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The neural dynamics of familiarity-dependent face identity representation

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Abstract

Recognizing a face as belonging to a given identity is essential in our everyday life. Clearly, the correct identification of a face is only possible for familiar people, but 'familiarity' covers a wide range—from people we see every day to those we barely know. Although several studies have shown that the processing of familiar and unfamiliar faces is substantially different, little is known about how the degree of familiarity affects the neural dynamics of face identity processing. Here, we report the results of a multivariate EEG analysis, examining the representational dynamics of face identity across several familiarity levels. Participants viewed highly variable face images of 20 identities, including the participants' own face, personally familiar (PF), celebrity and unfamiliar faces. Linear discriminant classifiers were trained and tested on EEG patterns to discriminate pairs of identities of the same familiarity level. Time-resolved classification revealed that the neural representations of identity discrimination emerge around 100 ms post-stimulus onset, relatively independently of familiarity level. In contrast, identity decoding between 200 and 400 ms is determined to a large extent by familiarity: it can be recovered with higher accuracy and for a longer duration in the case of more familiar faces. In addition, we found no increased discriminability for faces of PF persons compared to those of highly familiar celebrities. One's own face benefits from processing advantages only in a relatively late time-window. Our findings provide new insights into how the brain represents face identity with various degrees of familiarity and show that the degree of familiarity modulates the available identity-specific information at a relatively early time window.

KEYWORDS

EEG, familiarity, identification, identity, multivariate pattern analysis

1 | INTRODUCTION

Do you know who Angela Merkel is? If so, you can not only point out her face in Figure 1a but you will also recall some information regarding her life. If you are able to do this, it can be assumed that you have a certain representation of Angela Merkel in your brain. But do you know the people shown in the fourth, fifth and sixth places in Figure 1a? It is

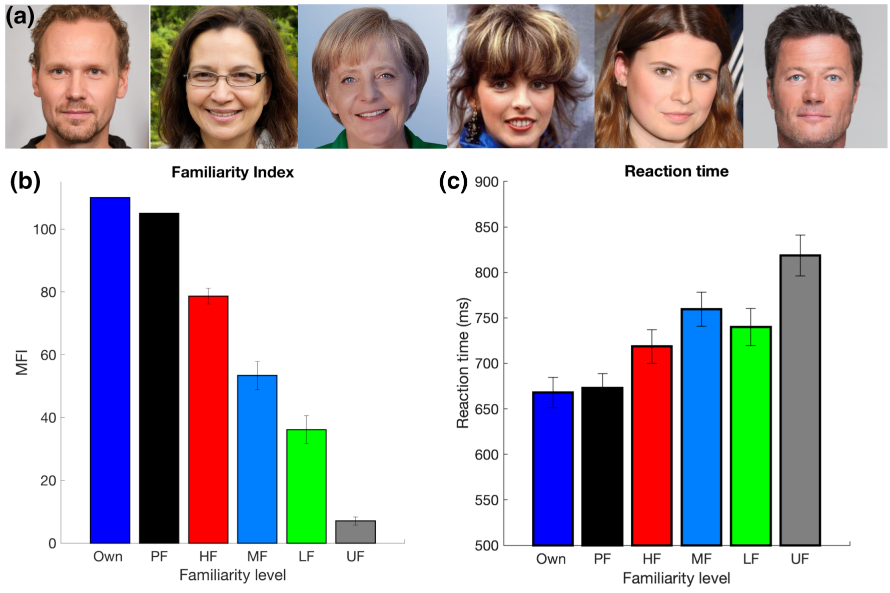

FIGURE 1 (a) A six example faces for illustration purposes (from left to right: the first two faces were created by https://this-person-does-not-exist.com/; the subsequent images of Angela Merkel, Nena, Luisa Neubauer and András Stohl were downloaded from world-wide web). (b) The average familiarity index. (c) The average reaction time in the face matching task for the six familiarity categories, analyzed separately in the classification analysis. OWN, participants' own face; PF, personally familiar faces; HF, highly familiar celebrity faces; MF, medium familiarity celebrity faces; LF, low familiarity celebrity faces; UF, unfamiliar faces.

highly likely that if you were a teenager in the 1980s, follow the current "Fridays for future" climate demonstrations in Germany or watch Hungarian talk-shows you would feel that you have seen some of them already and that they are familiar. But being familiar with someone does not necessarily mean that you "know" the person in the sense that you can also activate their representations, necessary for identification. In other words, familiarity involves the recognition of an object being novel or having been observed previously, while identification involves the additional recall of their biography, or the contexts in which you have perceived them. Indeed, current models propose that familiarity is the first step towards establishing identification (Rugg & Yonelinas, 2003; Yakovlev et al., 2008).

Recent years have seen considerable progress in identifying the neural correlates of familiarity, at least for faces. First, a broad range of behavioral studies have found vast perceptual differences between unfamiliar and familiar faces (for reviews, see, Gobbini & Haxby, 2007; Jenkins & Burton, 2011; Johnston & Edmonds, 2009; Ramon & Gobbini, 2018; Young & Burton, 2017, 2018). Consequently, neuroimaging studies have identified a large network of areas where familiarity modulates neural responses (for a review see Kovács, 2020). Further, electrophysiological studies, better suited to discovering the dynamics of neural processing, have identified an extended time-window, including several event-related potential (ERP) components, during which familiarity modulates neural activity. Specifically, ERP studies have found that familiar faces elicit more negative waves from 200 ms post-stimulus onset, corresponding to the N250 component (Bentin & Deouell, 2000; Caharel et al., 2011, 2014; Huang et al., 2017; Kaufmann et al., 2009; Schweinberger & Neumann, 2016; Wiese, Ingram, et al., 2019), extending towards 400–600 ms, where another ERP component has recently been labeled as the "sustained familiarity effect" (SFE; Wiese, Ingram, et al., 2019; Wiese, Tüttenberg, et al., 2019; Wiese et al., 2021). Consistent with these ERP studies, recent multivariate pattern analysis (MVPA) of EEG/MEG data have also found familiarity-related information from 200 ms onwards (Karimi-Rouzbahani et al., 2021; see Bayer et al., 2021 for an even earlier familiarity representation), peaking mostly in the 400–600 ms time-window (Ambrus et al., 2019, 2021; Dalski et al., 2022; Dobs et al., 2019; Li et al., 2022).

While familiarity has been studied extensively in the past, relatively less information is available on face identity (ID) representation. This is because the low spatial resolution of univariate electrophysiological methods makes it very difficult to study the neuronal processing differences of face IDs. Therefore, only a handful MVPA studies have so far evaluated the neural dynamics of face ID processing. These studies have found robust ID representations starting from 200 ms onwards and peaking at around 400 ms for both unfamiliar (Nemrodov et al., 2016, 2018; Vida et al., 2017) and familiar faces (Ambrus et al., 2019; Dobs et al., 2019). Importantly, while the earlier ID representations seem to be modulated by gender and low-level image properties, the later information, emerging around 400 ms, is unaffected by these factors, suggesting that they play a different role in identification (Ambrus et al., 2019).

As familiar and unfamiliar faces are processed quantitatively differently, it is also important to know how the neural dynamics of ID representation depends on familiarity. Unfortunately, so far only two studies have tested the familiarity dependence of ID representation. First, Dobs et al. (2019), using celebrities and unfamiliar faces found that familiarity enhanced face ID information between 100 and 570 ms. Second, Ambrus et al. (2021), familiarized participants experimentally either by passive exposure, media presentation or via personal interactions and found robust ID representations which, however, were not different before and after familiarization.

In addition, we know that (1) familiarity is not a threshold, rather a gradual, signal-detection process (Yonelinas, 1994; Yonelinas et al., 2010) and that (2) neural processing differences have been reported between highly familiar personally known faces and those of celebrities (for reviews see Kovács, 2020; Ramon & Gobbini, 2018). Therefore, it is important to study how ID is represented across several levels of familiarity in a systematic manner. For this purpose, we used the data reported in Li et al. (2022), where familiarity was estimated both by subjective ratings and by a familiarity-sensitive (Ambrus et al., 2017; Andrews et al., 2015; Clutterbuck & Johnston, 2004) face-matching task. This study also measured familiarity across a large set of identities, ranging from the participants' own face, via personally familiar (PF) and celebrity faces to unfamiliar ones, covering the entire familiarity spectrum (Figure 1a). As such, the data in Li et al. (2022) study are ideal for estimating ID representations across several levels of familiarity. For this purpose, we decoded ID information for same-gender face-pairs for several different levels of familiarity.

2 | METHOD

2.1 | Datasets

The identity classification decoding analysis was carried out using data from the second, EEG study reported in Li et al. (2022).

2.2 | Participants

The EEG data of 25 right-handed participants (19 females; average age 22.1 years, SD = 3.7) was used. Participants gave informed consent and received partial course credits or monetary compensation. They had normal or corrected-to-normal vision, and none had any history of neurological disorders. The study was conducted in accordance with the guidelines of the Declaration of Helsinki and was approved by the ethics committee of the Friedrich-Schiller-Universität Jena.

2.3 | Stimuli

Fourteen celebrities (7 females), representing a broad range of familiarity degrees, were selected from Study 1 of Li et al. (2022) and served as stimuli. These were all ambient, naturally variable faces, including nationally or internationally famous celebrities such as athletes, politicians, actors, and singers of both sexes, with a broad range of age. All images were collected using the Google image search engine. In addition, photographs of the participants' own faces and those of three PF persons were used. The PF persons were either family members and relatives or close friends, reported as being very familiar. For practical reasons, these IDs varied in gender across participants (for 12 we received the images of two IDs matching the gender of the participant and for 13 we received 1 gender matching ID only). These images were typical family snapshots of our participants, taken on their mobile phones or amateur cameras. Special care was taken to balance low and medium level features (such as viewing angle, facial expressions, eye-gaze, hair-color and style) among familiarity levels. In addition, two Hungarian celebrities, unknown to the participants, were added to the stimulus set to serve as unfamiliar identities. We collected ambient face images for each ID and presented in color, reflecting a large range of facial expressions and lighting conditions, but having similar luminance (average and SD of pixel intensity values: 123 ± 22; not significantly different across familiarity categories; one-way ANOVA: $F(5,1159) = 1.6$, $p = .16$; Shine toolbox; Willenbockel et al., 2010); and having identical resolutionresolution across familiarity levels (200×280 pixel, 72 DPI). The images were cropped and resized to $2.8 \times 3.9°$ (viewing distance: 108 cm), using GIMP 2.8.6 (data-security does not allow the presentation of actual images, but similar, representative faces are presented in Figure 1a).

We created a "mnemonic familiarity index" (MFI) from the results of the familiarity rating of the Study 2 of Li et al. (2022) and from the answers of the explicitly recalled memories the following way:

$$\mathrm{MFI} = 100 \times ([\mathrm{LR} \times 0.5 + \mathrm{MS} \times 0.5] / 7)$$

where LR is the Likert Familiarity Rating score and MS is the total memory score of the participants obtained for the four declarative memory questions (briefly, they were asked to recall the depicted persons' full name, occupation, any additional biographical details and personally related episodes; for details see Li et al. 2022). This combined MFI measures familiarity on a 0–100 scale and reflects both the subjective feeling of familiarity and the amount of explicitly recalled information about the persons, with an equal weight. We calculated MFI for each ID and participant separately and averaged them across the sample. Note that PF faces and the participants' own faces were assumed to be more familiar than the faces of the celebrities, and as such, to have an MFI above the maximum (100) attainable for the famous identities. We further assumed that the own face will be more familiar than PF faces. Thus, these identities were assigned, arbitrarily, the MFI values of 105 for PF identities and 110 for the own faces. Please note, that the exact values do not affect the results as ordinal statistics and rank correlations were used in the comparisons below (Figure 1b,c).

Altogether a total of 20 identities served as stimulus material for the EEG experiment, including participants' own face (OWN), three personally familiar faces (PF), four celebrity faces with high familiarity (two females; MFI above 60; HF), four moderate familiarity celebrities (two females; MFI between 40 and 60; MF), four low familiarity celebrities (two females; MFI between 10 and 40; LF) and four entirely unfamiliar faces (two females; MFI below 10; UF). Figure 1b shows the average MFIs per familiarity category. For each ID we collected 16 face images. For the EEG recording sessions we used 10 of these (Ambrus et al., 2019) while for the subsequent face matching-task five previously unseen images were presented, per ID. Additionally, 20 unfamiliar faces (10 female; similar age and hair color as the target faces) were selected as "foil" images for the face matching task (Ambrus et al., 2017).

2.4 | Procedures

The experiment was comprised of three phases: an EEG recording session, a subsequent face matching task and a final familiarity evaluation phase to calculate MFI. The EEG recording session was similar to that of Ambrus et al. (2019, 2021). A total of 1760 (1600 nontarget and 160 target) trials were presented in 8 runs, separated by self-paced breaks. Each run included one presentation of the 10 images of the 20 identities. Additionally, 20 target trials were added to each run in a pseudorandom order to avoid any consecutive presentations of identical images.

In each trial, a central fixation cross was presented for 250 ms, followed by the face stimulus for 600 ms and an Inter-Trial-Interval (ITI), selected randomly between 700 and 1000 ms. Participants were asked to press the space button when they saw a target image (1-back task; mean detection accuracy: $99.08 \pm 0.67\%$). These target trials were set to ensure that participants maintained their attention and were excluded from the analysis. PsychoPy (Version 3.0) was used for stimulus presentation and behavioral response collection (Peirce, 2009). Stimuli were presented centrally on a uniform gray background (23.0-inch EIZO display, 1920×1080 pixel resolution, refresh rate 60 Hz).

A face matching task was conducted after the EEG experiment where participants made same-different decisions about pairs of previously unseen images. Participants completed 800 trials (40 per ID), allocated into four blocks of 200 trials. Each trial started with a 250 ms central fixation cross, followed by a 1000 ms presentation of pair of face images. The face pairs consisted of either two different images of a given ID ('same') or an unseen image of a previously seen ID and an image of a "foil" identity ('different' condition), with equal probability. Next, a response screen was presented until participants signaled their answer by a button-press, followed by an ITI of 700–1000 ms. The participant's task was to decide whether the pair of faces belonged to the same ID or not. The experimental software was written in PsychoPy (Peirce, 2009). Figure 1c depicts the average reaction times for the various familiarity conditions, separately.

The experiment was concluded by a familiarity evaluation task whereby participants were asked to estimate the subjective familiarity of the identities on a 10-point Likert scale and answer four explicit memory questions regarding the biography of the presented identities. Finally, an MFI index was calculated for each participant and ID separately, as described above.

2.5 | EEG recording and preprocessing

Participants were tested in a dimly lit, electrically shielded and sound-attenuated cabin with 108 cm between the screen and the eyes, secured via a chin rest. The EEG recording was performed continuously, using a 64-channel BioSemi Active II system (BioSemi) with a 512 Hz sample rate (band with: DC to 120 Hz). Electrooculogram (EOG) was recorded by four additional electrodes, placed over the outer canthi of both eyes, and above and below the left eye.

EEG preprocessing was similar to that of Ambrus et al. (2021). The preprocessing pipeline was implemented in a combination of EEG-lab (Delorme & Makeig, 2004) and Modeling toolbox (ADAM, version: 1.07-beta; Fahrenfort et al., 2018). EEG data were first re-referenced to the average of the electrodes. EEG was notch-filtered at 50 Hz, band-pass filtered between 0.1 and 40 Hz, segmented from −200 to 1200 ms relative to stimulus onset, and baseline corrected with respect to the first 200 ms. The resulting data was downsampled to 100 Hz to increase signal-to-noise ratio in the multivariate analyses (Grootswagers et al., 2017).

2.6 | Decoding analysis

MVPA was performed on the raw EEG of all 64 channels, using the Amsterdam Decoding and Modeling (ADAM) toolbox (Fahrenfort et al., 2018). To that end, a 10-fold cross-validation scheme was used (data of individual participants was split into 10 equal-sized folds after randomizing the trial order). A linear discriminant classifier was then trained on the data of nine of these folds and tested on the data of the remaining one (leave-one-out procedure) and this procedure was repeated until each fold was used as test set exactly once. Finally, the classifier performance was averaged across the folds. For each condition, we trained a classifier to differentiate trials on which one of the targets was one image of a given ID versus an image of another ID. Ten images per ID were used and the resulting performance was averaged across images, leading to a single classification performance measure per identity pair. As a performance measure, we used decoding accuracy, being the most often used metric.

As prior studies suggest that the perceived gender of the face strongly influences identity representations (Ambrus et al., 2019) we tested classification for faces of the same gender (within-gender comparisons) and present the results of the same analysis for cross-gender ID pairs in the Supplementary material. We calculated classification performance for the previously established 6 familiarity categories of Li et al. (2022) separately. Specifically, first, we tested the neural signals for images of the own face of the participant against the faces of a same-gender PF person, selected randomly from the three available identities. This classification condition, reflecting the differential processing of one's own face from that of another, highly PF face is denoted as OWN. Second, the discrimination capacity of the neural data for two same-gender PF identities was tested. Next, we created two same-gender pairs from the four HF, MF, LF and UF identities separately. We tested the data for the 10 images of these same-gender ID pairs against each other and then averaged the classification performance of the female and male ID pairs for each familiarity category separately. This led to six classification performance measures (for each familiarity condition one) per time-point and participant. Group-level classification was then computed, using the individual first-level data. The decoding performance for a given condition was statistically tested against chance level (0.5) by running two-sided one-sample *t*-tests across participants for every time point. To correct for multiple comparisons, we used cluster-based permutation tests (10,000 permutations) on adjacent time points with the alpha level set to $\alpha = 0.05$ (Maris & Oostenveld, 2007).

To compare the temporal dynamics of ID information across familiarity conditions we identified three separate time-windows (100–200, 200–400 and 400–600 ms), based on previously available literature (Ambrus et al., 2019; Dobs et al., 2019; Wiese, Ingram, et al., 2019; Wiese, Tüttenberg, et al., 2019; Wiese et al., 2021). We calculated the integral under the decoding accuracy curves within each time-window for each familiarity condition and participant separately, using the *trapz* function in Matlab (R2022, The Mathworks, Inc.). These measures of classification performance were then compared using the Friedman test, the non-parametric alternative to the one-way ANOVA with repeated measures testing for differences between groups when the dependent variable being measured is ordinal. Finally, for each participant and time-window the decoding accuracy and the MFI were correlated using Spearman's rho rank correlations. Statistical analyses were performed by using JASP 0.11.1 (JASP Team, 2023).

2.7 | Data and code availability

Data and all applied codes of Li et al. (2022) are uploaded to OSF (https://osf.io/2czu5/). We have also uploaded the experimental stimuli, with the exception of personal photos of the participants and their friends, as well as the currently used scripts. The conditions of our ethics approval do not permit public archiving of these images and of study data. The entire data and stimulus sets will be made available to interested researchers following completion of a data sharing agreement and approval by the local ethics committee. The Matlab scripts for EEG preprocessing and MVPA analysis are available under https://osf.io/8zywd/. No part of the study procedures or analyses was pre-registered prior to the research being conducted.

3 | RESULTS

To reveal the neural dynamics of familiarity sensitive identity information in the EEG signals, we performed a classification analysis across time. We decoded face ID information for each participant, familiarity condition and time-point separately. The analysis showed a significant and long-lasting decoding performance that depended strongly on the prior familiarity with the identities (Figure 2).

Table 1 summarizes the properties of the neural dynamic curves, for each familiarity condition separately. First, face ID information emerged for each familiarity

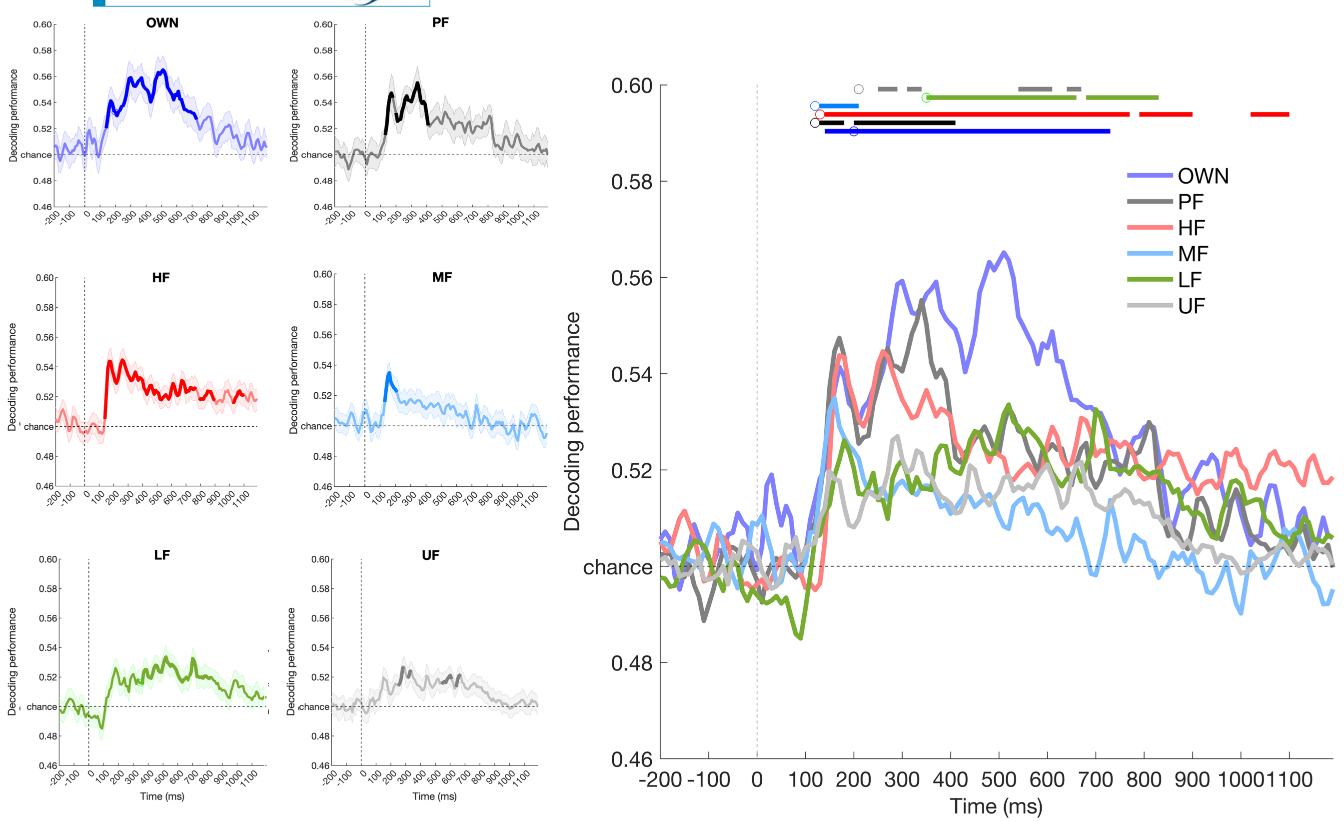

FIGURE 2 Time-resolved decoding accuracies (shaded regions represent SEM) separately for the six familiarity conditions (left) and for illustrative purposes superimposed on each other without SEM (right). Thicker curves (left) and horizontal lines (right) denote temporal clusters with significantly different decoding accuracies from chance (10,000 two-sided cluster-based permutations, $p<.05$). Different colors signal the level of familiarity with the classified identities. OWN, participants' own face; PF, personally familiar faces; HF, highly familiar celebrity faces; MF, medium familiarity celebrity faces; LF, low familiarity celebrity faces; UF, unfamiliar faces.

TABLE 1 Results of the time-resolved identity classification for each familiarity level, separately. Clusters marked as significant on Figure 2; two-tailed cluster permutation tests against chance.

Condition	Onset (ms)	Peak (ms)	End (ms)	Cluster based *p*-value
OWN	140	510	730	.0001
PF	130	150; 340	410	.01; .0002
HF	140	160; 850; 1060	1100	.0001; .03; .006
MF	130	140	210	.0008
LF	350	510; 700	660	.0001; .0005
UF	250	280; 320; 600	610	.01; .02; .004

condition at around the same time (110–140 ms post stimulus onset), except for LF and UF for which ID information could only be retrieved after 350 and 250 ms following stimulus onset, respectively. Second, ID information could be detected in the signal for an extended time-window up until 400–700 ms for most familiarity conditions. The only exception to this was the MF which only contained ID information in a relatively early and very short period.

To further explore the familiarity dependence of ID classification quantitatively we calculated the mean classification accuracy for the 100–200 ms, the 200–400 and the 400–600 ms time-windows, for the six familiarity conditions and each participant separately. Next, we compared these measures of classification accuracy, indexing the amount of available ID information across familiarity conditions, separately for each time-window (Figure 3). A non-parametric Friedman test of differences among repeated measures suggested a significant familiarity effect of ID classification performance only for the 200–400 and 400–600 ms time-windows (100–200 ms: $\chi^{2(5)}=6.9$, $p<.23$; 200–400 ms: $\chi^{2(5)}=16.474$, $p<.006$; 400–600 ms: $\chi^{2(5)}=32.046$, $p<.0008$). Pairwise comparisons, using Bonferroni corrections, revealed that the decoding performance depends on familiarity the most within the

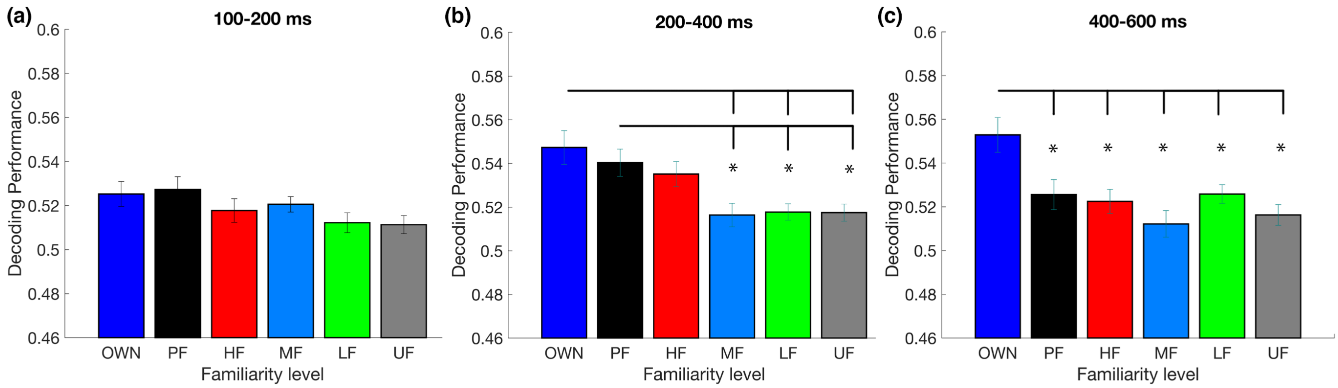

FIGURE 3 Decoding accuracy within the 100–200 (a), 200–400 (b) and 400–600 ms (c) time-windows (expressed as the integral of the classification performance curves within the respective time-windows), separately for each familiarity condition. Error bars denote SEM. $^*p<.05$.

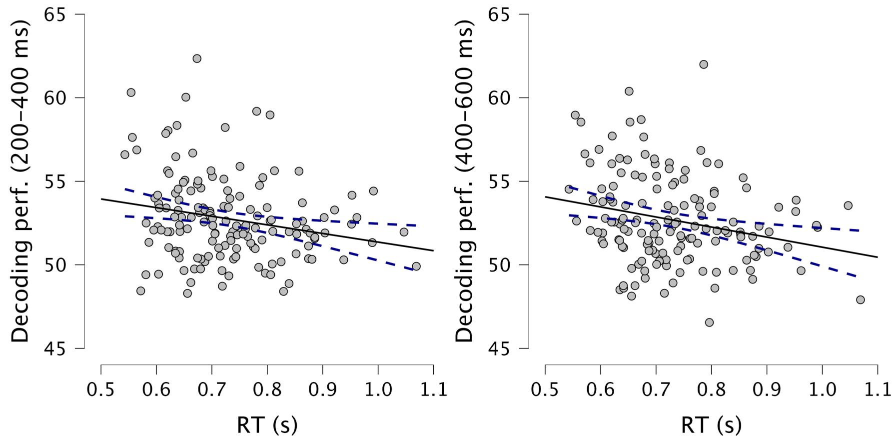

FIGURE 4 The correlation of neural identity decoding, expressed as the integral of the classification performance curve between 200 and 400 ms (left) and 400 and 600 ms (right), with the mean reaction time for the 20 identities, separately. Dashed lines denote 95% confidence intervals.

200–400 ms time-window: accuracy of OWN is significantly different from MF, LF and UF ($p_{BONF}<.003$ for each comparison), and PF is also significantly different from MF, LF and UF ($p_{BONF}<.05$ for each comparison). In addition, OWN differed significantly from all other familiarity conditions in the 400–600 ms time-window ($p_{BONF}<.02$). Please note that OWN was not significantly different from PF in the earlier time-windows but showed a strong difference in discriminability in the 400–600 ms window ($p_{BONF}=.015$), suggesting differential encoding only at this later time. Also, it is worth mentioning that facial ID was similarly represented for PF and HF conditions as suggested by the fact that they were not significantly different for either time-window ($p_{UNCORRECTED}=1.0$ for each time-window).

To evaluate whether gender information affects ID classification, we replicated the above analysis for ID pairs which also differed in gender. Table S1 contains the results of the time-resolved ID classification for these cross-gender ID classifications, for each familiarity level separately. These cross-gender analyses led to somewhat larger decoding performances in the early time-periods than the within-gender ID decoding, supporting prior findings (Ambrus et al., 2019). However, when tested formally against each other with a cluster-based permutation test (Figure S1), decoding performances were not statistically different for the within- and between-gender ID decodings, suggesting that perceived gender has relatively little interaction with the observed ID encoding.

To provide a different estimate of whether identity classification accuracy depends on the level of stimulus familiarity within the above time-windows, we correlated the reaction times in the face matching task with the ID decoding performances of the neural classifier for each participant, time-window and ID separately (Figure 4). We found a negative correlation (shorter reaction times for ID pairs, which could be classified better by the algorithm), which was significant for the 200–400 and 400–600 ms time-windows (Spearman's rho $=-0.22$; $p=.008$ and rho $=-0.24$; $p=.003$, respectively).

Overall, these results suggest that face ID information is present in the EEG signal from 100 ms onwards; it peaks at around 200–400 ms and it depends strongly on the level of existing familiarity with the persons.

4 | DISCUSSION

The major results of the current study are as follows. (1) Identity information is present very early in the EEG signal, but this encoding stage is relatively independent of the level of familiarity. (2) Later ID information, emerging between 200 and 400 ms is determined to a large extent by familiarity: it can be recovered with better quality and longer duration for more familiar faces. (3) Signals for faces of PF persons have not been shown to be better classifiable than those of highly familiar celebrities. (4) One's own face enjoys processing advantages only in a relatively late time-window.

4.1 | Familiarity determines identity encoding but only at later processing stages

In the current study we calculated pairwise face ID decoding with a linear discriminant machine learning algorithm from the EEG signal for six familiarity levels, separately. The results showed a rapidly emerging, very early onset of ID information, beginning for most familiarity conditions shortly after 100 ms post-stimulus onset. This onset is in accordance with prior findings for famous faces (Ambrus et al., 2019; Dobs et al., 2019) and for media familiarized faces (Ambrus et al., 2021) but it is earlier than we and others have observed for unfamiliar faces (Dobs et al., 2019; Nemrodov et al., 2018; but see Nemrodov et al., 2016 for an even earlier onset). The fact that the ID information between 100 and 200 ms is relatively weak and insensitive to familiarity degree is in accordance with previous findings showing that until 400 ms post-stimulus onset the ID signal is modulated by the perceived face gender and low-level image properties (Ambrus et al., 2019).

ID information from 200 ms onwards, on the other hand, is very strong and it shows dependency on and significant correlation with the degree of familiarity. The long-lasting nature of ID representation confirms prior studies (Ambrus et al., 2019, 2021; Dobs et al., 2019), which showed peaks of ID information between 200 and 400 ms. While Dobs et al. (2019) showed the disappearance of this information for unfamiliar faces, Ambrus et al. (2021), using brief media-based familiarization training, found similar decoding pre and post familiarization within this time-window. So far, however, the current study remains the only one to estimate familiarity dependence for several familiarity types and levels. Therefore, we argue that superior sensitivity of such measures explains the partially different results.

Overall, our results further support the idea that the representation of face ID involves several, functionally distinct steps and it starts with the encoding of visual characteristics, specific to a given person and enabling the discrimination and recognition of a face, even without familiarity. This idea is further supported by recent computational modeling results. Blauch et al. (2021) trained a deep neural network to discriminate face identity and found that representations in the early layers of the network remain similar, while later network representations change as faces become familiar.

But how does this familiarity-sensitive identity signal relate to the processes underlying familiarity discrimination? ERP studies demonstrated some time ago that familiar and unfamiliar faces elicit different responses from around 200 ms (Caharel et al., 2011, 2014; Huang et al., 2017; Schweinberger & Neumann, 2016; Karimi-Rouzbahani, 2021), reaching a peak between 400 and 600 ms (Wiese, Ingram, et al., 2019; Wiese, Tüttenberg, et al., 2019; Wiese et al., 2021). MVPA studies have recently confirmed these results as they typically find familiarity information in similar time-windows with peaks of information, usually at around 400–600 ms (Ambrus et al., 2019, 2021; Dalski et al., 2022; Dobs et al., 2019; Li et al., 2022). Li et al. (2022) found that the peak of correlation between behavioral familiarity measures and familiarity decoding performance was maximal between 450 and 550 ms. These values are somewhat later than the peaks we have now found for familiarity-sensitive ID decoding, except for the decoding of one's own versus a PF face (OWN; 490 ms). This is consistent with the theory that familiarity and ID processing do not necessarily evolve simultaneously: For example, Ambrus et al. (2021), using various experimental familiarization techniques reported strong familiarity representations without genuine changes in ID representations.

4.2 | PF versus famous faces

Several past studies have shown the important role of personal real-life interactions and the differential processing of PF and famous faces (Campbell & Tanaka, 2021; Ramon & Gobbini, 2018; Visconti di Oleggio Castello et al., 2017; Wozniak et al., 2018). In fact, our own prior study (Li et al., 2022) also found better familiarity discrimination when OWN and PF were included as compared to famous faces only. However, in the current study we found no significant differences in ID decoding between PF and the most familiar category (HF). We argue that there is no incompatibility here. Previous studies have typically not differentiated among familiarity levels for famous faces and have often confounded degree of familiarity with personal/media familiarity. Here, we incorporated variation in familiarity for those faces not known personally, allowing a comparison of highly familiar celebrities with

PF faces—a comparison which, interestingly, showed no differences in ID-decoding. This highlights the importance of not treating familiarity as a simple present/absent variable, but one which varies continuously. Further experimental work is necessary to understand whether any genuine differences arise in processing the faces of those we know personally and those we know through the media. Indeed, we acknowledge that the ID decoding remains significant for famous faces somewhat longer than for PF (compare PF and HF on Figure 2). But we refrain from drawing stronger conclusions regarding this difference as a formal test of PF and HF fails to show any significant differences (Figure S2).

4.3 | Own face processing

The encoding advantage for one's own face (self-face advantage) may be special for obvious reasons (Keyes & Brady, 2010; Tong & Nakayama, 1999). Recent ERP studies suggest that the P100 (Alzueta et al., 2019) or the N250 (Estudillo, 2017) components are the first to be sensitive to self-faces. Our results only partially support the advantage of own-face processing over PF faces: In the time-window of 400–600 ms, corresponding to its peak (490 ms), ID decoding is indeed significantly stronger for OWN when compared to other familiarity conditions. However, in the earlier periods, OWN and PF are not different in any way. This raises the possibility that the processing differences of one's own face develop at a relatively later stage only, possibly reflecting higher level processes, rather than any early perceptual advantage for recognizing images of oneself.

Two limitations of this conclusion are related to the nature of the applied stimulus set. First, we compared OWN against another ID from another (PF) familiarity category, meaning that the OWN is the only cross-familiarity level category comparison in our study and this confound might increase ID decoding artificially. This is, in fact, plausible, as most of the studies have found the highest familiarity encoding in the 400–600 ms time-window. Nonetheless, this confound is unavoidable as one can only have one ID categorized as "OWN". Second, both the within-gender as well as the between-gender decoding was based on a single pair of IDs, while we had two pairs for the famous IDs which might also affect decoding performances. The fact, however, that we observed higher performances for OWN and PF (where less data could be used for training and testing) as compared to HF, MF, LF and UF argues against the role of this difference in explaining our data.

In conclusion, our findings, obtained by the decoding analysis of the electrophysiological signal of Li et al. (2022), provide further information into how the brain represents the identity of faces with various degrees of familiarity. Our data shows that the degree of familiarity modulates decodability of facial identity at a relatively early time window: the more familiar a face is the better one can decode identity information from the EEG signal at around 200–400 ms.

AUTHOR CONTRIBUTIONS

Gyula Kovacs: Conceptualization; data curation; formal analysis; funding acquisition; investigation; methodology; project administration; resources; software; supervision; validation; visualization; writing – original draft; writing – review and editing. **Chenglin Li:** Conceptualization; methodology; software; writing – original draft; writing – review and editing. **Geza G Ambrus:** Conceptualization; formal analysis; methodology; software; writing – original draft; writing – review and editing. **Mike Burton:** Conceptualization; formal analysis; supervision; validation; writing – original draft; writing – review and editing.

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DATA AVAILABILITY STATEMENT

Data and all applied codes of Li et al (2022) are uploaded to OSF (https://osf.io/2czu5/). We have also uploaded the experimental stimuli, with the exception of personal photos of the participants and their friends, as well as the currently used scripts. The conditions of our ethics approval do not permit public archiving of these images and of study data. The entire data and stimulus sets will be made available to interested researchers following completion of a data sharing agreement and approval by the local ethics committee. The Matlab scripts for EEG preprocessing and MVPA analysis are available under https://osf.io/8zywd/. No part of the study procedures or analyses was pre-registered prior to the research being conducted.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Table S1. Results of the time-resolved identity classification for each familiarity level, separately for ID pairs differing also in gender

Figure S1. Time-resolved decoding accuracies (Shaded regions represent SEM) separately for the six familiarity conditions. Red curves represent within-gender, while green curves represent between-gender decoding performances for ID pairs.

Figure S2. The direct comparison of the ID decoding capacity temporal-dynamics for PF and HF.

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