 mV; d = -.08). In addition, the comparison between friend and unknown faces did not reach statistical significance (p = .064; Δ = 0.156 mV; d = .18).

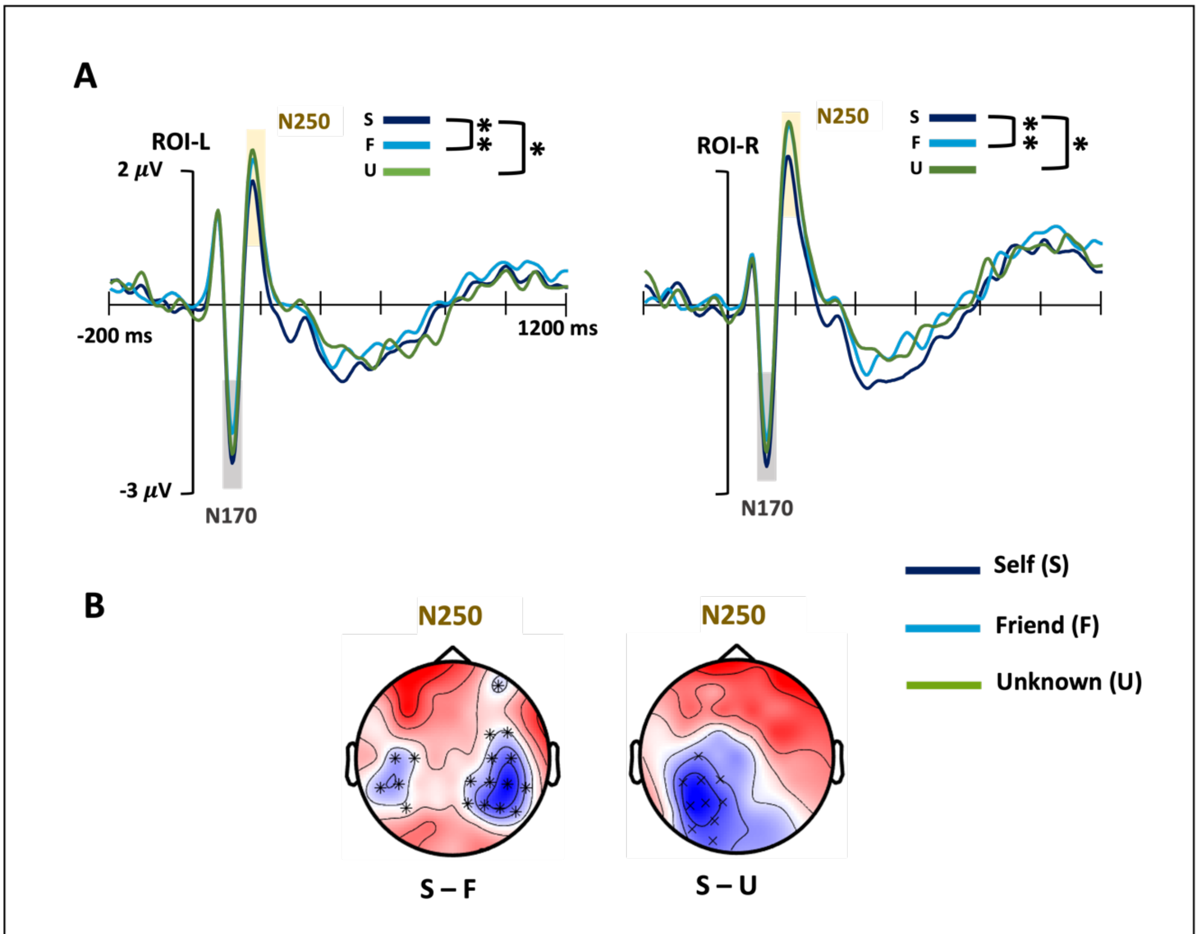

Figure 4.2 Grand average of the ERP waveforms corresponding to the main effects of Face Identity **(A)**. ROIs represent pooled electrodes falling into significant clusters. ROI-L pools PO7 and P7, whereas

ROI-R comprises PO8 and P8 electrodes. Significant cluster plots for each component, reflecting the channels that fall into the cluster **(B)**. Note that the blue color in the maps indicates a negative difference, while the red color represents a positive difference between conditions. Non-significant effects were found for the N170 component. Both correct and incorrect sentences are collapsed. Non-significant effects were found for the N170 component. * $p < .05$, ** $p < .01$.

4.3.3. Language-related components

The cluster permutation tests showed a significant effect between incorrect and correct sentences. These effects, in agreement with the topographic distribution displayed in Figure 4.3, were identified as the LAN component when the self ($p < .001$; $\Delta = -1.67$ mV; $d = -.86$), friend ($p < .001$; $\Delta = -.78$ mV; $d = -.33$), and unknown faces were presented ($p = .041$; $\Delta = -.487$ mV; $d = -.25$). This LAN effect displayed a long-lasting negativity for self-faces (240–1020 ms approximately) than for friend and unknown faces (around 210–790 ms and 540–600 ms, respectively). In addition, a P600 component was observed for the self ($p = .036$; $\Delta = 1.41$ mV; $d = .42$), friend ($p < .001$; $\Delta = 2.30$ mV; $d = .86$) and unknown faces ($p < .001$; $\Delta = 2.34$ mV; $d = .83$).

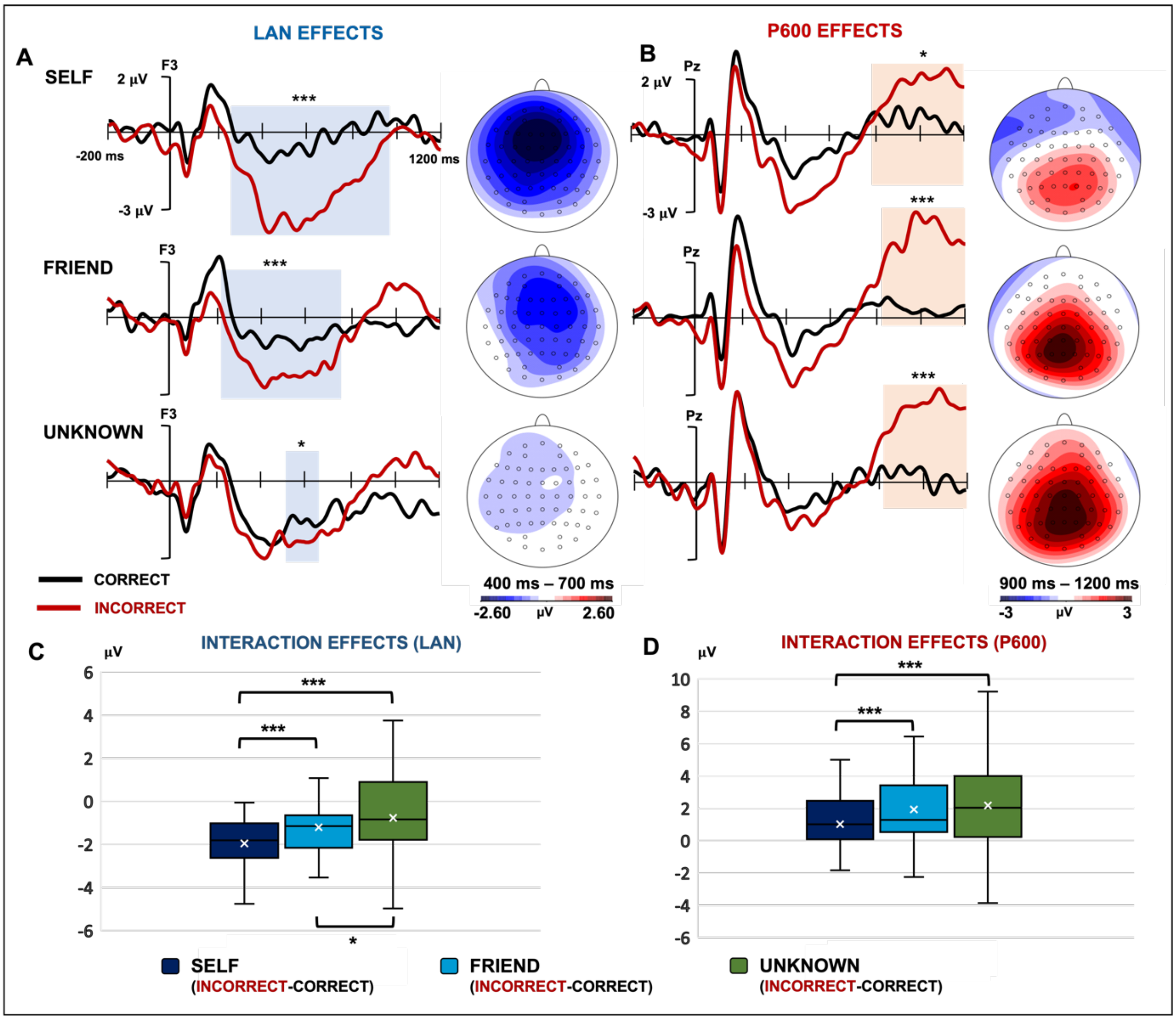

Figure 4.3 Grand average of LAN **(A)** and P600 **(B)** waveforms and their topographical distributions when comparing incorrect versus correct sentences for each face identity. Note that the ERPs were time-locked to the onset of the face and the critical word appeared 16 milliseconds later. ERP fluctuations to both correct and incorrect material are represented, the maps displaying the difference between these two conditions (incorrect minus correct, or Correctness effect). Box plots for the interaction effects between Face Identity and Correctness during the LAN **(C)** and P600 **(D)** time windows. * p < .05, ** p < .01, *** p < .001.

In order to test whether these LAN and P600 effects differed between facial identities, an additional analysis was performed using cluster-based permutation tests (p < .016 corrected for multiple comparisons). After subtracting the mean amplitudes between incorrect and correct sentences, the analyses indicated a significant difference for self-faces compared to the friend (p = .002; Δ = -1.35 mV; d = -.52) and unknown faces (p = .006; Δ = -1.84 mV; d = -.69), and between friend and unknown faces (p < .012; Δ = -.72 mV; d = -.31).

When testing for the P600 effects, the analyses revealed significant differences between friend and self faces (p = .003; Δ = 0.85 mV; d = .30) as well as between unknown and self faces (p < .001; Δ = 1.05 mV; d = .36), while no differences were observed between friend and unknown faces (p = .17; Δ = .30 mV; d = .11). Collectively, a larger and long-lasting LAN effect followed by a lower P600 effect was found for syntactically incorrect material after self-faces than after friend and unknown faces; whereas a larger LAN with no reduction of the P600 was found for friend faces, as compared to unknown faces.

4.3.4. Time-frequency and source reconstruction results

When testing alpha modulations, the cluster permutation tests showed a significant effect between incorrect and correct sentences only for self-faces at fronto-central sites (p < .001; Δ = -.99; d = -.41), while the contrasts for friend and unknown faces were non-significant (p = .605; Δ = -.18; d = -.06; p = .121; Δ = -.59; d = -.22, respectively). Similar to the interaction effects of both LAN and P600 components, after subtracting the power spectrum values for incorrect and correct sentences at the alpha band, the analyses indicated a significant difference between self-faces compared to friend (p < .001; Δ = -0.94; d = -.33) and to unknown faces (p = .01; Δ = -0.68; d = -.35).

To estimate the neural sources related to alpha band modulations, the whole time window and all scalp channels were included as input for the source analysis. The cluster permutation test at the source level revealed a significant difference only for the self-faces when comparing incorrect versus correct sentences (negative cluster: p = .046). After interpolating the output of this contrast into a structural MRI template (as shown in Figure 4.4), the highest peak was found in the left inferior frontal gyrus (IFG), particularly in BA 47 (p-value = .011). Hence, when participants had to judge the sentences in terms of syntactic correctness, a more significant alpha suppression was found over the left IFG only when the masked self-faces preceded the critical word.

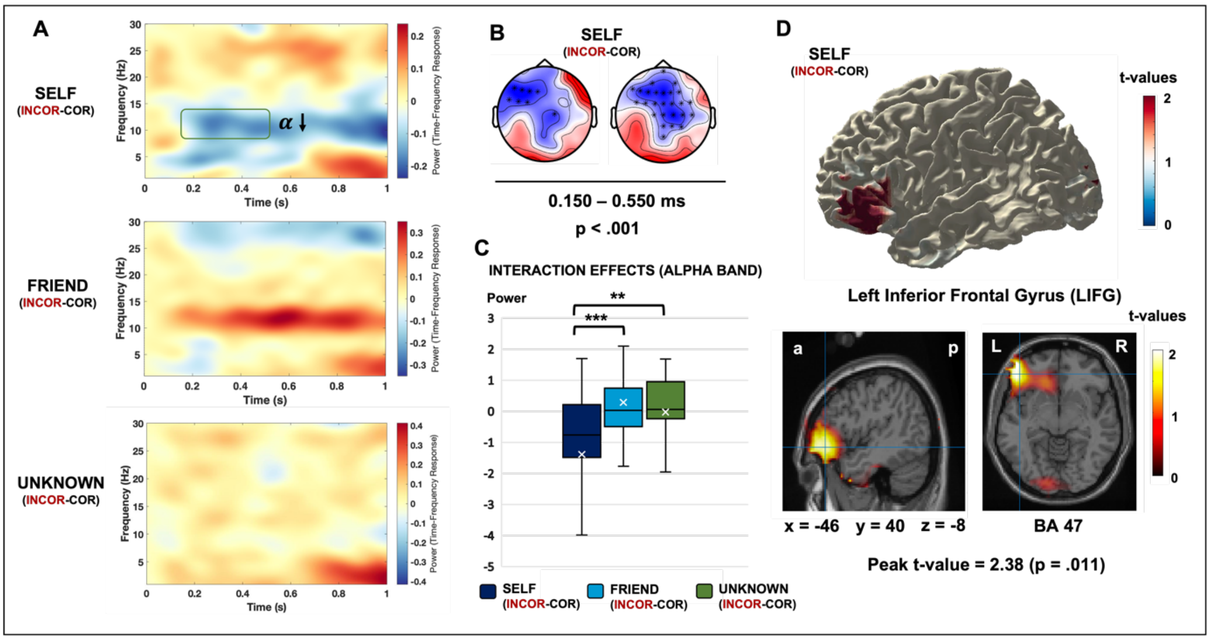

Figure 4.4 Grand average of time-frequency response (TFR) of spectral power over all scalp channels for the contrast between incorrect and correct for each face identity **(A)**. Cluster plots of alpha power (8–12 Hz) modulations when comparing incorrect and correct sentences when self-faces appeared before the target word **(B)**. Box plot for the interaction effects between Face Identity and Correctness **(C)**. Note that the values were extracted by computing the average over all scalp channels and time (150–550 ms) at 10 Hz. Source plots computed from the alpha power modulations **(D)**, masked by statistically significant clusters, for the contrast between incorrect and correct sentences when presenting self-faces (the contrasts for other identities were non-significant). The source plots are aligned following the Montreal Neurological Institute (MNI) coordinates. * $p < .05$, ** $p < .01$, *** $p < .001$.

4.4. Discussion

This study investigated whether syntactic speech processing can be affected by self-related stimuli under masked conditions and were task-irrelevant (i.e., without participants being aware of self-referential context). This study found a larger LAN followed by a reduced P600 effect only for self-faces, while a larger LAN with no reduction of the P600 was found for friend faces, as compared to unknown faces. Notably, the LAN effect exhibited the typically left-lateralized distribution for unknown faces, whereas it was frontocentral for self and friend faces. Moreover, a larger alpha suppression over the left Interior Frontal Gyrus (IFG) was found only for self-faces when contrasting with syntactic correctness. The possible mechanisms underlying this effect will be discussed below. Taken together, the data presented here suggest that syntactic processing, even at early stages, may be affected by self-related information without explicit awareness. These results provide further evidence for an interactive view of syntactic language processing, which contrasts with the traditional encapsulated view of syntax (Jiménez-Ortega et al., 2021; Lucchese et al., 2017; Münster & Knoeferle, 2018; Pulvermüller et al., 2009).

As far as face perception under reduced levels of visual awareness goes, the results of this study showed that the N170 component was insensitive to the facial identity, while the N250 component was the earliest neural marker discriminating self-faces from other identities, in accordance with previous studies using unmasked presentations (e.g., Miyakoshi et al., 2010; Rubianes et al., 2021). These findings provide evidence for the ongoing debate as to whether early face-related components may reflect self-prioritization over familiarity (Caharel & Rossion, 2021; Olivares et al., 2015; Schweinberger & Neumann, 2016). As such, these data suggest that self-face processing is driven by automatic prioritization mechanisms when accessing long-term memory representations after facial structural coding. Further, this pattern seems to be elicited even under reduced levels of awareness and regardless of task demands.

4.4.1. Behavioral findings

This study found no significant effects on participants' accuracy driven by face identity. A possible explanation could be that the self-reference effect on accuracy may be diminished when the self-related information is not explicitly presented. Previous research has reported better accuracy performance of self-related stimuli (Keyes & Dlugokencka, 2014; Macrae et al., 2018; Scheller & Sui, 2022), while other studies have failed to report this finding using implicit or masked paradigms (Bola et al., 2021; Geng et al., 2012; Yaoi et al. 2021). Regarding reaction times, the results of this study showed that participants responded faster to incorrect than to correct sentences. This finding is in line with prior language studies (e.g., Hernández-Gutiérrez et al., 2022; Hinchcliffe et al., 2020). However, no significant effects were found involving Face Identity as a factor. This result contrasts with previous studies on face recognition that observed shorter reaction times for self-faces (e.g., Geng et al., 2012). Notably, these differences can be due to the fact that the response window was adjusted after the end of the sentence in our study, meaning that participants had to wait to provide their response, thus reducing the differences between conditions.

4.4.2. Face perception under reduced levels of visual awareness

When it comes down to the neural correlates of self-related processing under reduced levels of awareness, the data of this study indicated that the N170 component was insensitive to facial identity, whereas the N250 component was the earliest neural marker discriminating self-faces from other identities. These results replicate prior research using unmasked presentations (e.g., Alzueta et al., 2019; Rubianes et al., 2021) and provide further evidence for the ongoing debate about whether early components related to face perception may reflect self-prioritization over familiarity (Caharel & Rossion, 2021; Olivares et al., 2015; Schweinberger & Neumann, 2016).

A growing body of evidence is showing that the self-reference effect could emerge automatically by capturing our attention under reduced levels of awareness (i.e., subliminally). When presenting subliminal self-faces as a task-irrelevant stimulus, previous studies using a dot-probe task found negative components over parieto-occipital regions related to self-face processing (200–300 milliseconds after stimulus onset), thus biasing attentional mechanisms during the early stages of processing (Bola et al., 2021; Wójcik et al., 2018). Collectively, the data presented here are also in line with the notion that self-related information can be prioritized at this stage without explicit perceptual awareness, relying on bottom-up mechanisms and activation of pre-established representation in LTM (Alzueta et al., 2020; Bola et al., 2021; Sui & Rothstein, 2019). Although considering the trend observed when comparing familiar and unknown faces during the N250 window ($p = .057$), further research is needed to elucidate to what extent personally familiar faces may also share such preferential access when the levels of perceptual awareness are limited.

4.4.3. On the interplay between self-reference and language syntactic processing

One of the main findings of this study is that syntactic computations can be modulated by self and familiar faces. This result is evinced by a larger LAN effect only for self and friend faces as compared to unknown faces, along with a fronto-central distribution of this typically left-sided component. Hence, the observed LAN modulations –in terms of amplitude, duration, and topographic distribution– could be explained by the interaction of linguistic processing with the cognitive mechanisms driven by self and familiar faces. Particularly, this pattern could reflect both initial morphosyntactic operations and the access in parallel to person-related information of self and familiar faces. Thus, an increased allocation of cognitive resources may occur during first-pass syntactic parsing in the presence of self-relevant information. This interpretation is consistent with long-lasting effects previously reported for self and familiar faces, involving more cognitive resources both when processed consciously and unconsciously (Fields & Kuperberg, 2016; Kotlewska & Nowicka, 2015; Rubianes et al., 2021; Wójcik et al., 2018). On the other hand, previous research has also observed a central distribution of the LAN component due to a higher load on language working memory processes (Coulson & Kutas, 2001; Kolk et al., 2003; Martín-Loeches et al., 2005; Tanner & Van Hell, 2014). This is also in accordance with an increase in attentional demands subsequent to self-relevant information. In addition, other studies have reported a centroparietal distribution of the LAN component as a result of shifting the processing strategy for solving morphosyntactic violations –toward a heuristic processing style instead of the algorithmic and rule-based strategy (Isen & Means, 1983)– triggered for instance, by the social presence (Hinchcliffe et al., 2020) or masked positively charged words (Jiménez-Ortega et al., 2017).

Remarkably, a larger LAN followed by a reduced P600 effect was observed only for self-faces. This biphasic pattern has been previously linked to good versus poor comprehenders (Coulson & Kutas, 2001), verbal working memory operations (Kolk et al., 2003; Martín-Loeches et al., 2005), or as a result of shifting the processing strategy to solve agreement anomalies (Hinchcliffe et al., 2020; Jiménez et al., 2021). Therefore, it could be possible that implicit self-relevant content elicited more cognitive resources during first-pass syntactic operations due to low-level attentional capture (i.e., bottom-up mechanisms), thereby reducing the processes reflected by the later P600. This interpretation is in line with similar biphasic patterns observed in previous studies when emotion-laden words precede morphosyntactic anomalies (Espuny et al., 2018; Jiménez-Ortega et al., 2021), suggesting that less reanalysis/repair processes may be necessary to successfully resolve the morphosyntactic mismatch (Hinchcliffe et al., 2020; van de Meerondonk et al., 2010). Thus, these results suggest that implicit self-referential information can be decoded from visual parameters, allocating more cognitive resources during first-pass parsing processes. Consistent with interactive models of language, the data presented here is compatible with the flexibility of early syntax processes and their interaction with semantic and contextual information

(Hagoort, 2017; Jiménez-Ortega et al., 2021; Münster & Knoeferle, 2018; Pulvermüller et al., 2009).

Interestingly, a larger alpha suppression was observed over the left IFG, presumably BA 47, only for self-faces when contrasting syntactically correct vs incorrect words, as early as around 150–550 ms. Different portions of the left IFG have been involved in several linguistic computations (Friederici, 2017; Hagoort, 2017; Matchin & Hickock, 2020). According to Hagoort (2017), BA 47 in the left IFG is involved in lexical access operations and in unifying the lexical building blocks obtained from memory in parallel with non-linguistic information, being BA 47 a key node within the semantic unification network. Following this framework, a possible interpretation of the results of alpha oscillations could be that semantic sentence processing was boosted by the presence of self-relevant information, only –or particularly– in response to a grammatical violation, this being straightforward evidence that semantic and syntactic domains interact early during sentence processing (in line with, e.g., Hagoort, 2017; Malaia & Newman, 2015; Pulvermüller et al., 2009). Overall, this study found both early semantic and syntactic boosting, specifically when one's own face and a morphosyntactic violation concur. This is evidence that the interplay between semantic and syntactic operations is clearly bidirectional, which is in line with several linguistic models (e.g., Jackendoff, 2007; Pulvermüller et al., 2009).

More broadly, it could be argued that this study deals with self-reference effects and not with effects related to an incongruence or mismatch in the simultaneous appearance of self-face and an unknown voice summoning attentional resources. The fact that the face of a good friend was also accompanied by the same unknown voice, but the effects were not as noticeable as for self-face implies that the main modulations observed are primarily the consequence of self-related content.

4.4.4. Limitations and concluding remarks

As for the limitations of this study, it should be mentioned that the face identity was presented 16 ms before the target word to test the modularity of syntactic processing. Thus, the mere presentation of face identity cannot be isolated due to the pseudo-simultaneous presentation of both stimuli (face and critical word) that could lead to a possible mixing between long-lasting face-related components (i.e., P3) and language-related components (i.e., LAN and P600). From a technical point of view, this question is settled for linguistic manipulation by comparing both correct and incorrect linguistic material under the same self-referential conditions. Indeed, the modulation of language-related ERP components by self-related information was the main purpose of the present study.

Another limitation of the study is related to the sample, as it was not equally balanced in terms of the number of women and men (twenty-four females, twelve males). Prior research has suggested that there might be sex differences in brain structure and function, probably reflecting differences in neural and cognitive processing (Cahill, 2006; Proverbio, 2023). For instance, it has been suggested that language is more left-lateralized in males while it is more bilaterally distributed in females (for a review, see Ullmann et al., 2007). However, current research in this regard remains scarce and inconclusive (Sato, 2020). It should also be noted that, to the best of the author's knowledge, no sex differences have been reported for either the LAN or the P600 components, even if these have been quite extensively studied.

An open question for future studies is to investigate the effects of self-reference in linguistic processing using an ecological approach (e.g., by manipulating the content of the language material along with the speaker's face). In addition, whether self-reference may facilitate or hamper language processing remains to be determined. This could be afforded, for instance, in a behavioral study without the limitations of the ERP procedures, that is, in which reaction times and accuracy are measured lime-locked to the occurrence of the linguistic anomaly. Finally, as the linguistic material was presented aurally and combined with the visual presentation of faces, functional connectivity analyses of visual and auditory brain regions (e.g., Keil & Senkowski, 2018) may be another source of potential interest for future studies.

To conclude, the results of this study demonstrate that identity-related information is rapidly decoded from facial cues under masked conditions (especially when it comes to self-identity), driven by automatic prioritization mechanisms. The data presented here indicate that the self-reference effect can be extended to core linguistic computations, as evidenced by the mobilization of cognitive resources during syntactic processing. Overall, this study provides further evidence for an interactive view of language processing in the human brain.

CHAPTER 5.
BEYOND EVENT-RELATED POTENTIALS: OSCILLATORY DYNAMICS AND NEURAL SIGNAL VARIABILITY UNDERLYING SELF-IDENTITY

Chapter 5. Beyond event-related potentials: oscillatory correlates and neural signal variability underlying self-identity

Highlights:

- This chapter investigates the oscillatory neural correlates and neural signal variability involved in self-referential visual processing.
- The study presented here showed that theta-band activity over posterior regions is specifically involved in visual self-recognition.
- Delta band modulations emerged in response to self-specific and familiar stimuli, probably indexing the retrieval of relevant information of oneself and close others.
- The possible mechanisms underlying these oscillatory responses are discussed.
- A lower entropy was observed for self-faces than for friend and unknown faces. In addition, a lower entropy was found for friend faces as compared to unknown faces.
- These findings revealed that self-related processing is characterized by more regular neural patterns over a wide range of temporal scales.
- The neural mechanisms underlying this pattern are discussed in light of similar characterization of the default mode network (DMN) activity.

5.1. Introduction

The representation of self is central to cognitive functioning. A large body of research has shown that self-related information is preferentially processed compared to non-self-related content, as proposed by different accounts (Cunningham & Turk, 2017; Qin et al., 2020; Sui & Rothstein, 2019). As such, this notion is supported primarily by evidence from different neuroimaging and behavioral measures. So far, most electrophysiological studies on self-related visual processing have focused on event-related potentials (ERPs), while other electrophysiological measures, such as time-frequency representations or brain signal entropy, remain largely unknown. Thus, this study aimed to explore this issue with the purpose of providing a deeper understanding of the neural underpinnings underlying self-referential processing. This chapter begins by reviewing electrophysiological research on visual self-recognition with a focus on neural oscillations. Thereafter, a broad view of brain signal entropy is outlined, followed by the aim and hypothesis of the study.

5.1.1. Neural oscillations

Electroencephalography (EEG) reflects a compound signal, comprising a superposition of many signals stemming from different sources, as introduced in *Chapter 1*. The resulting waveform can be decomposed into different frequency components with different amplitudes and phases (Buzsáki & Draguhn, 2004; Mitra & Pesaran, 1999). Both phase and amplitude (power spectra) can be characterized over time with respect to task events (e.g., event-related synchronization or event-related desynchronization). This approach can be performed by *time-frequency analysis* (for a recent review, see Keil et al., 2022). Current evidence suggests that there are at least two key principles regarding neural oscillations, which are: (i) different rhythms coexist and are often synchronized to each other or nested into each other (e.g., the amplitude of faster frequencies is modulated by the phase of slower frequencies); and (ii) they are most likely involved in the temporal coordination of information transfer across brain regions, as they are thought to reflect the timing of neural firing (Engel & Fries, 2010; Klimesch, 2018; Lakatos et al., 2005). From this view, neural oscillations are hierarchically organized in different frequency bands, ranging from infra-slow (0.01–0.1 Hz), slow (0.1–1 Hz), fast frequencies (1–100 Hz), to ultrafast frequencies (> 100 Hz) (Buzsáki &

Draguhn, 2003). This study will focus on the fast frequencies, particularly on the delta (1–4 Hz), theta (4–7 Hz), alpha (8–12 Hz), and beta (14–30 Hz) bands.

Thus far, just a few EEG studies have examined the neural oscillations involved in visual self-recognition (Alzueta et al., 2020; Haciahmet et al., 2023; Kotlewska et al., 2023; Miyakoshi et al., 2010; Sakihara et al., 2012). For instance, Miyakoshi et al. (2010) observed modulations of the theta and alpha phase synchrony over the right fusiform area when comparing self-faces with other identities (170–290 ms). They interpreted this result on the basis of a reduced functional demand for visual self-representation. Sakihara et al. (2012) reported increased power of theta, alpha and beta bands over occipitotemporal regions (from 0 to 200 ms after the onset of the facial stimulus). They suggested that this oscillatory pattern reflects the structural encoding of facial information, similar to the functional interpretation of the N170 component. In contrast with the study conducted by Miyakoshi et al. (2010), Sakihara et al. (2012) included personally familiar faces instead of famous faces. Although they both share visual familiarity, the episodic and semantic representations differ between them. Moreover, Sakihara et al. (2012) observed an increased delta power over parietal and left temporal regions in response to familiar faces (around 0–800 ms) in comparison with unfamiliar faces, probably related to the retrieving of person-related information. However, the sample size of this study was small (nine participants), which may affect the extent to which these results can be generalized.

More recently, Kotlewska et al. (2023) presented faces and names as stimuli: self, self from the past, friend, famous, and unknown. Their time-frequency results showed a smaller increase in theta-band activity over visual areas in response to self-faces compared to friend and unknown faces (from 100 to 300 ms after the stimulus onset), in line with Miyakoshi et al. (2010). This observation was interpreted in terms of facilitated visual processing during the sensory stages by means of a less effortful and more automatic processing of visual self-recognition. Interestingly, Kotlewska et al. (2023) also observed a significant burst of stimulus-related connectivity in the theta-band activity between midfrontal and occipitotemporal regions, a finding specific for self-faces (not self-names). This result suggests that theta phase coherence is involved in long-distance task-related connectivity. Thus, both power and phase in the theta-band activity seem to reflect event-related modulations for self-faces.

Alzueta et al. (2020) used a similar paradigm as in prior research (i.e., presenting the participant's own face, a friend's face and an unknown's face), but the facial stimuli included the person articulating speech sound (with the purpose of enhancing stimulus variability), besides the hair being covered. The results of this study showed a power suppression in the alpha/beta range over face-related brain regions for self-faces, as compared to other identities. More specifically, this larger alpha suppression (1200–1600 ms) was observed around the intersection between the posterior fusiform gyrus and the inferior/middle occipital gyri, this effect being more lateralized to the right hemisphere. Further, the beta rhythm (700–1300 ms) was distributed more bilaterally over the occipitotemporal cortex, engaging primary visual regions and face-related regions. These findings were interpreted on the basis of top-down attentional control mechanisms (Capilla et al., 2014; Spitzer & Haegens, 2017) by engaging task-relevant brain regions (e.g., face-related regions) for subsequent processing of personally relevant information (Alzueta et al., 2020; Engel & Fries, 2010; Jensen & Mazahari, 2010). Consistent with this view, the functional role of alpha modulations is often regarded as a primary inhibitory function, allocating cognitive resources to task-relevant brain regions while blocking off task-irrelevant regions (Jensen & Mazahari, 2010). Moreover, beta-band activity is thought to support the internally driven (re)activation of neuronal ensembles, which reflect currently task-relevant contents (Spitzer & Haegens, 2017).

Relatedly, Haciahmet et al. (2023) presented arbitrary geometric shapes previously associated with the self or to a stranger instead of facial stimuli. The purpose of this paradigm, which was introduced by Sui et al. (2012), is to avoid highly familiar concepts involved in one's own name or face by prior associations between different geometric shapes and identities. Haciahmet et al. (2023) observed an increase in delta/theta power (2–7 Hz) and a decrease in beta power (19–29 Hz) for self-associated stimulus processing (both emerging from 200 to 400 ms after stimulus onset). They interpreted such synchronization in the delta/theta bands as indicative of facilitated retrieval of self-relevant features. Moreover, they suggested that decreased beta suppression for the stimuli associated with the self might reflect more efficient sensorimotor processing of self-associated stimulus-response features.

5.1.2. Brain signal variability

The study of the neural dynamics of self-referential processing has been typically addressed using linear analyses (e.g., ERPs or TFRs). In this regard, spontaneous activity and signal variability are frequently regarded as noise (for a recent review, see Uddin, 2020). In turn, a growing body of evidence suggests that moment-to-moment signal variability, which can be found at every level of neural organization (Faisal et al., 2008; Shafiei et al., 2023; Yousefi & Keilholz, 2021), contains relevant information about the dynamics and complexity underlying neural and cognitive operations that can be empirically observed both in response to events and in resting-state activity (Baracchini et al., 2021; Grady et al. 2023; Kloosterman et al., 2020). In that vein, recent work suggests that local and large-scale intrinsic variability and connectivity are two key elements that characterize spontaneous brain activity both at the micro- and macro-scale (Baracchini et al., 2021; Shafiei et al., 2023).

As introduced in *Chapter 1*, one approach to quantifying such variability/complexity contained in a given physiological time series is by downsampling single-trial time series (from fine to coarse-grained timescales) and counting how often temporal patterns occur in the data at each timescale. This approach is conducted by multiscale entropy analysis (MSE, Costa et al., 2002) or its modified version (mMSE, Kosciessa et al., 2020). The rationale behind this analysis is that neural patterns that tend to repeat over time reflect lower entropy estimates, while non-repeating patterns (or more irregular signals) are assigned higher entropy estimates. Interestingly, prior research has found that the default-mode network (DMN) activity tends to display more regular patterns (i.e., less entropy) over a wide range of spatiotemporal scales (Deco et al., 2011; Uddin, 2020; Zanin et al., 2020).

Remarkably, no studies to date have examined the relationship between brain signal variability and self-referential processing. Considering that extant literature has suggested that DMN activity is primarily involved in self-related processing (e.g., Davey et al., 2016; Knyazev et al., 2020; Menon, 2023) and based on the observation that spontaneous brain activity is characterized by more regular (or non-random) neural patterns (e.g., Deco et al., 2011), it could be expected to observe a more regular neural patterns (that is, lower entropy) to self-referential processing due to the involvement of the DMN activity, as compared to non-self-referential processing.

5.1.3. The present study

The aim of this study is twofold: (i) to investigate the oscillatory neural activity involved in self-related processing using time-frequency representations; and (ii) to investigate the brain signal variability underlying self-related processing, as indexed by entropy estimates. The task of this study comprised an identity recognition task (as in *Chapter 3*). A noteworthy aspect of this study is that the facial stimuli were presented for three seconds to perform such EEG analysis. Based on the literature reviewed above, an increased delta/theta power and decreased alpha/beta power for self-faces were expected, compared to friend and unknown faces. Additionally, it was expected to observe a lower entropy for self-faces compared to other identities.

5.2. Methods

5.2.1. Participants

Thirty-two undergraduate and graduate students participated in this study ($Mean_{age}$ = 21.12; SD_{age} = 2.88). All participants were right-handed according to the Edinburgh Handedness Inventory (Oldfield, 1971) and declared normal or corrected-to-normal vision. No history of neurological or cognitive disorders was reported. The participants provided their informed consent prior to the EEG experiment. The study was carried out in line with the international protocol for human research (Declaration of Helsinki of the World Medical Association).

5.2.2. Design and stimuli

This study used a within-subjects design to assess identity-related manipulation (self, friend and unknown).

In order to collect and normalize the stimuli, each participant came to the lab accompanied by a friend before the EEG experiment, and a portrait photograph of them was taken as self and friend conditions, respectively. Each participant was photographed with three different facial expressions (happy, neutral and angry). By taking the photographs in the lab, all stimuli had the same luminance and distance. All stimuli were framed between 450 pixels in width and 600 pixels in height. All participants stated that they had been close or best friends for at least one year. The unknown condition was obtained from the pictures of a close friend of other participants of the same gender. At the end of the EEG experiment, all participants confirmed that they did not know the identity of the unknown person. Each facial stimulus was repeated thirty times. A total of 270 facial stimuli were presented. In addition, the stimuli order was randomized. With the purpose of focusing this study on facial identity effects, the different facial expressions were collapsed and not reported differentially here. The study presented here is part of an ongoing project, which addresses the interplay between facial identity and emotional expressions.

5.2.3. Procedure

Each trial started with a fixation cross of variable duration (750 ms, 1000 ms or 1250 ms, randomized), followed by a blank for 200 ms. The facial stimulus appeared for 3 seconds. After a blank for 200 ms, participants provided their responses by pressing one of three buttons with their index, middle, or ring fingers, respectively. The sequence of buttons was counterbalanced between the left and right hands. The response window was displayed for 1 second. Participants performed an identity recognition task; that is, they were asked to press a button to discriminate the face identity that they saw (self, friend or unknown). In addition, participants had to wait until the response window emerged to provide their responses. In this way, motor artifacts were reduced during the stimulus presentation.

5.2.4. EEG recordings and analysis

Continuous EEG was registered using 59 scalp electrodes (EasyCap; Brain Products, Gilching, Germany) in accordance with the international 10–20 system. EEG data were registered by BrainAmp DC amplifiers at a sampling rate of 250 Hz (band-pass from 0.01 to 100 Hz). All scalp electrodes plus the left mastoid were all referenced online to the right mastoid during the EEG experiment and then re-referenced off-line to the average of the right and left mastoids. The impedance of all electrodes was kept below 5 kΩ. The ground electrode was placed at AFz. Eye movements were recorded using two vertical (VEOG) and two horizontal (HEOG) electrodes placed above and below the left eye and on the outer canthus of both eyes, respectively.

The EEG was preprocessed using the software Brain Vision Analyzer (Brain Products). The raw data were filtered off-line with a band-pass of 0.1–40 Hz and subsequently segmented into 3000-ms epochs starting 200 ms before the onset of the facial stimulus. Baseline correction was applied from -200 to 0 ms. Both incorrect and omitted responses were excluded from the analyses. Common artifacts (eye movements or muscle activity) were corrected through infomax Independent Component Analysis (ICA, Bell & Sejnowski, 1995). Trials exceeding a threshold of 100 microvolts (μV) in any of the channels were semi-automatically rejected. For each condition, the mean and the standard deviation of segments were as follows: self (19.86 ± 4.06), friend (20.48 ± 4.46) and unknown faces (20.06 ± 4.80). Finally, separate averages were conducted for each condition and subject.

5.2.5. Time-frequency representations and entropy measures

The preprocessed EEG data were exported to Fieldtrip (Oostenveld et al., 2011), an open-source toolbox of Matlab (R2021b, MathWorks, Natick, MA, USA), for further analyses: time-frequency analysis, entropy analysis and cluster-based permutation tests.

Time-frequency representations of spectral power were computed over frequencies from 2–30 Hz (steps of 1 Hz). The time window selected was from -200 ms to 3000 ms (steps of 4 ms) with a Hanning window of 400 ms. The grand average of the power spectrum corresponding to each frequency band (delta [1–4 Hz], theta [4–7 Hz], alpha [8–12 Hz], and beta [14–30 Hz] was computed across each condition and participant.

Entropy estimates were calculated using a custom-written Matlab code based on the pipeline available on the Fieldtrip website[7]. The algorithm used was the modified version of multiscale entropy (mMSE; Kosciessa et al., 2020). The EEG data were coarsened by point skipping after low-pass filtering (for more details on the entropy signal procedure, see Kosciessa et al., 2020). Several parameters were the same as typically used in previous studies (e.g., Courtiol et al., 2016; Grundy et al., 2017; Kloosterman et al., 2020): similarity parameter (r = 0.5), pattern length (m = 2). The sliding window was fixed at 300 ms. The time window selected was from 0 to 3000 ms. With this time window, no trials emerged that could be too short to compute the sample entropy. The timescales ranged from 1 to 40. The grand average of sample entropy was then computed across each condition and participant.

5.2.6. Cluster-based permutation tests

Non-parametric statistics and cluster-based permutation tests were performed to statistically test the data obtained from the time-frequency and entropy analysis using functions

[7] For more details, see https://www.fieldtriptoolbox.org/example/entropy_analysis/

implemented in Fieldtrip (Maris & Oostenveld, 2007). In short, the significance probability is computed from the permutation distribution using the Monte-Carlo method and the cluster-based test statistic (whose *t*-values were larger than a certain threshold of .016, as the alpha was corrected by the number of comparisons). The permutation distribution was formed by randomly reassigning the values corresponding to each condition across all participants a number of times (8000 times). If the p-value for each cluster (calculated under the permutation distribution of the maximum cluster-level statistic) was smaller than the critical alpha level (.05), it was considered that the two experimental conditions were significantly different (i.e., self vs friend, self vs unknown and friend vs unknown).

5.3. Results

5.3.1. Time-frequency representations

Regarding time-frequency representations of power (Figure 5.1), the cluster-based permutation tests revealed a significant difference between self and friend faces across different frequency bands, that is, delta (positive clusters: $ps < .004$), theta (positive cluster: $p = .001$) alpha (negative cluster: $p = .031$) and beta (negative cluster: $ps < .045$) bands. These differences were more pronounced over posterior regions at different latencies. As far as the contrast between self and unknown faces is considered, the cluster-based permutation tests showed a significant difference in the delta (positive cluster: $p < .001$) and theta (positive cluster: $p < .001$) bands, while alpha (negative cluster: $p = .0507$) and beta bands (negative cluster: $p = .0508$) did not reach statistical significance. When comparing friend and unknown faces, the cluster-based permutation tests indicated a significant difference only in the delta band (positive cluster: $p = .007$). However, the theta (positive cluster: $p = .07$), alpha (negative cluster: $p = .32$), beta (negative cluster: $p = .45$) bands were non-significant.

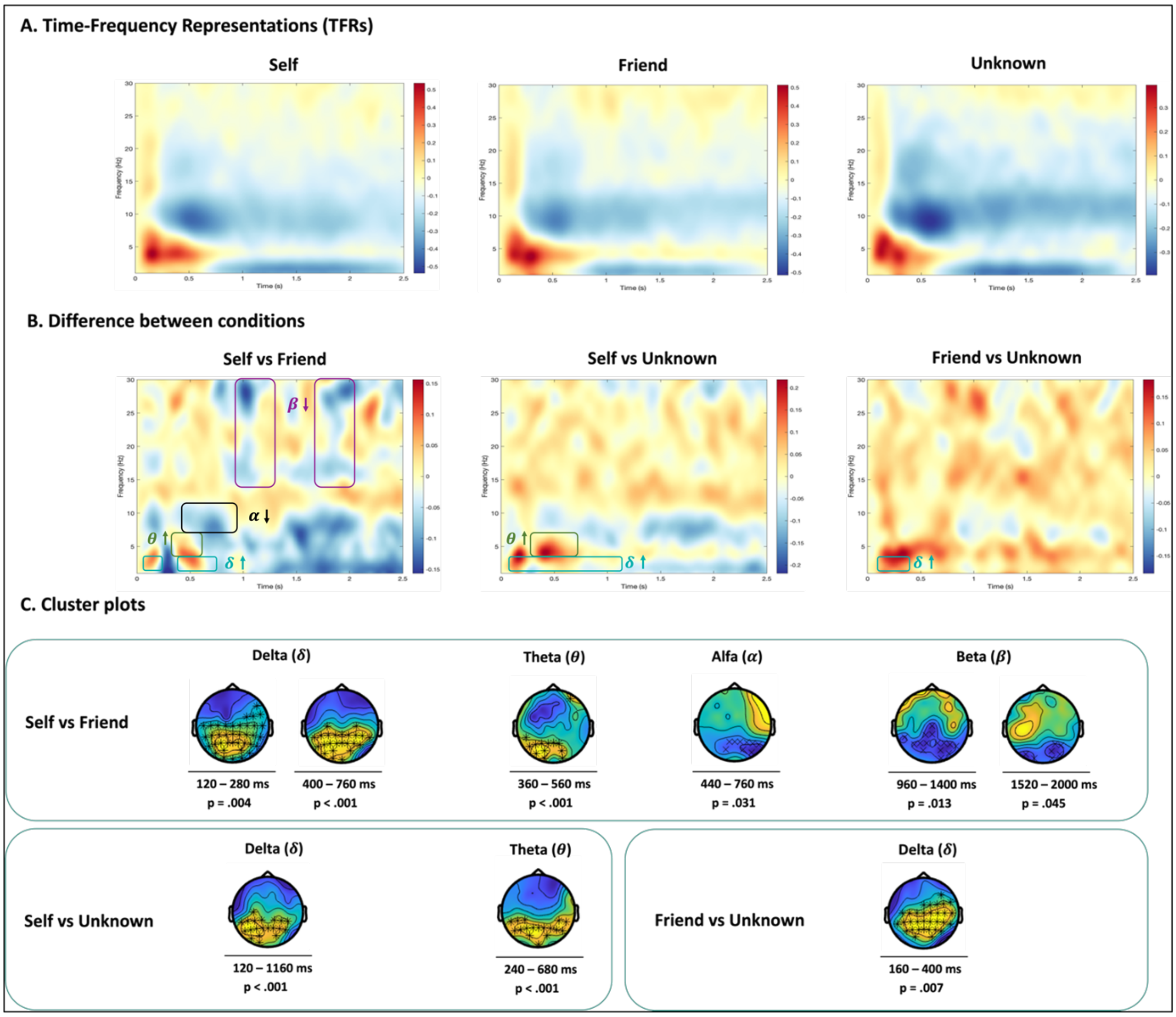

Figure 5.1 Time-frequency representations (TFRs) of power spectra corresponding to each identity **(A)**. Note that all channels were collapsed for visualization purposes. Pairwise comparisons of power spectra between identities **(B)**. Cluster plots for each comparison indicate the channels that fall into the significant cluster **(C)**.

5.3.2. Entropy estimates

As shown in Figure 5.2, the cluster-based permutation tests showed a significant difference between all comparisons, that is, self versus friend faces (negative cluster: $p < .004$), self versus unknown faces (negative cluster: $ps < .001$) and friend versus unknown faces (negative cluster: $p = .025$). Collectively, these results indicated a lower entropy for self-faces than for other identities, as well as for friend faces than for unknown faces.

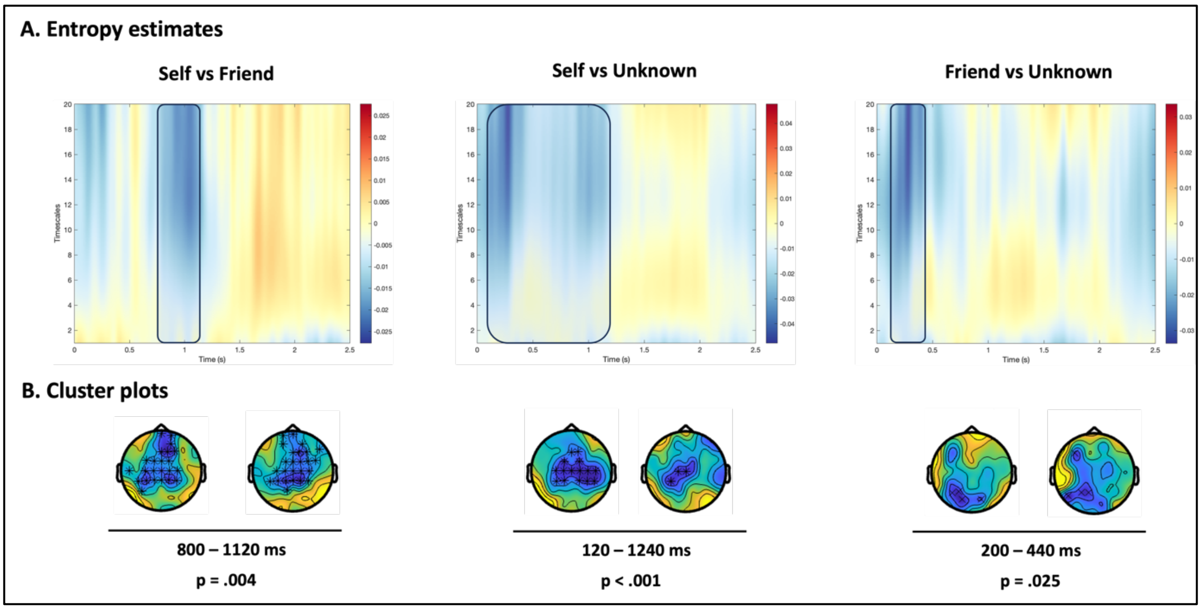

Figure 5.2 Pairwise comparisons of entropy estimates between identities **(A)**. Note that the shaded time window denotes the time window where the difference between conditions was significant. Cluster plots for each comparison indicating the channels that fall into the significant cluster **(B)**.

5.4. Discussion

This study investigated both oscillatory correlates and the signal variability involved in self-related processing. With respect to neural oscillations, the results of this study showed that theta-band activity is specifically involved in self-referential processing. Further, delta-band activity was more engaged when comparing face identities. A larger alpha/beta suppression was involved in self-faces as compared to friend faces. Taken together, these results provide further evidence for spectral signatures involved in visual self-recognition. The mechanisms underlying these effects will be discussed below.

Concerning neural variability, the results of this study indicated a lower entropy for self-faces as compared to friend and unknown faces. This finding suggests that self-related processing is characterized by non-random neural patterns over a wide range of temporal scales. This evidence is consistent with the DMN activity, which also tends to display more regular neural patterns (Davey et al., 2016; Deco et al., 2011; Uddin, 2020). Interestingly, personally familiar faces also seem to exhibit more regular neural patterns compared to unfamiliar faces. By contrast, more irregular neural patterns emerged in response to non-self-referential information. Collectively, the data presented here constitute novel evidence of the neural variability involved in self-referential processing, which resembles the DMN activity for "self-focused" mental processes (Menon, 2023).

5.4.1. Oscillatory neural activity involved in self-referential processing

One of the main findings of this study is the observation of theta-band increase over posterior regions specifically involved in self-referential processing. This finding is in general agreement with previous observations of theta-band modulations over visual regions only in response to visual self-recognition (Kotlewska et al., 2023; Miyakoshi et al., 2010). Interestingly, the fusiform gyrus has been shown to be primarily involved in this pattern of theta-band activity for self-faces (Kotlewska et al., 2023; Miyakoshi et al., 2010). These results support the view that theta-band modulations over posterior regions may reflect the visual processing of self-faces, this being stimulus-specific.

It is important to note, however, that these studies observed an increase in theta power around 100–300 ms, which was smaller for self-faces compared to other identities (Miyakoshi et al., 2010; Kotlewska et al., 2023). This pattern is consistent with the effects of early face-related components (i.e., N250) for visual self-recognition (Miyakoshi et al., 2010), presumably due to bottom-up mechanisms (Sui & Rothstein, 2019). Kotlewska et al. (2023) interpreted this pattern as a result of facilitated visual processing at the sensory stages by means of a less effortful and more automatic processing of visual self-recognition. In turn, the data observed here indicated an increase in the theta power around 240–680 ms, which was larger for self-faces compared to other identities, resembling a larger long-lasting positivity (e.g., P3) in response to self-referential visual processing (e.g., Rubianes et al., 2021). It is well established in the literature that the P3 component is a robust index of self-referential visual processing (e.g., Knyazev, 2013), reflecting an increased allocation of visual attention and more elaborate processing, due to a deeper attribution of relevant information associated with the self (e.g., Xu et al., 2017) and the involvement of top-down mechanisms (Sui & Rothstein, 2019). Thus, the data presented here suggest that theta-band activity might reflect the face-specific visual self-representation both at early and later stages.

Additionally, the results of this study showed that delta band activity is involved in processing both self-specific and familiar stimuli. These oscillatory correlates were more pronounced over posterior regions as well, but the effects lasted longer only for self and familiar faces, ranging from approximately 120 to 1160 ms. Sakihara et al. (2012) found a similar pattern in the delta-band activity over posterior regions for self-faces (from 200 to 800 ms). They interpreted this result on the basis of semantic encoding associated with memory retrieval. Similarly, Haciahmet et al. (2023) suggested that the retrieval of self-relevant features is supported by delta/theta activity (2–7 Hz). From this perspective, it could also be suggested that delta and theta frequency bands might also reflect the activation of different aspects of person-related knowledge from long-term memory, including semantic, episodic or biographic memory. This interpretation is consistent with prior findings from intracerebral recordings indicating that the theta-frequency band is also associated with memory function along with spatial behavior (Buzsáki et al., 2022; Etter et al., 2023; Nuñez & Buño, 2021).

Furthermore, it should be noted that these delta-band modulations over posterior regions have also been observed in response to facial expressions (Knyazev, 2012; Güntekin & Başar, 2014, 2016). In this regard, it has been suggested that delta-band activity is also related to arousal (Güntekin & Başar, 2014, 2016), as highly arousing pictures consistently showed higher delta responses as compared to less arousing pictures (e.g., Balconi et al., 2009; Klados et al., 2009). Therefore, an open question for future studies is to disentangle the exact relationship between the oscillatory neural correlates and the different subprocesses of face processing (Bernstein & Yovel, 2015; Haxby & Gobbini, 2007; Schweinberger & Neumann, 2016). Moreover, the neural generators (or other functional connectivity analyses) underlying the delta frequency band during face processing remain scarcely afforded in the literature.

On the other hand, this study only observed alpha- and beta-band modulations for the comparison between self and friend faces, whereas the contrast between self and unknown faces did not reach statistical significance (alpha-band: $p = .0507$; beta-band: $p = 0.508$). This result is partially consistent with the data reported by Alzueta et al. (2020), in which they observed a decrease in alpha/beta power specifically for self-faces over face-related regions, probably related to a top-down attentional control mechanism. Conversely, this study failed to replicate these findings, as a weaker suppression of alpha/beta power was observed for the contrast between self and unknown faces. Hence, further research is needed to elucidate to what extent alpha- and beta-band modulations are specific to self-referential visual processing, as prior research did not focus on alpha/beta bands and reported changes in power spectra within a much shorter temporal window (between –200 to 800 ms) (Miyakoshi et al., 2010; Haciahmet et al., 2023; Kotlewska et al., 2023).

5.4.2. Neural variability underlying self-referential processing

The results of this study indicated a lower entropy signal for self-faces as compared to friend and unknown faces. This finding suggests that self-related processing is characterized by more regular neural patterns over a wide range of temporal scales. To the best of the authors' knowledge, this has not been presented in the previous literature. Interestingly, the results presented here could be associated with a larger involvement of the DMN when processing self-related information (Davey et al., 2016; Knyazev, 2020; Yankouskaya & Sui, 2022). The DMN tends to display more regular neural patterns (Davey et al., 2016; Deco et al., 2011; Uddin, 2020). As such, the brain's spontaneous activity would not be reflecting just random activity; instead, this intrinsic activity pattern seems highly structured within characteristic spatiotemporal patterns. This can be illustrated by the so-called *resting-state networks* (RSNs), reflecting the intrinsic (i.e., non-stimuli- or task-evoked brain activity) anatomical connectivity across brain regions and their corresponding network dynamics (Deco et al., 2011; Greicius et al., 2003; Fox et al., 2005; Raichle, 2015). More recently, it has been argued that DMN activity plays a key role when it comes to the integration of both extrinsic (e.g., sensory inputs) and intrinsic (e.g., prior knowledge) information over time (Yeshurun et al., 2021).

Consistent with this perspective, a growing body of evidence indicates that the DMN is primarily involved in self-referential processing (Knyazev et al., 2020; Menon, 2023; Qin et al., 2020; Yankouskaya & Sui, 2022). For instance, Davey et al. (2016) compared self-referential and resting-state conditions using functional magnetic resonance imaging (fMRI) and identified overlapping activation in the medial prefrontal cortex (mPFC), posterior cingulate cortex (pCC), and left inferior parietal lobule (IPL). These brain regions, which are part of the core-self network (Sui & Gu, 2017) and key DMN nodes (Buckner & DiNicola, 2019; Raichle, 2015), are commonly engaged during rest and self-referential processing but also increased when thinking explicitly about the self (Davey et al., 2016; Harrison et al., 2008; Knyazev et al., 2020; Qin et al., 2016). In light of this evidence, it might be hypothesized that the neural signal characterization for self-referential processing observed here could be related to a larger engagement of the DMN than non-self-referential processing. This view is in line with recent accounts suggesting, in general terms, that the core self-referential processes are subserved by the DMN (Menon, 2023; Yeshurun et al., 2021).

Relatedly, this study observed a lower entropy for friend faces than for unknown faces. This result may indicate that neural signal variability follows a more regular pattern as a function of self-relevant information (self > friend > unknown) (e.g., Xu et al., 2017). Consistent with this, a meta-analysis performed by Qin et al. (2020) showed that there is an extensive overlap of DMN regions between self and familiarity (including the mPFC, pCC and IPL), which suggests that self-processing shares some similarities with familiarity-processing such as retrieval of semantic and personally relevant information, among others. Hence, it is likely that the neural signal variability in the presence of self-relevant content follows more regular patterns (or less random), which resemble resting-state characterizations of the DMN for "self-focused" mental processes (e.g., Davey et al., 2016; Deco et al., 2011). On the contrary, the neural signal variability seems more irregular when processing other-related content, presumably due to a decrease in the DMN along with an increase in the executive network (Sui & Gu, 2017). Nevertheless, further research is needed to determine the exact role of the DMN in neural signal variability during self-referential processing.

5.4.3. Limitations and Concluding Remarks

The main limitation of this study concerns the facial stimuli. As part of an ongoing project, the photographs corresponding to each identity were taken with different emotional expressions (happy, neutral and angry). Even though these facial expressions were collapsed for the different analyses, it is possible that emotion-related processes took place implicitly during the identity recognition task since emotional faces doubled neutral stimuli. Nevertheless, the main objective of this thesis can be addressed by the design presented here, in which different facial identities, equated in emotional features, are the main comparisons.

In conclusion, most EEG studies have focused on the neural dynamics of self-identity using ERPs. Thus, this chapter provides further evidence of the spectral signatures and signal entropy underlying self-referential visual processing. On the one hand, the data presented here indicated that theta-band activity is specifically involved in visual self-recognition. Relatedly, an increase in delta-band power was found in response to self-specific and familiar stimuli, most likely indexing the retrieval of person-related knowledge. On the other hand, these results are complemented by the observation of a lower entropy over a wide range of temporal scales for self-faces than for other identities. This finding suggests that the neural signal variability during self-referential processing is highly structured into characteristic spatiotemporal patterns, which is consistent with the notion of prioritization processing of self-related information. Collectively, this chapter provides novel insights into the sense of self in the human brain.

CHAPTER 6.
GENERAL DISCUSSION AND CONCLUSIONS

Chapter 6. General discussion and Conclusions

This chapter begins by reviewing the key findings of this thesis in line with the objectives outlined in Chapter 2. Subsequently, the implications of these findings are discussed. Limitations and further directions are also outlined. Finally, some concluding remarks are drawn.

6.1. Spatiotemporal neural patterns underlying self-identity

The study of the self has been of great interest since the beginning of modern psychology (James, 1890). With the advent of advanced neuroimaging techniques, research on the neural correlates of the self has increased considerably over the past few years. In this vein, a growing body of studies indicates that self-related stimuli are powerful cues for attention and decision-making, prompting the allocation of more cognitive resources than to non-self-related information (Cunningham & Turk, 2017; Estudillo, 2017; Sui & Rothstein, 2019). This evidence stresses the role of self-referential processing in cognitive functioning, which is of great relevance in both healthy and clinical populations (Benau et al., 2019; Feldborg et al., 2021; Scheller & Sui, 2022). However, how the sense of self is reflected in neural dynamics has yet to be determined in the literature. This thesis aims to provide a deeper understanding of the spatiotemporal neural dynamics underlying self-identity by investigating how visual self-recognition unfolds over time. To this end, participants were presented with facial stimuli corresponding to different facial identities (self, friend and unknown faces) while their electroencephalographic (EEG) activity was recorded. A wide range of analyses were conducted from the EEG signals with the purpose of providing a more precise picture of the neural dynamics involved in self-identity, namely event-related potentials (ERPs), time-frequency representations (TFRs), neural source reconstruction, and modified multiscale entropy (mMSE). The main advantage of these techniques is their fine-grained temporal resolution, which may shed light on the different subprocesses involved.

The main findings obtained in this regard are depicted in Figure 6.1. These results demonstrate spatiotemporal neural correlates that are specific to self-identity. Evidence from ERPs indicates that self-referential visual processing is reflected by middle (N250) and late (P3 and Late Positive Complex, LPC) components. As shown in Chapter 3, the N250 component was the earliest neural marker discriminating the self from other identities and may be related to a preferential access in long-term memory (LTM) regardless of task demands (Olivares et al., 2015; Schweinberger & Neumann, 2016; Tanaka et al., 2006). Conversely, the N170 component was insensitive to self-identity, which is in line with the notion that this component reflects the structural encoding of face configuration (e.g., Eimer, 2011; Schweinberger & Neumann, 2016). Interestingly, these ERP patterns were replicated in Chapter 4 by using a masked or subliminal paradigm. Taken together, this evidence indicates that self-referential visual processing can be reflected by the N250 component (picking around 250–300 ms over parietooccipital channels), irrespective of visual levels of awareness. In line with prior research, it might be suggested that visual self-recognition can be prioritized, relying on bottom-up mechanisms and activation of pre-established representation in LTM (Alzueta et al., 2020; Bola et al., 2021; Sui & Rothstein, 2019).

Regarding late face-related components (P3 and LPC), the results from the first study (Chapter 3) are consistent with the notion that the P3 component is the most robust index of self-specificity as well as discriminating familiar from non-self-related stimuli (Knyazev, 2013; see also: Estudillo, 2017), probably reflecting the engagement of higher-order cognitive functions (e.g., Polich, 2020). The LPC is thought to reflect a step further in cognitive resource allocation, as it has been associated with the detection of emotional properties and stimulus relevance (Cunningham & Turk, 2017; Xu et al., 2017) and the attribution of person-related information (Renoult et al., 2016; Tanguay et al., 2018). Accordingly, it can be argued that after the initial recognition of facial identity in LTM, as indexed by the N250, these late face-related components reflect a broad range of higher-order cognitive functions, including the retrieval of person-related knowledge (e.g., episodic memory, semantic memory, autobiographical facts), personal significance, and affective and evaluation processes related to oneself and others. Collectively, these ERP results are in good agreement with the notion that self-referential processing is based on the interplay between bottom-up and top-down mechanisms (Alzueta et al., 2019; 2020; Humphreys & Sui, 2016; Sui & Rothstein, 2019).

The ERP results are complemented by the estimation of neural sources. As shown in Figure 6.1, a distributed set of brain regions seem to support self-referential visual processing during middle latencies (250–300 ms), including the anterior cingulate cortex (aCC), anterior temporal lobe (ATL), dorsolateral and dorsomedial prefrontal cortex (dl/dmPFC), medial prefrontal cortex (mPFC), and temporoparietal junction (TPJ).

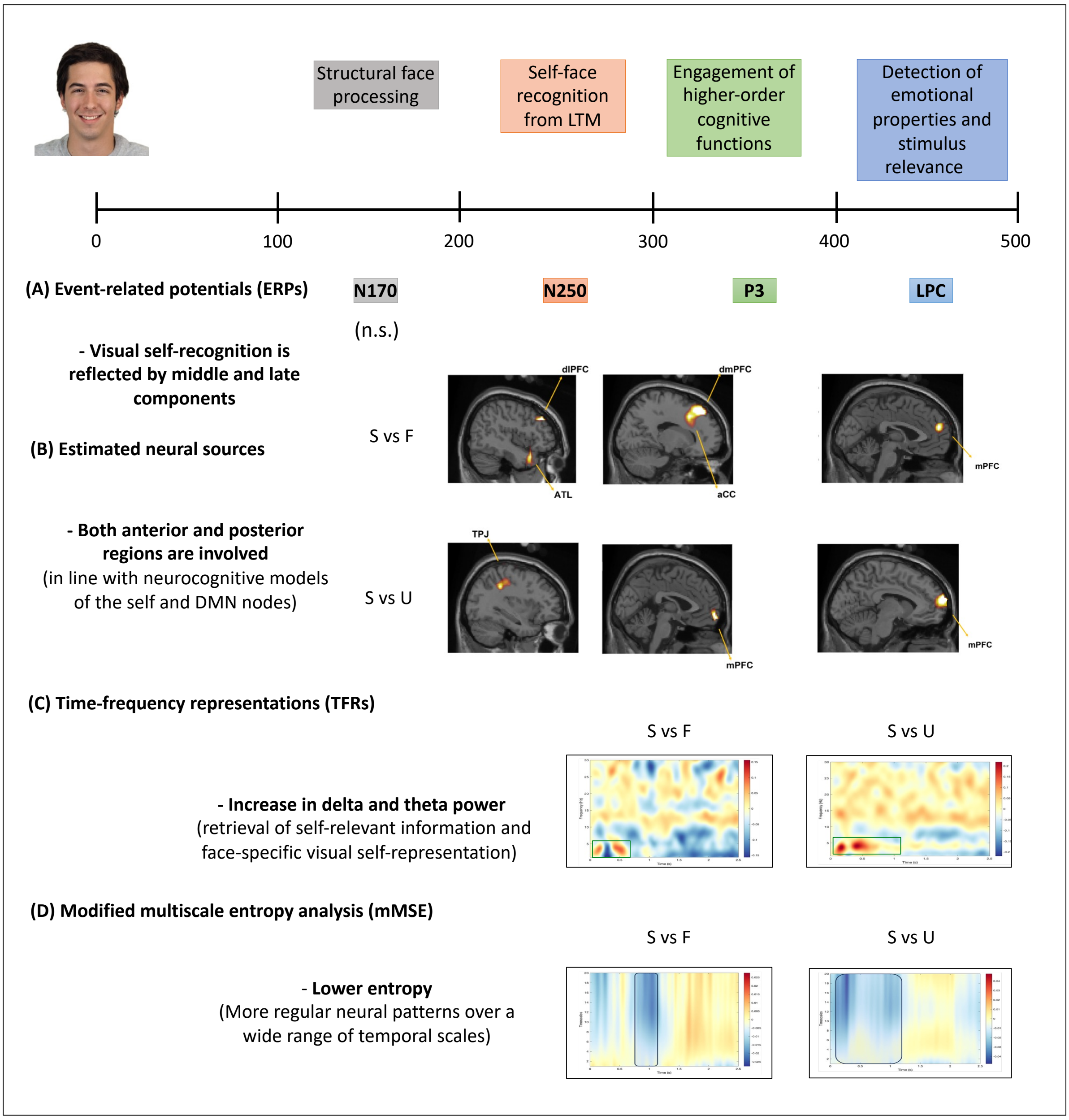

Figure 6.1 Summary of spatiotemporal neural dynamics during visual self-recognition. (A) Middle (N250) and late (P3, LPC) components reflect self-referential visual processing, as shown in Chapter 3 (B) Estimated neural sources observed in Chapter 3. During the N250 time window, a set of brain regions was involved, namely, anterior cingulate cortex (aCC), anterior temporal lobule (ATL), dorsolateral and dorsomedial prefrontal cortex (dl/dmPFC), medial prefrontal cortex (mPFC), temporoparietal junction (TPJ). During the P3/LPC time window, the main estimated neural source was the mPFC. (C) Time-frequency results observed in Chapter 5. An increase in delta/theta power was observed for self-faces. (D) Entropy estimates in response to self-faces. Note: LTM: long-term memory, S: self, F: friend, U: unknown.

Intriguingly, the source-level results observed in Chapter 3 are consistent with default mode network (DMN) nodes (e.g., Menon, 2023; Yeshurun et al., 2021). This similarity supports the view that the DMN is the primary network associated with the processing of self (Davey et al., 2016; Knyazev et al., 2020; Menon, 2023; Qin et al., 2020; Yankouskaya & Sui, 2022). Furthermore, this first study showed that the mPFC is a key brain region in relation to distinguishing self-identity from other identities during later latencies (300–600 ms). This finding is consistent with a wealth of neuroimaging studies (e.g., Apps et al., 2012; Levorsen et al., 2023; Murray et al., 2015) and neurocognitive models of the self (e.g., Sui & Gu, 2017; Qin et al., 2020).

To conclude study one (Chapter 3), a key aspect of self-identity was examined, which is the sense of continuity over time (“I am I” despite the physical changes over time). The results of this study showed that the LPC was the only component that reflected this sense of self-continuity, dissociating the current and the past selves. This result might indicate a higher allocation of specific personal relevance for the self across life stages. Moreover, this pattern was not affected by task demands. It is thought that this self-continuity is crucial when it comes to unifying temporally discrete self-related instances into a coherent whole and accessing self-knowledge (Klein, 2014; Northoff, 2017; Northoff & Horvart, 2022; Sedikides et al., 2023). Thus, self-awareness seems to maintain a unique sense of self irrespective of the physical changes that occur over time, which preserves a coherent identity across time (Klein, 2014). On the other hand, this study observed the involvement of both anterior and posterior brain regions in response to self-continuity (from 250 ms to 600 ms), including face-specific regions (fusiform gyrus), autobiographical memory regions (parahippocampal gyrus, precuneus/posterior cingulate cortex, temporal cortex), and executive regions (dorsolateral prefrontal cortex). These data provide novel evidence on the spatiotemporal neural dynamics of self-continuity, comprising a core component of self-identity (Gallagher & Cole, 2011; Northoff, 2017; Sedikides et al., 2023).

Furthermore, a more precise picture of the spatiotemporal neural patterns involved in self-identity is shown in Chapter 5. Most EEG studies on visual self-recognition have focused on ERP measures, whereas other electrophysiological measures, such as time-frequency representations or brain signal entropy, remain scarcely treated in the literature. Hence, the study presented in this chapter investigated the oscillatory correlates and signal variability involved in self-referential visual processing using time-frequency analysis and modified multiscale entropy analysis. As for the oscillatory correlates, this study observed increased theta-band power over posterior regions only in response to visual self-recognition, this being specific to the self. In addition, an increase in delta-band power was found in relation to self and friend faces, probably reflecting the retrieval of relevant information in relation to oneself and personally familiar individuals. Although similar oscillatory responses have been found in the extant literature (Miyakoshi et al., 2010; Sakihara et al., 2012; Haciahmet et al., 2023; Kotlewska et al., 2023), the functional interpretation of these oscillatory dynamics remains to be determined by further research. Moreover, an open question for future studies is to disentangle the exact relationships of the oscillatory dynamics involved in self-referential processing to the different subprocesses of face processing (Bernstein & Yovel, 2015; Haxby & Gobbini, 2007; Schweinberger & Neumann, 2016).

As far as the neural variability of self-identity is concerned, the results reported in Chapter 5 indicated a lower entropy in response to self-faces compared to friends and unknown faces. These findings revealed that self-related processing is better characterized by non-random neural patterns of oscillations over a wide range of temporal scales. This characterization of self-related processes has not been described in the literature so far. Interestingly, a similar pattern has been reported in the literature as related to DMN activity, which also tends to display more regular patterns (Davey et al., 2016; Deco et al., 2011; Uddin, 2020). Although the data of this study indicated that there were no differences between short and longer timescales, future studies may consider using a longer visual presentation (e.g., twenty seconds) to observe whether there are differences between timescales.

Taken together, the data reported in this thesis provide new insights into the neural dynamics underlying self-identity. This evidence has great implications for current theoretical models of the self (e.g., Northoff, 2017; Qin et al., 2020; Sedikides et al., 2023; Sui & Gu, 2017). Building on prior literature, the body of evidence presented in this thesis could be associated with the notion that self-relevant stimuli rapidly capture our cognitive resources in the service of efficiently adapting our behavior to environmental conditions, which is critical for our survival (Cunningham, 2016; Klein, 2012).

6.2. On the interplay between self-reference and other cognitive processes

The second objective of this thesis was to examine the interplay between self-referential processing and other cognitive processes, such as perception, attention and language processing. As mentioned above, the data presented in this thesis support the view that self-related stimuli are prevailing cues for attention driven by bottom-up and top-down mechanisms (Alzueta et al., 2019; 2020; Humphreys & Sui, 2016; Sui & Rothstein, 2019). Further, Chapter 3 showed that both self-reference and its continuity over time were unaffected by task demands.

Yet, an important study that addresses this general objective is presented in Chapter 4, which examines whether syntactic language processing can be affected by self-related information under reduced levels of visual awareness. In this study, participants listened to sentences that could contain morphosyntactic anomalies while self-related stimuli (presented for 16 ms) were masked with scrambled faces, being task-irrelevant. The results of this study concerning early face-related components indicated a self-specific response, as indexed by the N250 component (instead of the N170 component). Consistent with previous literature, this finding suggests that the self-reference effect could be automatically engaged even without explicit awareness, operating automatically during middle latencies (200–300 ms) (Bola et al., 2021; Wójcik et al., 2018).

These results also have implications for electrophysiological accounts of face perception (Caharel & Rossion, 2021; Hinojosa et al., 2015; Olivares et al., 2015; Schindler et al., 2023; Schweinberger & Neumann, 2016). Current research in this regard remains inconclusive as to whether N170 reflects a structural encoding mechanism or a face identification mechanism (perceptual and/or memory processes). In this vein, the results obtained in this thesis suggest a dissociation between perceptual and memory-related processes, as indexed by the N170 and N250 components, respectively. The ERP patterns found in this thesis are consistent with the proposal that the N170 reflects the processing of first-order structural face processing after low-level visual analysis, irrespective of face identity (Alzueta et al., 2019; Bentin & Deouell, 2000; Eimer, 2011). In turn, the N250 reflects a higher-level or second-order mechanism responsible for recognizing face individuals, which comprises associating the structural representation of a face with the information stored about the person to whom the face belongs, this being reflected by the N250 component (Miyakoshi et al., 2010; Schweinberger & Neumann, 2016; Tanaka et al., 2006; Woźniak et al., 2018).

On the interplay between self-reference and language processing, the results presented in Chapter 4 demonstrate that the self-reference effect can be extended to the language domain. More specifically, evidence from language-related components indicated that self-related content may impact cognitive processing during early and late syntactic processes, as indexed by the left anterior negativity (LAN) and P600 components, respectively. The largest LAN effect, followed by a reduced P600 effect, was found for self-faces. Similar biphasic patterns have been observed in the literature, for instance, when emotion-laden words precede morphosyntactic anomalies (Espuny et al., 2018; Jiménez-Ortega et al., 2021). The results obtained in this study suggest that self-related content elicited more cognitive resources during first-pass syntactic operations due to low-level attentional capture (i.e., bottom-up mechanisms), thus reducing the processes reflected by the later P600. Furthermore, this study also found a larger alpha suppression over the left inferior frontal gyrus (IFG), which is a crucial brain region for different linguistic operations (Friederici, 2017; Hagoort, 2017; Matchin & Hickock, 2020), when self-faces appeared before the critical word.

Thus, these findings have relevant implications for psycholinguistic models, as this study provides evidence in favor of interactive models of language (e.g., Hagoort, 2017; Malaia & Newman, 2015; McClelland et al., 1989; Pulvermüller et al., 2009). Broadly speaking, these models hold the view that semantic, syntactic, and contextual inputs interact with each other during the early stages of language processing. By contrast, these data speak against the traditional view of encapsulated syntactic processing, which posits that syntax is a module blind to other cognitive processes (e.g., Ferreira & Clifton, 1986; Frazier & Fodor, 1978; Hauser et al., 2002).

All things considered, the attention-capturing properties of the self were among the earliest findings of cognitive psychology, as illustrated by the classic “cocktail party effect” (Moray, 1959). Later on, the preferential processing associated with self-related content, known as the self-reference effect (SRE) on memory, was described (Rogers et al., 1977; Symons & Johnson, 1997). Theoretical accounts for the SRE have focused on the self-memory system (e.g., Conway, 2005) and attentional mechanisms (e.g., Humphreys & Sui, 2016). Over the past few years, an increasing body of evidence from behavioral and neuroimaging studies has shown how self-related stimuli are prioritized during different stages of processing, thereby biasing other cognitive processes beyond attention and memory, such as perception (Sui et al., 2015), reward (Northoff & Hayes, 2011), emotion (Herbert et al., 2011) or decision-making (Sui et al., 2023). In that vein, the data observed in this thesis indicates that this self-bias can be extended to spoken language processing even under reduced levels of visual awareness. Collectively, these findings stress the role of the self-processing system in human cognition, biasing more cognitive processes than previously thought.

Consistent with this notion, studies using prior self-associations with objects (e.g., Truong et al., 2017) and shapes (e.g., Scheller & Sui, 2022), which do not rely on prior autobiographical memory, showed similar prioritization effects with the traditional SRE (Cunningham & Turk, 2017; Sui & Rothstein, 2019). From a cognitive perspective, this observation has led some authors to propose that the self-processing system serves as an integrative or binding mechanism linking internal and external stimuli and different psychological processes (Sui & Humphreys, 2015). This view echoes recent accounts on the DMN (Yeshurun et al., 2021), which is regarded to be a dynamic network responsible for combining extrinsic with prior intrinsic information (that is, an individual's idiosyncratic past memories and knowledge). Moreover, others have argued that the self-processing system is included within the DMN (e.g., Menon, 2023). Thus, a still largely open issue in the current literature is how the self-processing system is organized in human cognition.

6.3. Limitations and further directions

Even though some of the limitations of the current work have been outlined in their respective chapters, there are additional technical restrictions as well. It is important to point out that neural source reconstructions of EEG data do not represent actual cortical activation. Unlike imaging results, source reconstructions serve as the best power estimates only for cortical dipoles that contribute to the EEG signals. Although the source-level results reported in Chapters 3 and 4 are consistent with the neuroimaging literature, caution should be exercised in interpreting these results, as those reported here are only approximate solutions with regard to the locations of brain activity. Nevertheless, beamforming techniques are well-established implementations in the current literature when it comes to estimating the dominant neural generators of EEG signals (Westner et al., 2022).

Moving on to the next point, it is important to consider some limitations regarding oscillatory neural correlates. It is argued that higher-level cognitive functions are represented by a different pattern of oscillation dynamics (e.g., Güntekin & Başar, 2016). As such, the same frequency range (e.g., delta-band activity) is supposed to reflect not just one but multiple functions, and each cognitive function is represented in the brain by the superposition of different frequency ranges. According to this superposition principle, integrative brain function is obtained by means of combined action of multiple oscillations (Başar, 2006). Therefore, the time-frequency results observed in Chapters 4 and 5 could be open to other accounts. It is worth mentioning that the functional roles associated with theta and alpha bands are better clarified in the extant literature compared to the delta band (Buzsáki & Vöröslakos, 2023; Fries, 2023; Klimesch, 2018; Palva & Palva, 2018). This underscores the need for further research to shed more light on the nature of neural oscillations in human cognition.

On another note, it is also important to consider that this thesis has focused only on facial stimuli to study the self- versus other-representations in the brain. The sense of self comprises multiple facets or levels, ranging from self-consciousness as an immediate subject of experience to the construction of oneself as a distinct entity with a personal history (Weiler et al., 2016). It is assumed that one's own face reflects both physical and social aspects of the self (e.g., Sugiura et al., 2012). The representation of this content is primarily supported by mental-self-processing (Qin et al., 2020). Although the results of this thesis are grounded on these socially visual stimuli, the nature of the self goes beyond this level of mental representation. Qin et al. (2020) proposed a three-level-processing model of self, comprising interoceptive-processing (i.e., representing internal sensory signals such as cardiorespiratory functions), exteroceptive-processing (i.e., representing proprioceptive information such as multisensory signals) and mental-self-processing (i.e., including a broad range of self-knowledge, self-related traits, etc.). Notwithstanding, both sociocultural (Markus & Kitayama, 2010; Lee et al., 2023) and phenomenological aspects of subjective experience (Woźniak, 2018) are also important constituents of the self. Therefore, the extent to which the results of this thesis reflect domain-specific or domain-general aspects of the self remains to be determined by future research.

In addition to the open questions outlined in their respective chapters, additional broader issues can be sketched. Considering the special status of the material that refers to the self, more focus should be devoted to studying the role of self-referential processing in clinical populations. In that vein, increasing studies are highlighting the clinical implications of atypical bias responses to self-processing in depression (e.g., Benau et al., 2019) or schizophrenia (e.g., Parnas & Zandersen, 2018), among other neuropsychiatric disorders.

For instance, Feldborg et al. (2021), using a self-emotional shape-label matching task (happy, neutral sad and control/line faces), observed that sub-clinically anxious individuals showed a diminished self-reference effect on reaction times, as compared to healthy controls. Similarly, individuals with depression tend to endorse negative self-referential sentences and reject positive ones compared to healthy controls, as reflected by an ERP component typically involved in the allocation of attention to motivationally salient stimuli, the late positive complex or potential (LPC/LPP; Hajcak & Foti, 2020). Thus, evidence from neuroimaging studies indicates that atypical activity over the medial prefrontal cortex (mPFC) during self-referential processing is associated with rumination in depressed patients compared to healthy controls (Lemogne et al., 2012; Nejad et al., 2019).

Of interest, there is evidence suggesting that people with memory disturbance (e.g., Alzheimer's disease or semantic dementia) can experience a sense of self-continuity in the absence of specific knowledge (Strikwerda-Brown et al., 2019). In addition, neurologically damaged patients with limited episodic memory can maintain a sense of self-continuity (Klein, 2014; Klein & Lax, 2010). These findings speak against the notion that there can be no sense of self without memory. Thus, first-person subjectivity does not necessarily depend on concrete autobiographical information (Sedikides et al., 2023). This line of research unravels how distinct alterations in self-continuity manifest across different clinical disorders. Hence, the sense of self has broad potential implications for understanding a range of neuropsychiatric disorders.

To conclude, studying the sense of self has great implications for both basic and clinical research. Thus far, a coherent body of knowledge comprising a cognitive explanation of the self is still lacking. Due to the complex and multifaceted nature of the self, there is a need in the current literature for a comprehensive account that integrates evidence from different perspectives, including behavioral, biological, cognitive, phenomenological, and sociocultural aspects. Looking at the big picture of the sense of self would be particularly important for addressing the mechanisms underlying the most human-specific behavior.

6.4. Concluding remarks

1. When it comes to self-identity and its continuity over time, this thesis showed that middle and late ERP components specifically reflect self-identity processing irrespective of time perspective (N250, P3, LPC), presumably indicating different subprocesses. The LPC was the only component that reflected self-continuity, suggesting that this component may be linked to self-relevant processes. Interestingly, these ERP patterns are supported by both posterior and anterior neural sources, which are consistent with current models of self and face processing.

2. On the interplay between self-reference and language processing, this thesis demonstrated that syntactic language processing can be modulated by self-referential information under reduced levels of awareness, as evinced by typical morphosyntactic language-related components (LAN and P600) and alpha-band power modulations. These data support the view for an interactive view between syntactic, semantic and contextual information. Furthermore, the results presented here indicated that self-referential processing is unaffected by visual awareness and task demands.

3. This thesis delves into understanding novel neurophysiological markers underlying self-identity processing. Time-frequency results showed an increase in theta-band power only in response to visual self-recognition, which may reflect face-specific visual self-representation. Of relevance, entropy estimates indicated that self-referential processing is characterized by more regular neural patterns over a wide range of temporal scales, which resembles the DMN activity.

4. More broadly, the findings obtained in this thesis provide new insights into the neurobiological underpinnings of self-identity. On the basis of this evidence, self-referential information is characterized by different neurophysiological signatures, which are not attributed to mere familiarity. These findings have implications for understanding human behavior in typical and atypical conditions.

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APPENDICES

Appendices

A. Supplementary materials (Chapter 3)

Contrasts	**Cluster *p*-value**		
	150-200 ms	**250-300 ms**	**300-600 ms**
Identity			
Self > Friend	.713	**.036**	**.026**
Self > Unknown	.837	**.007**	**.016**
Friend > Unknown	.270	.703	.531
Life Stage			
Adulthood > Adolescence	.286	.129	.078
Adulthood > Childhood	.557	**.041**	.170
Adolescence > Childhood	.612	.087	.317
Identity × **Life Stage**			
Self (Adulthood > Adolescence)	.175	.457	**.001**
Self (Adulthood > Childhood)	.505	**.018**	**.038**
Self (Adolescence > Childhood)	.636	**.027**	.706
Friend (Adulthood > Adolescence)	.406	.522	.529
Friend (Adulthood > Childhood)	.509	**.043**	.444
Friend (Adolescence > Childhood)	.576	**.032**	.350
Unknown (Adulthood > Adolescence)	.360	.313	.440
Unknown (Adulthood > Childhood)	.471	.729	.917
Unknown (Adolescence > Childhood)	.602	.848	.975

Table A1. Statistical report.

B. Supplementary materials (Chapter 4)

	p-value	Clusterstat	Effect size (mean difference)	Time
N170				
Self vs Friend	0.1406	-155.0731	-0.2390(-0.1933)	n.s.
Self vs Unknown	0.1009	202.7201	0.1949 (0.1505)	n.s.
Friend vs Unknown	0.0049	923.0237	0.5113(0.4382)	t = 0.124 to 0.184
N250				
Self vs Friend	0.0079	-877.9639	-0.2905(-0.2928)	t = 0.228 to 0.284
Self vs Unknown	0.0381	-342.4690	-0.1865(-0.1692)	t = 0.216 to 0.276
Friend vs Unknown	0.0567	321.6005	0.1803(0.1563)	n.s.
LAN				
Self (inc-cor)	9.999e-05	-2.0595e+04	-0.8611(-1.6735)	t = 0.244 to 1.012
Friend (inc-cor)	9.999e-05	-1.3087e+04	-0.2274(-0.4282)	t = 0.216 to 0.78
Unknown (inc-cor)	0.041	-446.8560	-0.3299(-0.7836)	t = 0.544 to 0.6
P600				
Self (inc-cor)	0.036196	2.3834e+03	0.42(1.4054)	t = 0.932 to 1.192
Friend (inc-cor)	< .001	8.7230e+03	0.8608(2.3001)	t = 0.836 to 1.192
Unknown (inc-cor)	< .001	1.1258e+04	0.8339(2.3372)	t = 0.816 to 1.192
Interaction effects				
LAN				
Self(inc-cor) vs Friend (inc-cor)	0.0025	-4.3450e+03	-0.5167(-1.3449)	t = 0.548 to 1.016
Self(inc-cor) vs Unknown(inc-cor)	0.0064	-4.5345e+03	-0.6925(-1.8418)	t = 0.412 to 0.756
Friend(inc-cor) vs Unknown(inc-cor)	0.0128	-978.6349	-0.3090(-0.7232)	t = 0.464 to 0.56
P600				
Friend(inc-cor) vs Self(inc-cor)	0.0031	7.5093e+03	0.2997(0.8536)	t = 0.428 to 1.116
Unknown(inc-cor) vs Self(inc-cor)	0.0007	1.1073e+04	0.3586(1.0501)	t = 0.372 to 1.116
Unknown(inc-cor) vs Friend(inc-cor)	0.1701	659.4863	0.1089(0.2956)	n.s.

Alpha power modulations				
Main effects				
Self (inc-cor)	0.001(-)	-642.0388	-0.41(-0.9931)	t = 0.144 to 0.544
Friend (inc-cor)	0.605(-)	-4.2366	-0.0615(-0.1818)	n.s.
Unknown (inc-cor)	0.121(-)	-85.3500	-0.2175(-0.5933)	n.s.
Interaction effects				
Self(inc-cor) vs Friend (inc-cor)	0.006(-)		-0.3287(-0.9435)	t = 0.184 to 0.464
Self(inc-cor) vs Unknown(inc-cor)	0.010(-)	-238.5665	-0.3487(-0.6762)	t = 0.184 to 0.544
Friend(inc-cor) vs Unknown(inc-cor)	0.357(+)	17.6670	0.1435(0.4336)	n.s.

Table B1. Statistical report.