THE PSYCHOPHYSICS OF EMPATHY: USING REVERSE-CORRELATION TO QUANTIFY THE OVERLAP BETWEEN SELF & OTHER REPRESENTATIONS OF EMOTIONAL EXPRESSIONS

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ABSTRACT

Empathy, theory of mind and imitation, all key building blocks of human social cognition, are thought to rely mechanistically on overlapping representations between the self and the others, but the extent and informational content of such overlap has been difficult to quantify experimentally. Here, we report on a novel psychophysical paradigm in which real photographs of participants' own faces can be manipulated algorithmically to generate arbitrary facial expressions. Using reverse-correlation, we show that we can reconstruct what sensory representations subserved participants' perception of their and another person's smiling face, in a way that can be compared within and across participants. Using this procedure, we show that participants' mental representations of their own smiling face generally matched the representations they had of others', but were unrelated to how participants actually smiled. Strikingly, similarities between self- and other-representations correlated with participant empathy and alexithymia: participants high on empathy mentally represented others as more similar to themselves, and participants low on alexithymia more accurately represented how they actually smile.

Our current understanding of social cognition is that it is subserved by a series of cognitive functions, such as empathy[42], theory of mind [23] and mimicry [11], that are all conditioned on the existence of overlapping representations between the self and the other [17, 50]. Empirical evidence for this representational overlap stems notably from the observed spatial similarity of neural responses involved e.g. while observing someone's pain and feeling it oneself [42], mentalizing about the behaviour of others and about one's future actions [69], or observing and imitating smiles [39]. Performance on selected behavioural tasks also indicate that, when self and other representations are aligned, we can predict the outcome of one's own actions more accurately than another person's [38] or report on one's own personality traits faster [13].

Yet, while we know that self/other representations overlap and that the extent of that overlap influences social cognition, it has remained difficult to quantify the exact informational content of empathic representations (i.e., "what is shared" between self and other observation, [8, 41]). For instance in facial mimicry, it is unclear whether the same dynamic patterns of facial action unit (AU) activation are involved in the perception of other's smiles [34] and the internal representation and motor programming of one's own smile. These could in fact differ in shape (e.g., participants may imitate facial expressions with a slightly different set of facial muscles that the one they observe, such as *corrugator supercilii* for fear [46]) or spatial resolution (e.g. participant may overrepresent certain parts of their own face, such as the nose and lip [53]); they may also differ in specificity: rather than representing the other's expression and mental states, activation of areas such as the anterior midcingulate cortex (aMCC) found in empathic pain responses may reflect representations of a face's arousal or saliency [41] that are less specific than how the observer would mentally represent their own pain.

Perhaps even more importantly, we have very little understanding whether and how the information content of empathic representations, i.e. the nature and extent of the psychophysical overlap between self and other representations, is subjected to individual differences. People may differ in the resolution of their mental representations of other people's expressions (perhaps linked to the observer's trait anxiety or neuroticism [49] - but see [48]), in the accuracy of their own face representations (perhaps linked to alexithymia [62]), and in how closely they correspond to one another. Yet, while that degree of correspondence is likely critical to such varied social cognitive functions as empathy, mentalizing and imitation [9], we currently have no systematic way to quantify it.

One major methodological difficulty in quantifying the psychophysical overlap between self and other representations is how to access mental representations of the *self*. Research on representations of own's one face so far has mostly used qualitative paradigms involving e.g. drawing one's head outline [7] or pointing to locations on one's own photograph and face [24, 53]. For instance, in [21], participants used a photo-editing tool to manipulate the relative size of selected face areas (eyes, mouth and nose) and increase their perceived attractiveness. While such paradigms allows comparing the relative weight of facial areas in explicit evaluations of self-recognition or self-esteem, they do not provide a psychophysical access into what exact facial features are used to compute these judgements.

In recent years, facial psychophysics has increasingly relied on data-driven paradigms in which observers' classifications of randomly manipulated facial stimuli are used to reconstruct the perceptual representations that underlie their judgments in an agnostic, *a posteriori* manner [3, 35]. That procedure was used, e.g., to uncover subtle differences between the mental representations of reward, affiliation and dominance smiles [61], intense pain and pleasure [12] or, in the vocal domain, confidence and honesty [29]. Two recent studies [51, 47] have used data-driven methods (namely, reverse-correlation or bubbles [55]) to investigate self-representations, by asking participants to rate how much manipulated photographs of a single composite face (the same for all participants) looked like their own face, and then asking a second set of participants to rate the visual properties of the obtained representations. In [51], the perceived valence of the participants' representations of their own face correlated with their self-esteem and extraversion and, negatively, with social anxiety. In [47], the accuracy of the representations (i.e. how much they matched participants' real portraits) also correlated with participant's social self-esteem.

While these studies suggest that data-driven methods can be used to investigate the content of self representations, the direct comparison, within the same observer, of judgements on both self and other stimuli remains difficult. First, because traditional reverse correlation randomizes stimuli in pixel-space [51, 47], the obtained mental representations are quantified relatively to the base stimuli (e.g. how larger the eyes, or how thinner the chin) and their morphological features cannot be directly compared to representations obtained from manipulations of other photographs. Second, while recent data-driven studies have used more advanced generative models in which reverse-correlation noise is added to the space of facial action-unit activations [72], these so far have required using synthetic avatar faces which resemble neither the self or any specific other. To directly compare reverse-correlation representations between self and other stimuli, we would need the best of both worlds, i.e. facial transformations that can not only manipulate high-level visual features such as facial AUs in a manner that's comparable between stimuli, but are also able to do so realistically on a participant's real photograph.

To do so, we developed a novel stimulus generation technique inspired from our recent work in smile synthesis [4], which is able to apply random perturbations of facial expressions in arbitrary face photographs (Figure 1). We used this technique to present participant with randomly manipulated stimuli of both their own face and the face of actors, in the same task, and used reverse correlation to extract and compare how participants mentally represented a common social expression (the affiliation smile [61]) in self and others. Using this procedure (Figure 2), we were able to examine, first, whether participants' mental representations of their own smiling face generally matched the representations they had of others' (i.e. whether they psychophysically *expect* others to produce smiles of similar morphology as their own); second, to test whether similarities in self- and other-representations correlated with participant's empathy and alexithymia. Our hypotheses, which we preregistered [1], were that overlap between self and other representations would statistically associate with participant empathy (e.g. participants high on empathy may mentally represent others as more similar to themselves) and overlap between self representations and actual behaviour would associate with alexithymia (e.g. participant with low alexithymia may have perceptual representations of the self smile that more closely reflect how they actually smile).

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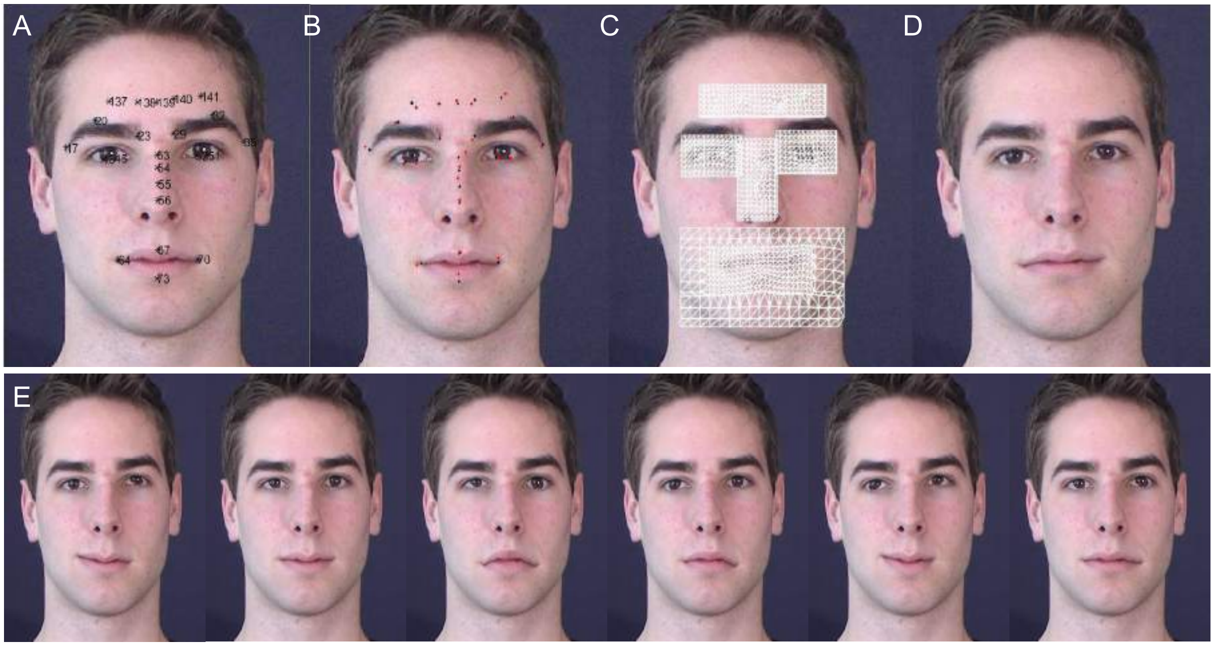

Figure 1: **Stimulus generation:** We generated facial reverse-correlation stimuli using a novel face deformation technique able to apply random perturbations of facial expressions in arbitrary face photographs. **A:** We first use video tracking software to extract the 2D coordinates of the same 23 facial landmarks on the actor's eyes, forehead, nose and mouth. **B:** We then generate new random positions (red) for the landmarks by adding gaussian noise to the (x,y) coordinates of original landmarks (black). **C:** We then deform the original photograph in the neighborhood of each landmark, using a pixel mapping technique called rigid Moving Least Square (MLS). **D:** The resulting image is a smooth interpolation of pixels in between landmarks, mimicking a random facial expression. **E:** Illustration of random manipulations obtained with this procedure. In the present work, we use these photographs as stimuli in two reverse-correlation experiments.

Results

Facial configurations over the group

N=24 participants (M=23.8; female: 12) participated in a series of tasks involving, first, producing a posed smile of affiliation and, then, observing pairs of manipulated facial photographs (in one block, their own face; in another, that of unknown others) to report which expression in each pair is most affiliative (Figure 2). For each participant, this procedure allowed computing three types of psychophysical kernels [55], which described (1) the specific displacement of facial features involved to generate the participant's smiling face from their resting face (*Production kernel*), (2) what displacement should be applied to the participant's own resting face in order to increase the probability that they select the resulting face as affiliative (*Self kernel*) and (3) what displacement should be applied to an unknown other's face in order to increase that same probability (*Other kernel*). All three types of kernels had the same format, and consisted of the (x,y) coordinates of the displacement vectors for each of 23 facial landmarks (left eye: 2 points; left eyebrow: 3; right eye: 2; right eyebrow: 3; nose: 4; forehead: 5; mouth: 4), in normalized, arbitrary units of displacement - see *Materials and Methods*.

To test for the statistical significance of kernel deviation at each landmark over the group (N=24), we projected each landmark's (x,y)-deviation (in each of the N=24 individual kernels) on that landmark's averaged direction of deviation over the group, and tested whether that projection statistically differed from zero.

Despite being measured with different stimuli, one week apart, self and other perception kernels were remarkably similar over the group (Figure 3-B & C). Both had significant displacements (at the $\alpha = 0.002$ level, Bonferroni-corrected over 23 landmarks) at the same 3 lip points (*right corner 64*: self: t(23)=12.43, p<.0001; other: t(23)=12.43, p<.0001 – *left corner 70*: self: t(23)=16.62, p<.0001; other: t(23)=14.88, p<.0001 – *lower lip 73*: self: t(23)= 7.63, p< .0001;

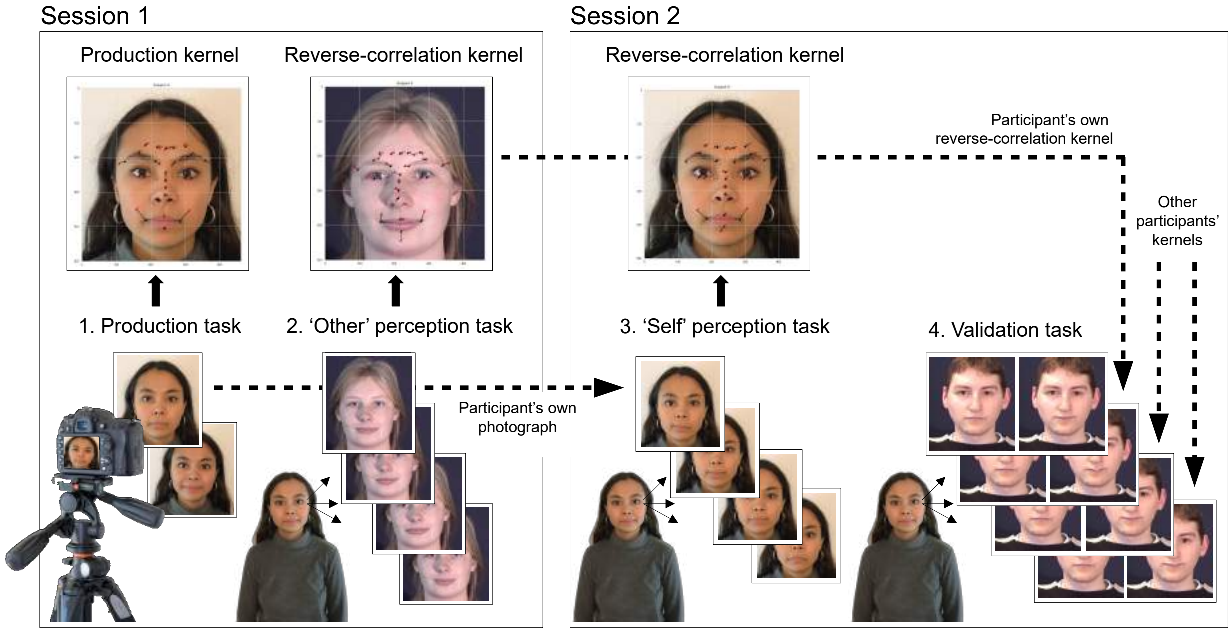

Figure 2: **Experimental set-up:** Participants took part in two experimental sessions, separated by one week; such that data collected in session 1 was used to generate the experimental stimuli for session 2. In session 1 (left), participants were first recorded while displaying a prototypical smile of affiliation; and then participated in a reverse-correlation task judging expressions of affiliation on unknown actors. In session 2 (right), they again participated in the same task, only this time with stimuli corresponding to their own photograph taken from session 1; finally they rated the intensity of smiling faces generated with expressions corresponding to their and all other participants' reverse-correlation results obtained from session 1.

other: t(23)=8.96, p<.0001), and over the 4 eye points (*right lower lid 45*: self : t(23)=4.03, p=.0005; other: t(23)=5.83, p<.0001– *right lower lid 46*: self: t(23)=4.03, p=.0005; other:t(23)=5.83, p<.0001 – *left lower lid 51*: self: t(23)=4.38, p=.0002; other: t(23)=4.21,p=.0003 – *left lower lid 52*: self: t(23)=4.38, p=.0002; other: t(23)=4.21,p=.0003).

Production kernels (Figure 3-A), which correspond to the participants' actual smiling behaviour, featured displacements at the same lip (*right corner 64*: t(23)=26.55, p<.0001 – *left corner 70*: t(23)=41.92, p<.0001) and eye locations (*right lower lid 45*: t(23)=5.48, p<.0001 – *right lower lid 46*: t(23)=5.90, p<.0001 – *left lower lid 51*: t(23)=5.26, p<.0001 – *left lower lid 52*: t(23)=5.96, p<.0001) as the perception kernels. In addition, production kernels also included significant displacements at a more varied set of landmarks (Figure 3-A) in the nose (landmarks 53,54,55,56; all ps<.0001) and brow regions (landmarks 17,20,23,29,32,35; all ps<.002). These latter changes likely reflect more global changes of facial configurations (e.g. a general downward change of face inclination) than what can be explored by the reverse-correlation stimuli used in the two perception tasks.

To quantify morphological differences between kernels, we then used principal component analysis (PCA) to re-encode each kernel along a set of more meaningful facial deviation patterns in the eye and lip regions, learned from the data (see **Materials and Methods**). We extracted 4 principal components (PCs) from the eye region, which we found corresponded approximately to facial action units AU7 (lid tightening), AU5 (lid raiser), AU6 (cheek raiser) and AU46 (wink) (Figure 3-D, top). Similarly, we extracted 4 PCs over the 4 mouth lip landmarks, which corresponded approximately to AU20 (lip stretcher), AU12 (lip corner puller), AU16 (lower lip depressor) and AU14 (dimpler) (Figure 3-D, bottom).

We tested for morphological differences between the three types of kernels with separate repeated-measure ANOVAs on kernel weights along each of the 8 PCs, using kernel type (production, self perception, other perception) as within-factor (Bonferroni-corrected level $\alpha = .00625$). In the mouth region, the kernels significantly differed along the PC1 (lip stretcher) dimension (F(46,2)=56.09, p<.0001), with actual smiling behaviour (production) involving more horizontal stretching than self and actor perception kernels (Figure 3-E). In the eye region, the kernels also differed along PC1 (lid

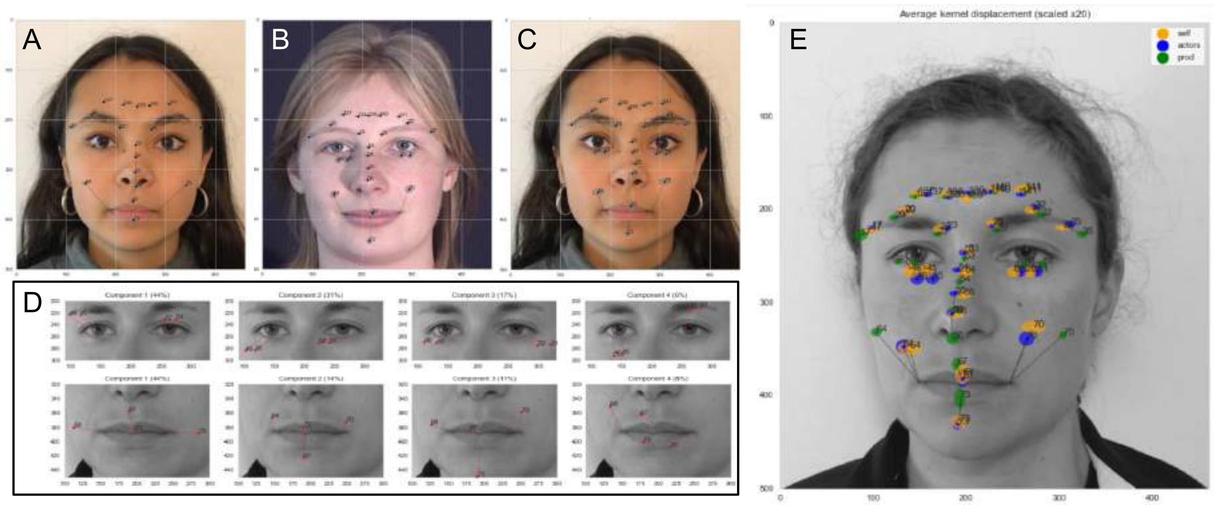

Figure 3: **How smiling differed between self-perception, other-perception and actual behaviour. A:** Production kernels, computed using face tracking software on video recordings of the participant's actual smiling behaviour, represent the displacement to be applied to the participant's resting face to generate their smiling face. **B:** Other-perception kernels, computed using psychophysical reverse-correlation, represent the displacement to be applied to an unknown person's photograph in order to increase the probability that the participant selects the face as smiling. **C:** Self-perception kernels are the same as (B), using a task where the participant judges photographs of their own face. **D:** Principal components extracted from the deviations of the 4 eye (top) and 4 lip (bottom) landmarks, over the set of all 3 kernels for all 24 participants. **E:** Overlay of the three kernels (A,B,C) on the same participant's face. Despite being measured with different stimuli, one week apart, self and other perception kernels were remarkably similar over the group; while production kernels displayed wider lip stretching and eye tightening.

tightening; more in production, $F(46,2)=56.62$, $p<.0001$), PC2 (lid raiser; more in perception, $F(46,2)=7.78$, $p=.001$) and PC3 (cheek raiser; more in production, $F(46,2)=12.86$, $p<.0001$).

Kernel comparisons between tasks at the individual level

To examine whether participants had similar perceptual strategies between self and other perception, and whether these corresponded to their individual smiling behaviour, we then computed correlations between the PC weights of the different types of kernels across the group of N=24 participants. Participants' self and other representations correlated for 3 of the 4 lip principal components (PC1: R=0.588, p=.0025; PC2: R=0.555, p=.0049; PC3: R=0.518, p=.0095; Bonferroni-corrected $\alpha = .00625$) as well as, marginally, in one eye component (PC4: R=0.424, p=.0390; albeit non-significantly). This indicates that, at least in the mouth region, participants used similar perceptual representations to judge smiles of affiliation in both the self and other: participants who internally represented their own smiling face with e.g. wider lip stretch (Figure 4-A) also represented others with wider smiles.

In contrast, there was strikingly no correlation between the participants' self perception and production kernels, on any of the lip (all ps>0.31) and eye region PCs (all ps > 0.14), nor between the participants' other perception and production kernels (lip: all ps >0.34; eye: all ps >0.08). This indicates that participants' internal representations of how they thought of themselves and others are not directly correlated with how smiles are really produced. For instance, all produced smiles have a wider stretch than in perception, but over the group there was no systematic relation between the individual degree of stretch between production and perception.

In short, kernel comparisons at the individual level provides psychophysical evidence that participants internally represent others using similar representations as they use to perceive themselves, but also that these self-representations are not significantly correlated with how they really produced smiles.

Correlations with individual differences in empathy and alexithymia

At the end of the procedure, participants completed two questionnaires measuring alexithymia (Toronto Alexithymia Scale, TAS-20) and trait empathy (Basic Empathy Scale in Adults - BESA, see **Materials and methods**).

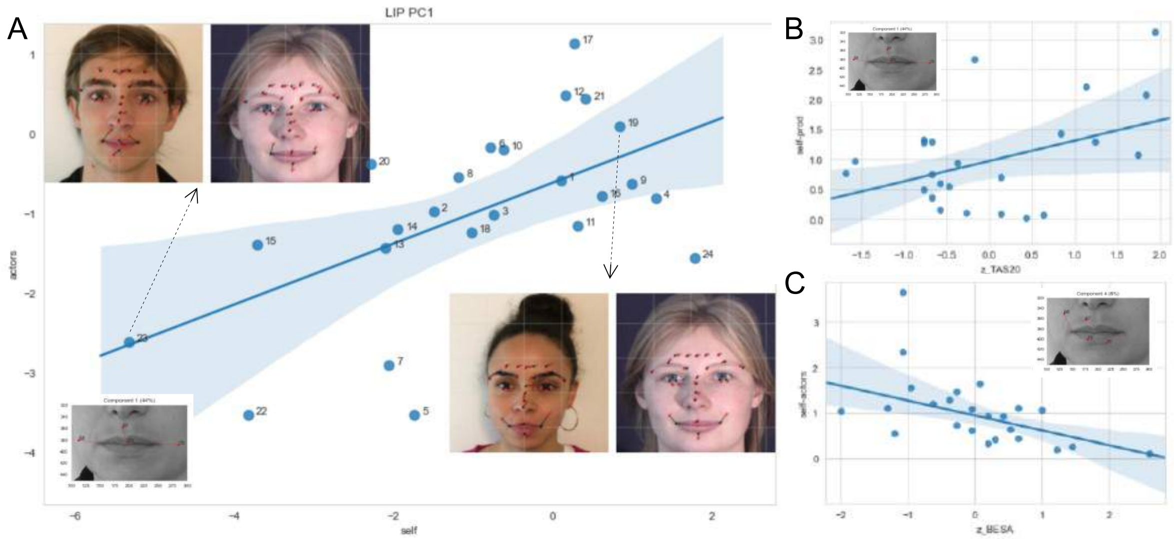

Figure 4: **Similar perceptual representations underlie self and other perception, and are modulated by individual characteristics in empathy and alexithymia. A:** Participants' self and other representations correlated for 3 of the 4 lip principal components (here, PC1, lip stretcher) and one eye component: illustrated here, participants who internally represented their own smiling face with e.g. wider lip stretch also thought of others as having wider smiles. **B:** Positive correlation between the distance of participants' production and self-perception kernels along lip PC1 (lip stretcher) and participant alexithymia: Participants scoring high on alexithymia had representations of their own smiling face that differed more from their actually produced smiles than participants low on alexithymia. **C:** Negative correlation between the difference of self and other perception kernels along lip PC4 (dimpler) and participant empathy: the sensory representations of self and others in participants with more empathy were more closely matched.

We first tested for possible statistical associations between individual kernel morphology (e.g., whether participants see themselves smiling with wider lip stretch, using the self-perception kernel weights along lip PC1) and individual differences in alexithymia and empathy, using separate correlations for each PC, kernel type (production, self, other) and questionnaire. As could be expected, there was no evidence that individual alexithymia and empathy influenced how participants smiled (Production: all ps $>$.04, $\alpha_c orr = .003$), or internally represented smiles either in the self (all ps $> .11$) or in others (all ps $>$.056).

We then tested for possible associations between the *similarity* of kernel morphologies between tasks (e.g. the extent to which participants internally represented themselves smiling with a similar morphology as their actual smiling behaviour, computed as the difference between production and self-perception kernel weights along each face PC) and individual characteristics. Although these associations were limited and our statistical power was only moderate (achieved power $1-\beta$=.81 for R=0.5, N=24), they were all in our predicted directions: first, we found a significant (albeit non-corrected) positive correlation between the distance of production and self-perception kernels along lip PC1 (lip stretcher) and participant alexithymia: R = 0.453, p=.026, corrected $\alpha = .00625$ (Figure 4-B). This suggests that participants scoring high on alexithymia had representations of their own smiling face that differed more from their actually produced smiles than participants low on alexithymia. In contrast, alexithymia did not associate with any measure of distance between self and other kernels.

Second, although self and other kernels were tightly correlated for most facial PCs (Figure 4-A), their difference along one non-correlated component (lip PC4, R=0.188, p=.38) was significantly, and negatively, correlated with participant empathy: R = -0.550, p=.0053, corrected $\alpha = .00625$ (Figure 4-C). This suggests that the sensory representations of self and others in participants with more empathy were more closely matched on fine aspects of smile morphology (here, AU14 - *dimpler*). Contrary to alexithymia, empathy did not associate with any measure of distance between self and production kernels.

Behavioral consequences of kernel morphology on perceived smile intensity

Finally, to validate whether individual differences in kernel morphology have behavioral consequences on how participants evaluate smiles, we applied the N=24 individual smile kernels learned from the **Other perception** task to 6

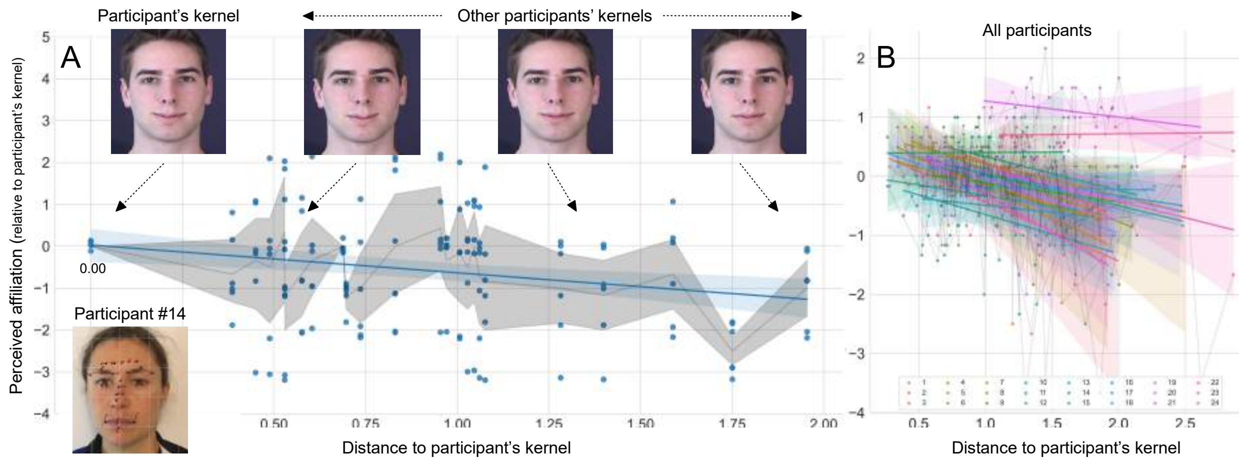

Figure 5: **Participants judged their own idiosyncratic smile as more affiliative than other participant's. A:** A participant's set of judgements of the intensity of affiliative display in faces manipulated with their own and others' smile kernels, ranked by increasing distance to the participant's own kernel. The more stimuli matched the participant's own kernel (left), the more affiliative they though they were. Faces on top illustrate experimental stimuli (kernels applied to actor photographs). Face in bottom left illustrates the participant's own kernel, which is the same as applied in the top leftmost stimuli. **B:** Individual slopes linking (normalized) ratings of affiliation to the distance between the presented kernel and the observer's own kernel were all significantly negative.

additional actor photographs. In a separate rating task, we then let the same N=24 participants judge the intensity of affiliation in manipulated and non-manipulated photographs that, without their knowing, represented either their or everybody else's kernels (see **Materials and Methods**).

As expected, participants judged photographs manipulated with smile kernels overall more intensely affiliative than the corresponding non-manipulated photographs (M=6.49>5, $t(24) = 17.465$, $p < .001$). However, observers ratings of stimuli constructed with other participants' kernels differed according to how well they matched their own kernel. For each participant, we ranked all n=24 stimuli by increasing distance to the participant's own kernel, and found that the individual slopes linking (normalized) ratings of affiliation to the distance between the presented kernel and the observer's own kernel were all significantly negative (rm-correlation: $r(527)=-0.35$, 95% CI [-0.42,-0.27], p=2e-16). In other words, observers judged facial affiliation using their own kernel as a yardstick: the more stimuli matched the observers' own reverse-correlation kernels, the more affiliative observers thought they were (Figure 5).

Discussion

Empathy, theory of mind and imitation, all key building blocks of human social cognition, are thought to rely mechanistically on overlapping representations between the self and the others [17], but the extent and informational content of such overlap has been difficult to quantify experimentally [8, 41]. Here, we designed a novel psychophysical paradigm in which real photographs of participants' own faces can be manipulated algorithmically to generate arbitrary facial expressions. Using reverse-correlation, we then reconstructed what sensory representations subserved participants' perception of their and another person's smiling face, in a way that can be compared and correlated to individual differences in empathy and alexithymia. We also used the same computational techniques to compare with how participants really smiled, in a posed production task.

While our participants' representations of affiliation smiles generally matched what was known from previous research (displacements in the mouth area corresponding to AU20-16-16-14 and in the eye areas corresponding to AU7-5-6-46; Figure 3-E), we found that each participant had a subtly idiosyncratic way to produce and represent smiling faces, involving various degrees of horizontal *vs* vertical lip motion (Figure 4-A), or eye widening *vs* squinting. While individual differences in the morphology of emotional expressions are a well-described phenomena in the computer science literature attempting to recognize or synthesize facial emotions [59, 73], this phenomenon is relatively under-studied in the psychological literature [14]. Individual differences in smile morphology (e.g. wider or narrower lip stretch) may have anatomical causes such as musculoskeletal differences in e.g. muscle insertion [20] or may be grounded in cultural/developmental factors such as parental imitation [52]. Here, we did not find reliable associations between participants' kernel morphology and individual differences in alexithymia and empathy (for instance, participants higher on empathy did not tend to smile e.g. with broader smiles), which is perhaps unsurprising. Nevertheless, our paradigm would easily allow investigating associations with a wider range of individual factors, such as personality and interpersonal constructs, and comparing siblings and parents from the same family [58].

These individual differences in how participants internally represented the smile of others (other kernels) were not only covert psychophysical analytical constructs, but directly translated into overt social evaluative behaviour. Participants judged actors whose photographs were manipulated to smile with features that matched their own reverse-correlation kernels as more affiliative than stimuli that matched other participants' kernels (Figure 5). This is reminiscent of a variety of resemblance effects where humans favor similar-looking others in trust games [15], political vote [6] and emotional ratings [22]. Because there is some debate whether such effects reflect true social preference for similar individuals or kin, rather than lower-level perceptual advantage for familiar stimuli [26], it would be interesting to test whether the effect of kernel similarity seen here is specific to affiliation judgements, or whether it would also be true for e.g. other types of smiles [61] or facial expressions. More generally, our methodology opens new avenues for learning personalized expression filters from participants, mapping them on photographic or video stimuli of other people, and exploring a variety of self-resemblance effects in (potentially real-time) social interactions [4].

More specific to our research question, while smiles were subtly different from one participant to the next, their morphology was strikingly similar between each participant's self and other perception kernels (Figure 4-A). Because they were measured with different stimuli and one week apart, these similarities are unlikely to result from carry-over effects from one task to another, but rather reflect true psychophysical evidence that participants internally represent others using similar representations as they use to perceive themselves. To date, evidence for the existence of shared representations between self and others were mainly taken in the spatial overlap of neural activity measured in self and other observation tasks [42, 39]. The present results both confirm and extend these findings, by providing a data-driven way to quantify what exact informational content is shared, at the individual level. For instance here, representational overlap was stronger for mouth/lip features than in the eye region, which may indicate that the neural embedding of facial features in areas involved in shared self and other processing over-represents certain areas, e.g. lower over upper face as in somatosensory representations [53]. What facial features are shared or not are likely to have profound mechanistic consequences on e.g. what aspects of a facial expression participants are prone to imitate [46]; it would be interesting, for instance, to test whether a given participant's psychophysical measure of self-other similarity in the mouth and eye regions matches whether they tend to mimic mouth and/or eye behaviour in others. It would also be interesting to investigate whether shared self-other features depend on cultural learning, e.g. in asian populations where facial expressions emphasize eye gaze direction [33]. More fundamentally, these results raise the hard developmental question of whether we first perceive others as ourselves, or perceive ourselves as others [28]. Our paradigm could be used to measure the stability of self and other representations across development, and whether one converges to match the other.

In addition, we found limited but theoretically consistent evidence that the extent of self-other overlap scaled with participant empathy: in particular, the sensory representations of self and others in participants with more empathy were more closely matched on AU14 (Figure 4-C). This result is reminiscent of the fact that individuals showing strong automatic facial mimicry tend to have high levels of empathy [67]. Stronger overlap of self and other representations may be a consequence of empathy, as participants with more empathy may seek and experience more opportunities for perceptual learning involving expressive signals both in the self and others [68]; empathy may also be a consequence of overlap, in that the capacity to emphasize with others may be subtended by sensory representations that allow the accurate co-registering of self and other features. By providing a way to quantify the extent of overlap in self and other representations, the present methodology may provide novel markers of mechanistic dysfunction in psychiatric conditions associated with deficits or even lack of empathy, such as antisocial personality disorders, borderline and narcissistic personality disorders [16], as well as possible targets for interventions [40].

In contrast, we found only limited support for the idea that participants' self- and other-representations would match how they really produced smiles. Participants' self and other kernels on the one hand, and production kernels on the other, were not statistically correlated on any of the facial principal components considered here. In other words, while participants perceptually expected others to smile with similar features (e.g. wide vs narrow lip stretch) as they also envisioned themselves to smile, theses features typically did not represent their actual motor behaviour accurately. This pattern of results appears at odds with "motor simulation" theories of social cognition which argue for the critical involvement of motor or sensorimotor processes in action observation [71, 56]. For instance, preventing participants to smile by e.g. biting on a pen was found to interfere with the accuracy [57], speed [70] and depth [60] of facial expression recognition in others; similarly, patients with lesions in the right somatosensory cortex are poorer at recognizing facial expressions [2]. Here, the fact that self and other mental representations do not seem to be informed by the idiosyncrasies of a participant's genuine motor repertoire rather suggests, with a number of others [36, 65, 45, 32], that motor simulation may not be a necessary constituent in perceiving others' expressive actions. It remains possible, though, that this correspondence between production and perception was obfuscated by measuring the former using only posed expressions of affiliation, or that a stronger correspondence could be elicited using a more challenging perceptual task, as also seen for the involvement of motor areas in speech perception [1]

Even though perception and production kernels were not statistically correlated, we found that how much they differed from one another (on the lip stretcher dimension) scaled with participant alexithymia: participants scoring high on alexithymia (HA) had representations of their own and others' smiling face that differed more from their actually produced smiles than participants low on alexithymia. While alexithymia is typically discussed as a deficits in the representations of emotion words or concepts [5], this result is consistent with past research suggesting that it is also linked to atypicalities in a range of sensory processes including interoception [54], exteroceptive visual and auditory processing [25, 27], and the integration thereof [63, 31]. This is theoretically important in several respects. First, there is debate whether and how cognitive and affective components of alexithymia map to deficits of interpersonal perception and/or empathy [30, 8]. Here, because self and other representations were typically similar in all (including HA) participants, our pattern of results suggest that HA participants not only have difficulties remapping their own somatosensory systems onto emotional expressions seen on their own face, but also in others [31], i.e. that impaired representational overlap in alexithymia is manifest in both intra and extrapersonal processing. Second, given the predominance of overt judgements and self-report in alexithymia research, it has also been suggested that HA individuals in fact have accurate representations of affective responses but that these representations tend to remain consciously inaccessible [43, 66]. Here, the fact that we were able to quantify impaired overlap between exteroceptive and sensorimotor representations psychophysically in a data-driven indirect task suggests that alexithymia is related to genuine impairments at the representational level.

In sum, by providing psychophysical access into the quantity and quality of overlap between self and other representations, we believe our paradigm opens opportunities for novel mechanistic insights into a range of social cognitive functions spanning empathy, theory of mind and mimicry in both health and disease. To support reproducibility and data collection on larger samples and a wider range of populations, we implemented our novel face randomization procedure as part of the open-source reverse-correlation library CLEESE [10], and are making it available with the present article.

Materials and Methods

Participants

N=24 participants (M=23.8; female: 12) took part in the experiment. All were French residents, recruited by the INSEAD-Sorbonne Université Behavioural Lab among a young, western and educated population consisting mainly of university students.

General Procedure

Each participant took part in two experimental sessions, separated by one week, in such a way that the data collected in session 1 was used to generate the experimental stimuli for session 2 (Figure 2).

In the first session, participants were first asked to display an affiliation smile, while their facial expression was captured on camera (see below, **Production task**). Participants then took part in a 30-minute visual reverse-correlation task, in which they were presented pairs of unknown actor photographs with manipulated facial expressions and asked to identify, in each pair, which expression displayed the most affiliative smile (see below, **Other perception task**).

In the second session, participants first took part in another 30-minute visual reverse-correlation task, in which they were this time presented manipulated pairs of their *own* smiling face, obtained from session 1 (see below, **Self perception task**). Participants were then presented with isolated smiling faces of a larger set of unknown actors, each manipulated with all N=24 facial expressions derived from analysing session 1's reverse-correlation data (i.e. actors that smiled according to each participant's preferred smile, as measured experimentally), and asked to rate the intensity of their smiles compared to that of a neutral image using a rating scale (see below, **Validation task**). Finally, participants filled in a questionnaire with items measuring trait empathy (BES-A) and alexithymia (TAS-20).

In summary, between the first and second session, we used data from session 1's **Production** task to obtain a facial photograph of the participant to be used as stimuli for the self-perception task in session 2; and used data from session 1's other-perception task to compute each participant's reverse-correlation kernel, and to apply each of the N=24 kernels to actor photographs for the rating task in session 2. Accordingly, all participants completed session 1, before any one participant started session 2.

Production task

Procedure

At the beginning of session 1, participants were briefly explained what was considered affiliation, told that every person might smile to signal affiliation in a slightly different way, and that we were interested in what their own personal way to signal affiliation was. We then asked each participant to imagine themselves in a situation where they were part of an in-group of friends or colleagues, noticed an out-group bystander looking lonely and hesitant to join the group, and smiled to that person to signal that they were welcome to join in. Each participants then produced between 2-5 dynamic smiles that they judged would be appropriate in that situation, starting from a static neutral face and evolving into a smile over the course of 2-3 seconds. All smiles were captured on video (see video example in SI).

Production kernels

We analysed each participant's video manually to extract two static frames: one of the participant's neutral/resting face, and one at the apex of the smile expression. We then used video face tracking software (Dynamixyz, `https://www.dynamixyz.com`) to detect the boundaries of the participant's face; crop, rotate and resize the two photographs to isolate the face region and normalize its coordinates in the 2D plan; and finally extracted the 2D coordinates of 23 facial landmarks on the left eye (2 points), left eyebrow (3), right eye (2), right eyebrow (3), nose (4), forehead (5) and mouth (4).

Normalized photographs of the participants' resting face were kept to be used as stimuli for session 2's **Self perception** task. In addition, for each participant, we computed the difference between the (x,y) coordinates of all 23 matching landmarks in the resting and smiling face. This 23×2-dimension 'Production kernel' (illustrated in Figure 2 - top,left) represents the displacement to be applied to the participant's resting face to generate their smiling face, and is to be compared to the participant's Other and Self reverse-correlation kernels (see below), which have the same format.

Self and Other perception task

Image generation procedure

We generated facial reverse-correlation stimuli using a novel face deformation technique inspired from our recent work in visual smile synthesis[4], and which is able to apply random perturbations of facial expressions in arbitrary face photographs. Using a single photograph of one unknown actor's resting face, we first used video tracking software to extract the 2D coordinates of the same 23 facial landmarks on the actor's eyes, forehead, nose and mouth as for the above Production kernels (Figure 1-A); we then generated new random positions for the landmarks by adding gaussian noise to each of the (x,y) coordinates: $X_i^d = X_i + \mathcal{N}_i(0, \sigma)$ where $X_i = (x_i, y_i)$ are the original coordinates of the i^{th} landmark, X_i^d their newly-obtained deformed coordinates and $\mathcal{N}_i$ is a random sample from a truncated gaussian distribution of mean $\mu = 0$, standard deviation σ, truncated at $\pm 2\sigma$. In order to obtain realistic deformation, we set σ empirically to be equal to $1/20^{th}$ of the pixel distance between the eyes of the original photograph (Figure 1-B). We then deformed the original photograph to match the position of the new landmarks, using a pixel mapping technique called rigid Moving Least Square (MLS) [64]. MLS produces a function f that maps pixels in the undeformed image to the deformed image, in a manner which transforms landmarks X_i to X_i^d, and smoothly interpolates all pixels in between. As in our previous work [4], we make here two approximations to the standard MLS procedure: first, we apply MLS only to areas of the image around the eyes, mouth, nose, and forehead regions, and leave other regions untransformed. Second, we do not apply the algorithm to every pixel of these areas but approximate the areas with grids and apply the deformation function to each vertex in the grid (Figure 1-C). We then fill the resulting triangles using affine warping (Figure 1-D). Figure 1-E illustrates some possible outputs of the procedure. For reproducibility purposes, we implemented this novel face randomization as part of the open-source reverse-correlation library CLEESE [10], and make it available with the present article.

Stimuli

In the **Other perception** task (session 1), we used the procedure above to generate, for each participant, two sets of 1,400 random face manipulations using one male and one female actor photograph (Figure 2-2). All random stimuli were different from one participant to the other, resulting in $2 \times 1{,}400 \times 24 = 67{,}200$ manipulated photographs.

In the **Self perception** task (session 2), we used the same procedure to generate, for each participant, one set of 1,400 random face manipulations using the participant's own photograph, as taken from session 1's **Production** task (Figure 2-3).

Procedure

In both tasks, participants were presented with pairs of random facial manipulations (2×700 pairs for the male and female actor in session 1; 700 pairs for their own face in session 2). Participants were asked, in each pair, which of the two manipulated face displayed the most affiliative smile (2-alternative forced choice).

In both tasks, pairs were presented in blocks of 100 trials, separated by a short pause. In the **Other perception** task, all pairs from a single actor were presented in successive blocks (male: 7 blocks; female: 7 blocks), and the order of the actors was counter-balanced across participants. The whole procedure took about 40 min in session 1 for the **Other perception** task (1,400 trials) and 20 min in session 2 for the **Self perception** task (700 trials).

Reverse-correlation kernel

For each participant and each task, we computed first-order kernels from reverse-correlation data using the classification image method [55]. We computed the average random (x,y) displacement for each of the 23 landmarks in the n=700 photographs classified as affiliative, and subtracted the average random displacement of the photographs classified as non-affiliative. Kernels were then normalized by dividing them by the absolute sum of their values. For each participant, this procedure resulted in a 2×23 vector of (x,y) coordinates, of the same format as the participants' Production kernels (see above), and representing the displacement to be applied to a given photograph in order to increase the probability that the resulting face be selected as affiliative by a given participant.

Kernel statistics

Statistical significance

To test for the group statistical significance of the kernel deviation at each landmark, we projected each landmark's (x,y)-deviation (in each individual kernel) on that landmark's averaged direction of deviation over the group, and tested whether that projection statistically differed from zero: first, we computed group-average kernels by averaging landmark deviation over the participant's individual kernels; for each participant and each landmark, we then computed the dot product between the landmark's (x,y)-deviation and the group's (x,y)-deviation; finally, for each landmark, we tested that the mean dot product of the group's distribution differed from zero using a one-sample t-test, Bonferroni-corrected for the number of landmarks (23).

Kernel similarity

To quantify the similarity of kernels at the individual level, e.g. to correlate self and other kernels over the group (Figure 4), we used principal component analysis (PCA) to re-encode each kernel along a set of more meaningful facial deviation patterns in the eye and lip regions, learned from the data.

Specifically, we re-encoded the kernel (x,y)-deviations over the 4 eye landmarks along 4 principal components (PCs), learned over 72 4-dimensional observations corresponding to the displacements of the 4 eye landmarks in the N=24 individual kernels × 3 tasks. We found that the 4 eye PCs corresponded approximately, in order to explained variance, to Ekman's upper facial action units [19] *AU7 - lid tightening* (PC1, 44%), *AU5 - lid raiser* (PC2, 31%), *AU6 - cheek raiser* (PC3, 17%) and *AU46 - wink* (PC4, 6%; Figure 3-D, top). Similarly, we extracted 4 PCs over the 4 mouth lip landmarks, which corresponded a posteriori to *AU20 - lip stretcher* (PC1, 44%), *AU12 - lip corner puller* combined with *AU24 - lip pressor* (PC2, 14%), *AU16 - lower lip depressor* (PC3, 11%) and *AU14 - dimpler* (PC4, 8%; Figure 3-D, bottom).

All correlations and distances between kernels in the present work were then computed as the absolute difference of the kernel weights along each of the above 8 PCs.

Validation task

Stimuli

We applied the N=24 individual smile kernels learned from the **Other perception** task to 6 actor photographs (3 male, 3 female), using the same procedure as used to generate the random reverse-correlation stimuli: face tracking software was used to extract 23 landmark coordinates in the neutral/resting photographs of each actor; these coordinates were then modified by adding the (x,y)-deviation of each kernel; and the manipulated photograph was reconstructed using MLS. Because reverse-correlation kernels were normalized to arbitrary units, we multiplied their pixel intensity by an empirical factor of 5 in order to generate macroscopically visible facial expressions.

Procedure

Participants were presented with 144 pairs of photographs (6 actors $\times$ 24 kernels), each composed of one neutral face and one manipulated expression of the same actor. In each pair, the manipulated expressions corresponded to smile kernels learned from the **Other perception** task in session 1. Each participant rated trials manipulated with the kernels obtained from all participants, including themselves: among these trials, 6 corresponded to photographs manipulated with the participant's own kernel, and $6\times23=138$ to photographs manipulated with kernels obtained from other participants (Figure 5-A). Participants were unaware that the expressions were manipulated based on their and other participants' data, and which kernel each trial corresponded to.

In each pair, participants were thenasked to judge the intensity of the affiliative expression in the manipulated photograph, compared to the neutral face, using a 9-point Likert scale anchored by 0: *a lot less affiliative*; 5: *similarly affiliative*; 9: *a lot more affiliative*. All trials were presented in random order.

Empathy and Alexithymia questionnaires

Finally, participants filled in a questionnaire with items measuring trait alexithymia and empathy. We measured participant's alexithymia using the French version of the Toronto Alexithymia Scale (TAS-20) [5, 44]. The TAS-20 is a self-report scale composed of 20 items measuring a respondent's difficulty to identify emotions (5 items, e.g. *"When I am upset, I don't know if I am sad, frightened, or angry."*), describe emotions (7 items, e.g. *"It is difficult for me to find the right words for my feelings"*) emotions, as well as their tendency to focus their attention on "externally", non-psychological things (8 items, e.g. *"I prefer talking to people about their daily activities rather than their feelings"*). All items are rated using a 5-point Likert scale anchored by 1: *strongly disagree* and 5: *strongly agree*; and 5 items (items 4, 5, 10, 18 and 19) were reverse-coded. The total alexithymia score is the sum of responses to all 20 items, with scores greater than 61 generally taken as indicating alexithymia.

We measured participant's trait empathy using the French version of the Basic Empathy Scale in Adults (BES-A) [37, 18]. The BES-A is self-report scale composed of 20 items measuring a respondent's cognitive empathy (9 items, e.g. *"I have trouble figuring out when my friends are happy"*) and affective empathy (11 items, e.g. *"I get caught up in other people's feeling easily"*) empathy. All items are rated using a 5-point Likert scale, 7 of them reverse-coded. Total empathy score ranges from 20 (deficit in empathy) to 100 (high level of empathy).

Ethics: All participants tested at the Sorbonne-INSEAD Center for Behavioral Science. The experiment was approved by the Institut Européen d'Administration des Affaires (INSEAD) IRB (Study"Représentations Mentales du Sourire Visuel"; decision of 25 October 2019). All participants gave their informed consent for the study, were debriefed after the study, and were compensated for their participation at a standard rate.

Data Access: Experimental data and analysis code (open-source, Python) will be made available as supplementary material with the final manuscript

Authors contributions: SZ, CS and JJA designed the experiment. SZ and CS implemented the image transformation technique. SZ and JJA collected data. JJA analysed data, with contributions of SZ and CS. JJA wrote the manuscript.

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