



# Temporal self-compression: Behavioral and neural evidence that past and future selves are compressed as they move away from the present

Sasha Brietzke<sup>a</sup> and Meghan L. Meyer<sup>a,1</sup>

<sup>a</sup>Department of Psychological and Brain Sciences, Dartmouth College, Hanover, NH 03755

Edited by Jonathan W. Schooler, University of California, Santa Barbara, CA, and accepted by the Editorial Board October 13, 2021 (received for review January 25, 2021)

**A basic principle of perception is that as objects increase in distance from an observer, they also become logarithmically compressed in perception (i.e., not differentiated from one another), making them hard to distinguish. Could this basic principle apply to perhaps our most meaningful mental representation: our own sense of self? Here, we report four studies that suggest selves are increasingly non-discriminable with temporal distance from the present as well. In Studies 1 through 3, participants made trait ratings across various time points in the past and future. We found that participants compressed their past and future selves, relative to their present self. This effect was preferential to the self and could not be explained by the alternative possibility that individuals simply perceive arbitrary self-change with time irrespective of temporal distance. In Study 4, we tested for neural evidence of temporal self-compression by having participants complete trait ratings across time points while undergoing functional MRI. Representational similarity analysis was used to determine whether neural self-representations are compressed with temporal distance as well. We found evidence of temporal self-compression in areas of the default network, including medial prefrontal cortex and posterior cingulate cortex. Specifically, neural pattern similarity between self-representations was logarithmically compressed with temporal distance. Taken together, these findings reveal a “temporal self-compression” effect, with temporal selves becoming increasingly non-discriminable with distance from the present.**

default network | self | prospection | retrospection | compression

**A**cross the lifespan, humans change dramatically. Not only do we change in our physical appearance but also in our preferences and even in our personality traits (1–3). Moreover, people both appraise that they have changed from their past (4–6) and expect to make changes in the future (7–12). In the face of these real and perceived changes, many scholars have wondered how we mentally map our separate selves that vary across time. One popular idea suggested by modern philosopher Derek Parfit is that temporal selves are organized as a chain, with selves closer in time overlapping with one another (13). Yet, despite widespread interest and speculation on identity over time, empirical research has not yet fully determined the representational structure of temporal selves.

Insight may come from cognitive psychology and neuroscience research on how distance from an origin point impacts perception and mental representation of later points. Weber–Fechner law refers to the observation that across perceptual domains (vision, hearing, taste, touch, and smell), physical changes in stimuli are logarithmically compressed in perception such that the farther they are from an original stimulus, the less well people differentiate between them (14). Specifically, in the cognitive sciences, “compressed representation” refers to the phenomenon in which representations do not show the same degree of acuity for all parts of the scale on which they are measured, with later ends of the scale harder to tell apart (i.e., “compressed”) than earlier ends of the scale (14, 15).

Representations outside of direct perception demonstrate a similar compression phenomenon. The internal representation of numbers abides by logarithmic compression, including in the neuronal code of monkey prefrontal cortex (16–18). For example, in humans, numbers of greater magnitude become less distinguishable on the number line than numbers of smaller magnitude (15, 19–21). Moreover, there is evidence that memories are also logarithmically compressed with time: the farther from the present the memory, the less discriminable it is from an earlier memory (22–24). Indeed, it has been suggested that it is easier to recall recent events because they “pop out” during retrieval, whereas it is easier to knit distal memories together because the far past has reduced representational acuity between memories (15).

Given that information is compressed with distance across several psychological domains, might the same principle apply to self-representation? Although to our knowledge, no research has tested whether self-representations are temporally compressed (i.e., logarithmically compressed with temporal distance from the present), there is social psychological evidence consistent with this possibility. People think their distant future self will be less nuanced than their more recent and present self (25–27), which suggests a lack of uniqueness in distant temporal self-representations. There is also extensive evidence in

## Significance

**For centuries, great thinkers have struggled to understand how people represent a personal identity that changes over time. Insight may come from a basic principle of perception: as objects become distant, they also become less discriminable or “compressed.” In Studies 1–3, we demonstrate that people’s ratings of their own personality become increasingly less differentiated as they consider more distant past and future selves. In Study 4, we found neural evidence that the brain compresses self-representations with time as well. When we peer out a window, objects close to us are in clear view, whereas distant objects are hard to tell apart. We provide evidence that self-perception may operate similarly, with the nuance of distant selves increasingly harder to perceive.**

Author contributions: S.B. and M.L.M. designed research; S.B. performed research; S.B. analyzed data; and S.B. and M.L.M. wrote the paper.

The authors declare no competing interest.

This article is a PNAS Direct Submission. J.W.S. is a guest editor invited by the Editorial Board.

This open access article is distributed under Creative Commons Attribution-NonCommercial-NoDerivatives License 4.0 (CC BY-NC-ND).

<sup>1</sup>To whom correspondence may be addressed. Email: meghan.l.meyer@dartmouth.edu.

This article contains supporting information online at <http://www.pnas.org/lookup/suppl/doi:10.1073/pnas.2101403118/-DCSupplemental>.

Published November 30, 2021.

support of construal level theory from social psychology (28), which contends that when we reason about distal pasts and futures (including distal past and future selves), we focus on more abstract (versus concrete) features (29). Thus, construal level theory is compatible with the idea of logarithmic compression, as temporally compressed past and future selves would provide less discriminable features to reason about and hence facilitate relying on abstractions. Despite these clues, to date, it remains unknown whether distant past and future selves, like other perceptions and cognitions, are compressed with distance from the present self.

The current research bridges social psychological findings on changes in self-perception across time with psychophysical principles regarding compressed representations to gain traction on how self-continuity may break down as people reflect on themselves farther out in time. Our first goal was to assess the possibility of “temporal self-compression”: whether changes in self-perception are logarithmically compressed such that the farther they are from the present, the less differentiated they become. In Studies 1 through 3, we leveraged social psychological findings that people tend to perceive they will be better versions of themselves in the future (8–12) and were worse versions of themselves in the past (4–6) to test our predictions. Participants rated themselves on multiple positive personality traits across various points in their past and future. The temporal self-compression hypothesis posits that the amount of perceived future self-improvement (e.g., in confidence) will be greater between time points closer to the present than between time points farther in the past and the future. Just as numbers of greater magnitude become less distinguishable on the number line than numbers of smaller magnitude, selves of greater distance from the present self will become less distinguishable in their amount of change than selves closer to the present self.

Our second goal was to seek neural evidence of temporal self-compression. Assessing this possibility is critical to the temporal self-compression hypothesis, as it would suggest that self-report evidence of self-compression is not wholly due to biased reporting but rather may reflect an underlying self-representation that is compressed with time. There is extensive evidence that self-representations are supported by the brain’s default network (30, 31), particularly medial prefrontal cortex (MPFC) (32, 33). For example, the MPFC has been robustly implicated in self-reflection tasks, such as assessing one’s own personality traits (34–36), reflecting on one’s own emotions (37, 38), and engaging in self-affirmation (39–41). To date, brain-imaging research investigating the impact of time points on self-representation has found that MPFC is more associated with reflecting on the present self versus the past and future self (42–44). However, no brain-imaging research has parameterized the distance into the past and future with which participants consider the self, and thus, it is unknown whether self-representation in the MPFC follows a temporal self-compression principle.

To determine whether brain regions, particularly MPFC, show evidence of temporal self-compression, in Study 4, participants considered their past and future selves’ positive and negative personality traits across multiple time points while undergoing functional magnetic resonance imaging (fMRI). Our brain-imaging paradigm further allowed us to arbitrate between two possible ways in which the brain may compress self-representations with time. One possibility is that past and future selves are compressed as their own, separate representations: past selves may be represented separately in the brain from future selves, distinctly compressed away from the present self. Because the brain-imaging paradigm included positive and negative traits, we were able to test whether—beyond valence differences between appraisals of past and future selves (5, 7, 8, 10–12)—temporal selves may be distinctly represented from one another and separately compressed away from the present. The alternative possibility, however,

is that the temporal compression of self-representations is organized irrespective of past versus future. That is, past and future selves may be collectively compressed with time away from the present. This possibility is consistent with cognitive neuroscience research suggesting that prospection and retrospection rely on overlapping neural mechanisms in the default network, including MPFC (45, 46). Multivariate pattern similarity analysis was used to determine which of these competing possibilities underlies temporal self-compression. Across studies, if findings support our hypotheses, they would provide evidence of temporal self-compression and how it is reflected in the brain.

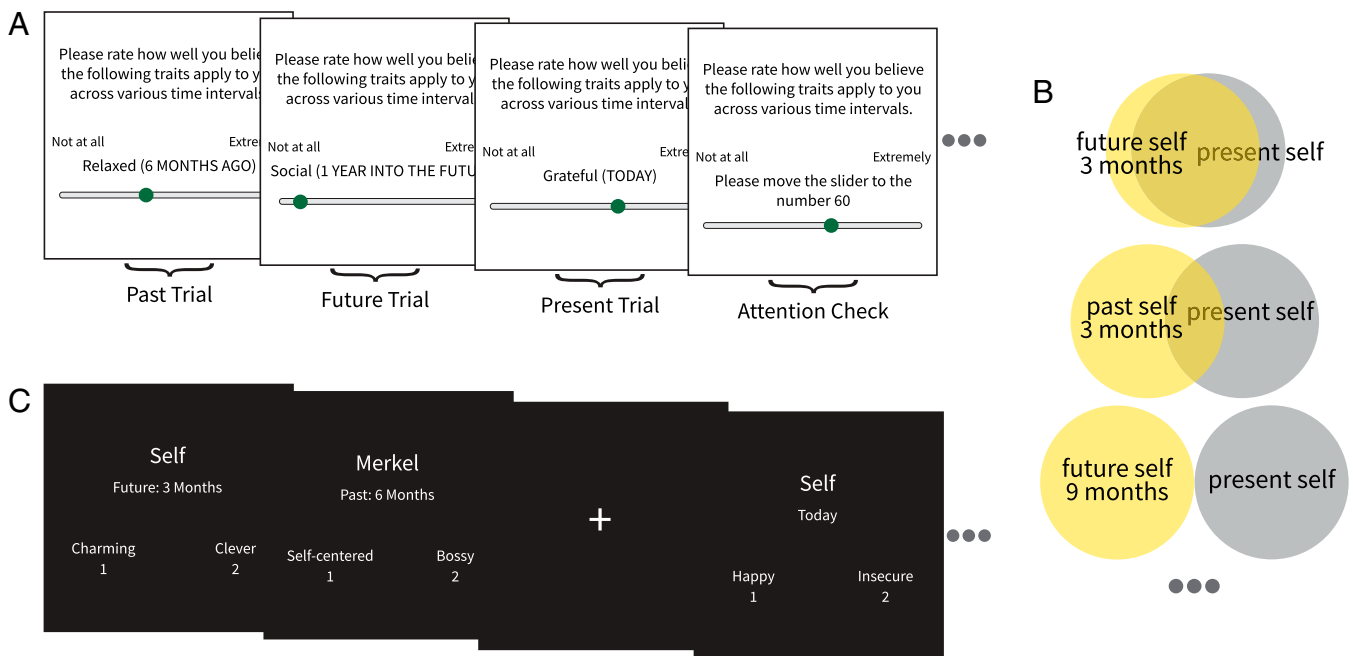
## Results

**Study 1a and 1b.** The goal of Study 1 was to test whether perceptions of past and future selves are logarithmically compressed with distance from the present. Participants ( $n = 178$ ) rated themselves on 20 positive personality traits (0, not at all to 100, extremely; Fig. 1A, Study 1a). Positive personality traits were selected to be in line with past social psychology research, which consistently shows that individuals appraise their past self less positively than their present self and their future self more positively than their present self (4, 5, 10–12), while still testing the prediction of temporal self-compression. Personality traits for all studies were normed for perceived change using ratings from an independent sample (see *Materials and Methods*) and controlled for likeability using the Dumas person-descriptive word list (47). Each trait was rated across nine time points, up to 1 y in the future and 1 y in the past. The 1-y range was selected because past work shows that considering the self as early as 1 y away from the present is enough to show disconnection from the self (43). This observation allowed us to therefore ask whether self-perceptions are compressed as they move closer to this distance. Every time scale rated was spaced 3 mo apart. Trait presentation was fully randomized across time points.

A linear mixed model revealed a significant linear ( $\beta = 2.25$ , standardized  $\beta = 0.24$ ,  $t$ -statistic = 10.14,  $df = 82.78$ , and  $P < 0.001$ ) and cubic ( $\beta = -2.17$ , standardized  $\beta = -0.09$ ,  $t$ -statistic =  $-8.36$ ,  $df = 31,645.86$ , and  $P < 0.001$ ) relationship of time on personality trait ratings. As shown in Fig. 2A, there are rapid changes in self-perception occurring in the time periods adjacent to the present, which then tapers out with increased temporal distance. Note that the cubic effect in this instance is consistent with past work finding logarithmic compression with distance because participants are demonstrating logarithmic compression in separate directions into the past and future, with less positive self-perceptions into the past and more positive self-perceptions into the future.

Given past research showing age impacts temporal self-appraisal (48, 49), we also assessed our model including age as a covariate to rule out the possibility that our findings were solely driven by age. While older people did rate themselves more positively ( $\beta = 7.87$ , standardized  $\beta = 0.09$ ,  $t$ -statistic = 2.30,  $df = 177.46$ , and  $P = 0.021$ ) and exhibited less linear ( $\beta = -2.29$ , standardized  $\beta = -0.07$ ,  $t$ -statistic =  $-3.96$ ,  $df = 390.96$ , and  $P < 0.001$ ) and cubic compression ( $\beta = 2.27$ , standardized  $\beta = 0.03$ ,  $t$ -statistic = 2.47,  $df = 31,645.90$ , and  $P = 0.014$ ) compared to younger adults, our primary effect of cubic compression of trait ratings remained significant when age was included in the model ( $\beta = -10.17$ , standardized  $\beta = -0.09$ ,  $t$ -statistic =  $-3.25$ ,  $df = 31,645.90$ , and  $P = 0.002$ ).

Participants also completed an adapted version of the inclusion of other in self scale (50). Here, participants rated the extent to which they included their present self with a self from another time point. Participants’ responses to this task allowed us to test whether the temporal self-compression effect conceptually replicates in another commonly used assessment of



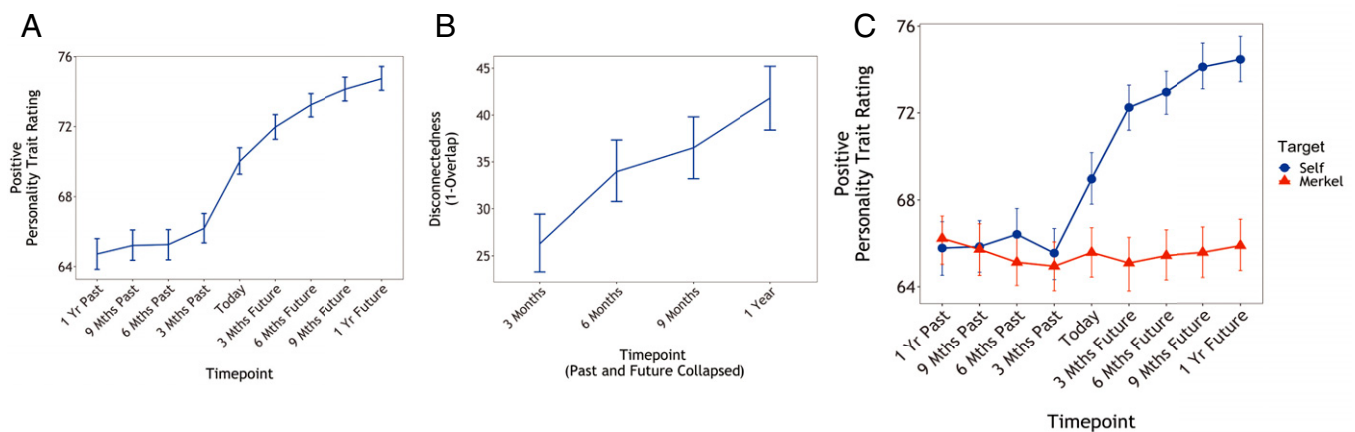
**Fig. 1.** Paradigm schematics. (A) In the behavioral paradigm for Studies 1 through 3, participants rated themselves on positive personality traits on a sliding scale (0, not all to 100, extremely) across nine time points in the past and future. Attention checks that prompted participants to move the slider to a certain value were included to assess data quality. (B) In addition to the trait ratings, participants in Study 1 were prompted to drag a dynamic yellow circle representing a future or past self either closer to or farther away from a gray circle representing a present self. (C) Across four runs in the fMRI paradigm, we asked participants to choose which of two traits either self or, separately, Merkel embodied more across nine time points in the past and future. Each trait was presented for 5 s and included 30% jittered trials of fixation.

overlapping self-representations (44, 51). It further allowed us to rule out a strictly motivational account of temporal self-compression by demonstrating compression with stimuli unrelated to positive valence.

For this task, participants were instructed to drag a yellow circle—representing a past or future self—closer to or farther away from a gray circle—representing a current self—to indicate how similar or dissimilar each participant felt between their respective temporal selves. Participants completed distinct circles for the present self and each time point in the past and future: 3 mo, 6 mo, 9 mo, and 1 y (Fig. 1B). Not only did this task prompt participants to consider similarity in personality between temporal selves but also more holistic features of self (e.g., major likes and dislikes, beliefs, values, ambitions, life

goals, and ideals). If a compression account holds for this more abstract task, then motivation for self-improvement (i.e., in positive personality characteristics) cannot be the sole driver of this phenomenon.

A linear mixed model revealed a significant logarithmic ( $\beta = 10.90$ , standardized  $\beta = 0.18$ ,  $t$ -statistic = 11.32,  $df = 169.94$ , and  $P < 0.001$ ) relationship of temporal distance (collapsed across past and future) on disconnectedness scores to present self. Similar to the trait study, disconnectedness scores grew and subsequently plateaued when participants considered more distal selves (Fig. 2B). In contrast to the trait study, we did not display a cubic effect, because here, the stimuli were not valenced. Again, when age was added to the model, there was a significant interactive effect of age on logarithmic time ( $\beta = -14.22$ , standardized



**Fig. 2.** (A) Study 1a demonstrates significant temporal self-compression of personality trait ratings. (B) Study 1b demonstrates significant temporal self-compression as measured by the dynamic, temporal self-continuity task. (C) Study 2 demonstrates that temporal compression is preferential to the self, relative to another well-known person, Angela Merkel.

$\beta = -0.07$ ,  $t$ -statistic =  $-4.66$ ,  $df = 167.61$ , and  $P < 0.001$ ), such that older adults displayed less compression relative to younger adults and displayed less disconnectedness overall ( $\beta = -19.85$ , standardized  $\beta = -0.29$ ,  $t$ -statistic =  $-2.91$ ,  $df = 171.79$ , and  $P = 0.004$ ). However, our primary effect of logarithmic compression remained statistically significant even when age was added as a covariate in the model ( $\beta = 61.25$ , standardized  $\beta = 0.18$ ,  $t$ -statistic =  $5.64$ ,  $df = 167.71$ , and  $P < 0.001$ ).

**Study 2.** We next aimed to determine whether temporal self-compression is relatively preferential for the self or whether it extends to other people more generally. Consistent with past research on the self (52), we selected a politician for the other-person condition: German chancellor Angela Merkel. To ensure all participants had similar knowledge about Angela Merkel, participants were provided a short biography of Merkel prior to performing their ratings. Participants ( $n = 174$ ) rated themselves and Merkel on the same personality traits used in Study 1a and across the same time points (i.e., present, past, and future ratings spaced 3 mo apart up to 1 y).

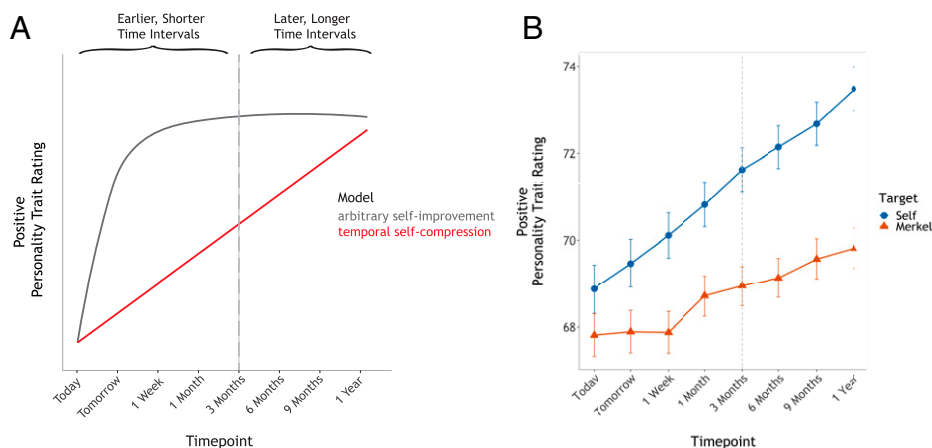
A linear mixed model demonstrated a significant interaction effect between linear time and target ( $\beta = 2.06$ , standardized  $\beta = 0.21$ ,  $t$ -statistic =  $8.94$ ,  $df = 30,953.38$ , and  $P < 0.001$ ), and cubic time and target ( $\beta = -2.01$ , standardized  $\beta = -0.08$ ,  $t$ -statistic =  $-3.39$ ,  $df = 30,953.38$ , and  $P = 0.001$ ), such that the ratings for self displayed stronger linear and cubic effects relative to Merkel. In other words, and as shown in Fig. 2C, temporal compression was preferential to self-ratings (versus Merkel ratings). It is noteworthy that we also observed a significant effect of target on personality trait ratings ( $\beta = 4.08$ , standardized  $\beta = 0.16$ ,  $t$ -statistic =  $17.97$ ,  $df = 30,953.38$ , and  $P < 0.001$ ), such that ratings for the self were higher than ratings for Merkel.

Although there was no significant effect of age on trait ratings when both targets were considered simultaneously ( $\beta = 1.00$ , standardized  $\beta = 0.01$ ,  $t$ -statistic =  $0.29$ ,  $df = 178.06$ , and  $P = 0.775$ ), there was a significant interaction between age and target ( $\beta = 11.06$ , standardized  $\beta = 0.13$ ,  $t$ -statistic =  $13.94$ ,  $df = 30,953.37$ , and  $P < 0.001$ ), such that trait ratings were higher among older adults for self but not for Merkel. Consistent with Study 1a and 1b, even after controlling for age (i.e., adding it as a covariate), there was a significant interaction between linear time and target ( $\beta = 2.06$ , standardized  $\beta = 0.21$ ,  $t$ -statistic =  $8.96$ ,  $df = 30,953.37$ , and  $P < 0.001$ ) and cubic time and target

( $\beta = -2.01$ , standardized  $\beta = -0.08$ ,  $t$ -statistic =  $-3.40$ ,  $df = 30,953.37$ , and  $P = 0.001$ ), suggesting that age-related effects do not explain temporal self-compression.

**Study 3.** Results from Studies 1 and 2 are consistent with the temporal self-compression hypothesis. However, an alternative interpretation of these results is that individuals are accessing a generic rating of their perceived self-change invariant to the time point considered. People may have a theory of self-change that is logarithmic regardless of the actual time point into the past or future considered. In other words, temporally distant selves may not be compressed but rather represent a categorical difference in self-perception from the present self. To rule out this possibility of “arbitrary self-improvement”, we would need to include time points closer to the present than 3 mo. If changes in self-perceptions are compressed specifically as people consider more distant time points, as we propose in the temporal self-compression hypothesis, then the compression should not occur for times closer to the present. If this were the case, then we would expect two findings: 1) earlier temporal time points (e.g., the self in 1 wk or 1 mo) should not be rated equivalently to more temporally distant time points (i.e., 3 mo and beyond) and 2) the amount of perceived self-change in smaller increments of time (e.g., 1 d versus 1 wk) should be similar to the perceived amount of change in later, longer intervals of time (e.g., 9 mo versus 1 y). This latter point would reflect that the amount of self-change that one can imagine in their more distant future is compressed relative to the amount of change during earlier, smaller time intervals. It also fits with the idea of “scale-invariance” in logarithmically compressed representations (15). For example, a consequence of the observation that numbers of greater magnitude become less distinguishable on the number line than numbers of smaller magnitude is that the difference between, for example, 10 and 11 is perceived as more similar to the difference between 100 and 110 than to the difference between 100 and 101 (15, 19–21) (refer to Fig. 3A for a schematic of the temporal self-compression hypothesis versus the alternative, arbitrary self-improvement hypothesis). Likewise, the amount of perceived change in the self between tomorrow and 1 wk may counterintuitively be similar to the amount of perceived change in the self between 3 mo and 6 mo, despite the latter capturing a longer interval of time.

To adjudicate between the competing possibilities of temporal self-compression versus arbitrary self-improvement, in Study



**Fig. 3.** Results for Study 3. (A) Schematic of two competing possibilities for self-perception: temporal self-compression (red line) versus arbitrary self-improvement (gray line). The “arbitrary self-improvement” model demonstrates the possibility that individuals access a generic rating of future self-improvement. The “temporal self-compression” model predicts a gradual, not abrupt, transition when earlier time points with smaller intervals of time are assessed. (B) Empirical findings abide by the temporal self-compression model: Study 3 demonstrates a significant linear trend for self-ratings that is preferentially stronger for the self (versus a well-known other, Angela Merkel).

3, participants ( $n = 192$ ) made their personality trait ratings for the self and Merkel using the following intervals into the future: today, tomorrow, 1 wk, 1 mo, 3 mo, 6 mo, 9 mo, and 1 y. We focused on the future specifically given that Studies 1 and 2 showed effects for both past and future (and thus it was not necessary to include both here) and to minimize participant burden given the additional temporal conditions.

Consistent with the temporal self-compression prediction, a linear mixed model revealed a significant interaction between time and target ( $\beta = 0.34$ , standardized  $\beta = 0.04$ ,  $t$ -statistic = 3.95,  $df = 30,324.0$ , and  $P < 0.001$ ), demonstrating that the linear effect of perceived self-improvement was stronger for the self than for Merkel (Fig. 3B). In other words and as shown in Fig. 3B, we saw evidence of strong linear self-improvement with time, demonstrating that 1) earlier time points are not rated equivalently to later time points and 2) the rate of perceived self-change between smaller temporal increments at earlier time points is similar to the rate of perceived self-change between larger, more distant time points. There was also a significant effect of time ( $\beta = 0.31$ , standardized  $\beta = 0.03$ ,  $t$ -statistic = 3.10,  $df = 288.1$ , and  $P = 0.002$ ) and target ( $\beta = 0.88$ , standardized  $\beta = 0.11$ ,  $t$ -statistic = 2.01,  $df = 30,324.0$ , and  $P < 0.044$ ), such that personality trait ratings were higher for self and for time points farther ahead in the future. Critically, if the arbitrary self-improvement account was correct, then when compression terms are added to the model, the interaction between logarithmic time (used instead of a cubic term because this study only included the future) and target would be statistically significant, but that was not the case (compression term  $\beta = 0.27$ , standardized  $\beta = 0.01$ ,  $t$ -statistic = 0.38,  $df = 30,324.0$ , and  $P = 0.701$ ). Thus, the arbitrary self-improvement account can be ruled out.

We also assessed our model including age as a covariate. Replicating our previous results, we found that older people rated themselves more positively ( $\beta = 15.18$ , standardized  $\beta = 0.20$ ,  $t$ -statistic = 4.50,  $df = 191.74$ , and  $P < 0.001$ ) and exhibited less of a linear trend across time ( $\beta = -1.15$ , standardized  $\beta = -0.02$ ,  $t$ -statistic =  $-3.78$ ,  $df = 192.0$ , and  $P < 0.001$ ) compared to younger adults. Critically, the interaction between logarithmic time and target was still not statistically significant ( $\beta = -0.17$ , standardized  $\beta = 0.01$ ,  $t$ -statistic = 0.38,  $df = 30,324.02$ , and  $P = 0.701$ ) when age was controlled for (i.e., added as a covariate).

**Study 4.** The goal of Study 4 was to search for neural evidence of temporal self-compression. This would not only add additional support for the hypothesis; it would further suggest that results from Studies 1 through 3 are not merely an artifact of self-report bias (53) but rather may reflect an underlying mental representation of the self that is compressed with time. If self-representations are temporally compressed, then we would expect brain regions associated with self-representation to show less neural pattern similarity between the present self and selves 3 mo away and greater neural pattern similarity between selves as participants reflect farther out in time (e.g., neural pattern similarity between 3 mo away and 6 mo away; 6 mo away and 9 mo away; and 9 mo away and 1 y away). Moreover, we assessed which of two competing possibilities best explain how the brain temporally compresses past and future selves: whether past and future selves are compressed as their own, separate representations or whether past and future selves are represented similarly to one another and collectively compressed with time away from the present.

Participants in Study 4 ( $n = 43$ ) completed a trait reflection task while undergoing fMRI. For the scanner task, participants chose which of two traits best reflected themselves (self-condition) separately across the nine time points used in Studies 1 and 2 (i.e., Future-3 Months). Participants also completed trait reflection trials across these time points for Merkel. As in our previous studies, participants received a short biography of

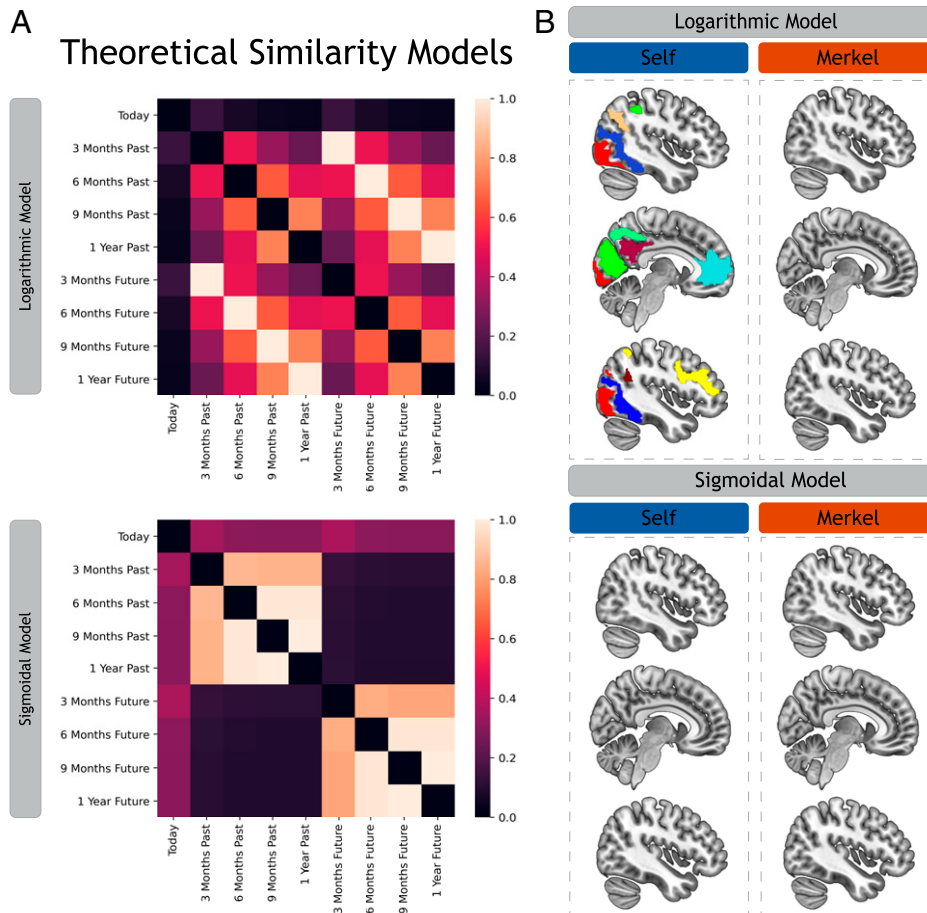
Angela Merkel before completing the task. Critically, in Study 4, one-third of trials showed two positive trait options (e.g., charming and wise), two negative trait options (e.g., insecure and lazy), or a combination of positive and negative traits (e.g., charming and insecure). Including positive and negative traits helps ensure that neural results reflect a compressed self-representation as opposed to changes in similarity in valence more generally. As is the case for the positive traits, negative traits were normed on perceived change and controlled for likeability using the Dumas word list. Every subject completed the same number of positive-positive, negative-negative, and positive-negative trait rating trials for their scans although trait pairings were counterbalanced between self and Merkel targets to help ensure participant engagement.

To test the competing possibilities of temporal self-compression, we employed representational similarity analysis (RSA) (54) to search for regions across the brain that may fit the competing predictions. We constructed two theoretical representational dissimilarity matrices: a sigmoidal model differentiating past and future selves and a logarithmic model in which past and future selves are represented similarly (Fig. 4A). Both models assume temporal self-compression (i.e., greater similarity in representations further out in time with dramatic shifts closer to the present) and only differ in whether past and future selves are separately versus collectively represented.

We looked for significant correlations between the two theoretical structures across targets (self and Merkel) across the whole brain. The sigmoidal model, which would reflect past and future selves are separately and distinctly represented and temporally compressed, yielded no statistically significant results for either the self or Merkel (Fig. 4B). However, the logarithmic model, which reflects past and future selves as collectively represented and compressed with time, showed significant results in brain regions previously associated with self-representation: MPFC as well as other default network regions (posterior cingulate cortex [PCC]), bilateral precuneus, and right middle temporal gyrus (for full list of regions, refer to *SI Appendix, Table 1*;  $FDR < 0.05$ , false discovery rate [FDR]-corrected for multiple comparisons). Additional regions also showed this relationship, including regions in the frontoparietal control network, dorsal attention network, and visual system (*SI Appendix, Table 1*). In contrast to the self-condition, no regions of the brain were associated with the logarithmic model for the Merkel condition (Fig. 4B). For a breakdown of trial-by-trial similarity within and between each time point condition, refer to *SI Appendix, Fig. 1*.

Mean univariate activity was also extracted from core regions of interest (ROIs) in the default network (e.g., MPFC and PCC). Replicating previous work (43, 55), we found that mean activation was higher for present self in both MPFC ( $\beta = 0.26$ , standardized  $\beta = 0.38$ ,  $t$ -statistic = 5.67,  $df = 351$ , and  $P < 0.001$ ) and PCC ( $\beta = 0.20$ , standardized  $\beta = 0.23$ ,  $t$ -statistic = 3.65,  $df = 351.0$ , and  $P < 0.001$ ) compared to all time points collapsed in the past and future. Further, there was no difference in mean deactivation between past and future in MPFC ( $\beta = 0.06$ , standardized  $\beta = 0.08$ ,  $t$ -statistic =  $-0.73$ ,  $df = 351.0$ , and  $P = 0.467$ ) and PCC ( $\beta = -0.04$ , standardized  $\beta = -0.04$ ,  $t$ -statistic =  $-0.78$ ,  $df = 351.0$ , and  $P = 0.433$ ), consistent with findings reported by Schacter and colleagues (46, 56) (*SI Appendix, Fig. 2*).

**MPFC ROI Pattern Similarity Analysis.** We next sought to further probe whether MPFC voxels in the brain specifically associated with self-representation adhere to the logarithmic model. To assess MPFC voxels associated with self-representation defined independently of our own data, we applied a Neurosynth-derived MPFC ROI using the search term “self”; this ROI has been used in past research on the self (57, 58). For every contiguous time point (separately for the self and other; e.g., similarity between  $Self_{Today}$  and  $Self_{3-MonthsFuture}$ ), similarity



**Fig. 4.** Whole-brain representational similarity analysis. (A) We constructed two theoretical representational dissimilarity matrices (RDMs): a logarithmic model in which past and future selves are represented similarly and a sigmoidal model differentiating past and future selves. Each RDM is symmetrical about a diagonal of zeros and only the vectorized lower triangle is extracted (without the diagonal) (54). (B) Spearman rank correlations were conducted between each RDM and each region of interest in the Yeo parcellation scheme for self and Merkel beta images separately. Brain regions across the brain, including default network regions previously associated with self-reflection (e.g., MPFC; PCC), were significantly associated with the logarithmic model for the self (FDR < 0.05). No brain regions were significantly associated with any of the other models.

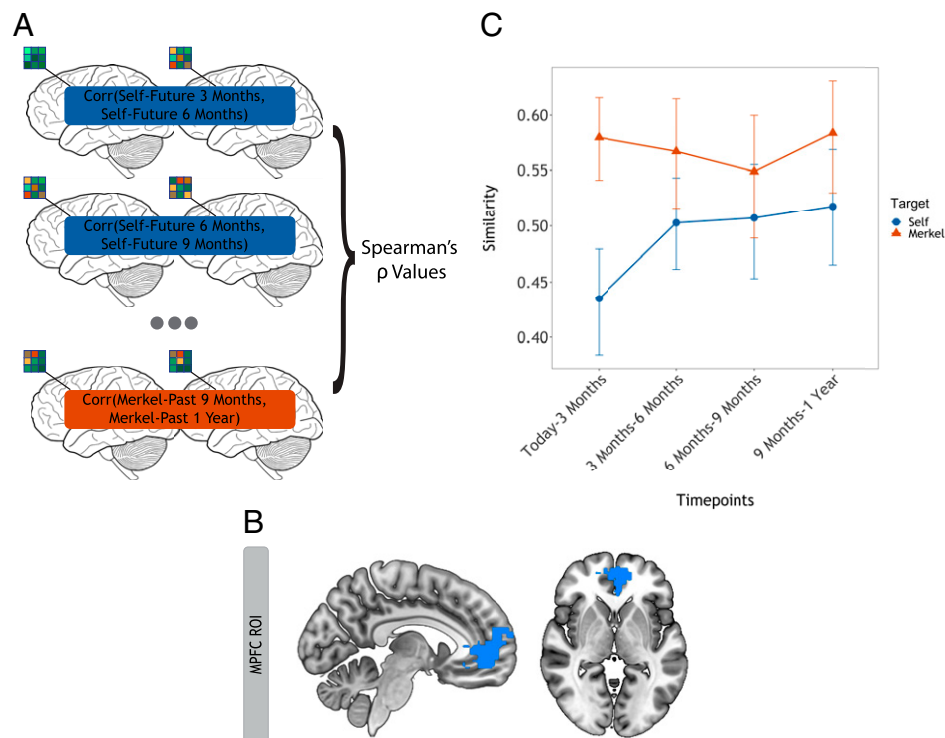
between the two MPFC ROI beta images was calculated via Spearman rank correlations within each subject (refer to Fig. 5A for a schematic of the analysis plan).

A linear mixed model revealed a significant interaction effect between logarithmic time and target ( $\beta = 0.06$ , standardized  $\beta = 0.15$ ,  $t$ -statistic = 2.50,  $df = 546$ , and  $P = 0.013$ ), meaning that the MPFC pattern similarity displayed between contiguous time points across time (today to 1 year) was more logarithmic for the self than for Merkel (Fig. 5C). Put simply, neural pattern similarity for the self in the MPFC was lowest for the most proximal time points (i.e., more differentiated), then increased in similarity when comparing more distal time points (i.e., less differentiated) ( $\beta = 0.06$ , standardized  $\beta = 0.14$ ,  $t$ -statistic = 2.47,  $df = 39$ , and  $P = 0.013$ ). Because we did not find a statistically significant difference in the logarithmic effect in future and past for the self in the brain data, we collapsed the directionality for this analysis (SI Appendix, Fig. 3). The same relationship was not statistically significant when considering Merkel ( $\beta = -0.01$ , standardized  $\beta = -0.01$ ,  $t$ -statistic =  $-0.31$ ,  $df = 273$ , and  $P = 0.75$ ). The linear mixed model also identified an effect of target on similarity value across time ( $\beta = -0.13$ , standardized  $\beta = -0.35$ ,  $t$ -statistic =  $-5.30$ ,  $df = 546$ , and  $P < 0.001$ ), such that MPFC similarity between contiguous time points (e.g., Self<sub>Today</sub> and Self<sub>3-MonthsFuture</sub>) was lower for the self than for Merkel.

## Discussion

Across domains studied outside of social psychology, changes in stimuli are logarithmically compressed such that the farther they are from an original stimulus, the less discriminable they become. In four studies, we found evidence suggesting temporal self-perception abides by this principle as well. Study 1 demonstrates that people compress their future and past selves such that distal selves are perceived more similarly to one another compared to current and proximal selves. Study 2 replicates this finding and further shows that this compression effect may be relatively preferential to the self. Consistent with Weber–Fechner’s law that distant perceptions specifically are compressed, Study 3 showed that temporal self-compression occurs at more distant but not more proximal time points. Finally, in Study 4, we found that neural representations of past and future selves are also collectively compressed with time away from the present. Our results suggest that Parfit may have been partially correct: people represent temporal selves closer in time more similarly to one another. However, Parfit’s model comes with a caveat: the degree of representational similarity between selves varies in systematic ways and akin to logarithmic compression.

Our findings may help explain some of the counterintuitive ways people treat their temporally distant selves. For example, an extensive literature on hyperbolic discounting suggests that



**Fig. 5.** Self-specific MPFC similarity analysis. (A) Schematic of the analytic procedure. For every contiguous time point for both the self and other (e.g., Self-Today and Self-3 Months in the Future), neural pattern similarity between the two masked beta images was calculated via Spearman rank correlations within each subject. (B) Neurosynth-derived MPFC ROI using the search term “self” used in this analysis. Voxels in the association map test were restricted to Brodmann Area 10, a region particularly associated with self-representation. (C) Results show a significant interaction effect between logarithmic time and target, meaning that the MPFC pattern similarity displayed between contiguous time points across time (today to 1 year) was preferentially logarithmically compressed with time for the self (versus another well-known person, Angela Merkel).

people display preferences for selecting a smaller monetary reward immediately rather than waiting to receive a larger sum (59). Because this formulation is hyperbolic, rather than exponential, the value of immediate reward is unduly high such that people succumb to instant gratification; yet, when asked to choose between two temporally distant choices, people manage to exhibit more restraint. Why would multiple future selves be short changed for the present self in a time-inconsistent way? Our results indicate that more distant future selves are not easily distinguishable from one another. The representational similarity between more distant selves would thus make it easier to not treat them differently from one another and hence be willing to wait for the larger reward—it’s the “same” self anyways. Relatedly, people are less prone to hyperbolic discounting when making decisions for others (60), and recent research has shown that representations of others’ internal states (in the present) are also less differentiated from one another than internal representations of the self’s states (in the present) (61). This further speaks to the possibility that difficulty distinguishing between distant self-representations may facilitate delayed gratification in choices.

We replicate past social psychology research demonstrating that people perceive their past selves less positively than their present self and their future self as even better (10–12). This phenomenon is thought to occur for motivational reasons: people derogate their past selves to boost their current self-worth (4, 5) and see their future self through rose-colored glasses to sustain optimism for their future (7, 8, 62). Our addition to this literature is that this bias in self-perception follows basic principles of other forms of perception and mental representation: as individuals consider more distant past and future selves, their ability to perceive them as uniquely

worse or better is increasingly attenuated. Indeed, in Study 1b, we demonstrated that temporal self-compression replicates with a task unrelated to self-improvement (i.e., the “temporal self-continuity” task) (50, 51). This suggests that temporal self-compression may be a general principle of self-representation above and beyond motivational reasons to perceive self-improvement.

If perceived self-improvement is not the sole driver of the compression effect, why do we not observe temporal compression for the other target, Angela Merkel? One possibility is that considering the present self utilizes first-person perspective taking, whereas thinking about future and past selves requires third-person perspective taking. Indeed, prior work suggests that we may treat past and future selves as “others” (51, 63), which may reflect third-person perspective taking. Considering a not-personally known other (e.g., Merkel) may offer no differentiation in perspective taking across time. Consequently, perceptions of that person have no direction to move away from the present, which provides no opportunity for compression with distance. Manipulating participants’ perspective taking while they complete compression experiments may shed light on this possibility. Future work should also assess compression of other-person representations, especially since reflecting on close others (e.g., friends and family) activates MPFC to a greater extent than well-known others such as Merkel (52). In fact, including trials of disliked but familiar others (e.g., “enemies”) as well as assessing temporal self-compression in individuals who do not feel intrinsically positive about the self (e.g., individuals with low self-esteem) will further clarify whether temporal compression in MPFC reflects compressed representations of the self and/or close others above and beyond “positive” person representations (64, 65).

It is worth noting that people do not always treat their temporal selves as disconnected from their present self. Another literature suggests that people construct personal narratives about their identity, which may help generate a unitary sense of self over time (66, 67). Indeed, it has been shown that narrative identities adhere to systematic themes (e.g., a storyline of redemption) and that individual differences in the narrative structure behind our life stories relate to mental health (68). At first blush, our findings on temporal self-compression may seem at odds with the personal narrative account. This may not be surprising, given that some accounts of the self suggest trait representation and narratives may be distinct aspects of identity (69, 70). By extension, temporal self-compression may be a phenomenon of self-representation that is unrelated to narrative identity. Alternatively, it is possible that temporal self-compression is reflected in our narrative identities as well. For example, the details of our life stories may be compressed for “scenes” that occur farther out in time. Additionally, individual differences in compression may relate to the quality (e.g., vividness) of our life narratives. An interesting future direction will be to test for temporal self-compression of personal narratives, for example with natural language processing methods. Including narratives, combined with confidence and vividness ratings for various distal timepoints, may shed further light on the underlying mechanism of temporal self-compression.

Our results revise the view that the self is “special.” Multiple pieces of evidence point to the possibility that self-representation is unique from other types of knowledge representation (32, 71–73). For example, self-reflection is preferentially associated with portions of MPFC (32, 33, 71–73) and self-relevant information is privileged in memory (71, 73). Yet here, we found that self-perception is susceptible to Weber–Fechner’s law much like other forms of perception and mental representation. In fact, our MPFC ROI is constrained to brain voxels preferentially responsive to the self, and these voxels demonstrated this ubiquitous principle of compression. How can our results be compatible with past findings suggesting the uniqueness of self-knowledge? One possibility is that self-knowledge may be stored separately from other representations, but the organization of that knowledge abides domain-general principles such as temporal compression. Future research that includes temporal self-appraisal stimuli along with perceptual stimuli that vary in distance from an origin point can help test this possibility. This approach may also clarify whether regions outside of the default network that showed evidence of temporal self-compression (e.g., portions of the frontoparietal network) may play a domain-general role in this phenomenon.

The present work complements and extends prior neuroimaging findings suggesting that prospection and retrospection rely on the same brain regions. Regions of the default network—not only MPFC but also precuneus and medial temporal lobe—are consistently recruited when simulating episodes in the past and thinking about a hypothetical situation in the future (46, 56, 74). Though our behavioral data could suggest that past and future selves are represented separately from one another (because past selves were rated as “worse” than future selves), once trial types sampled traits that varied in valence, past and future selves showed no evidence of discrete representation (i.e., the sigmoidal model that searched for past and futures selves separately compressed from the present correlated with no regions in the brain). Instead, we found remarkable overlap between the brain regions that fit the logarithmic model indicating collective representation of past and future selves compressed with time and the brain regions that are commonly recruited for prospection and retrospection (46). Such similarities are despite the fact that our paradigm tests semantic memory (i.e., personality traits) rather than episodic memory. Our findings are thus compatible with prior work on retrospection

and prospection, with the addition that temporal selves are logarithmically compressed with time.

Not all age groups compress equally, however. In Studies 1 through 3, we found that older individuals (versus younger individuals) displayed less change in self-perception (i.e., attenuated linear and cubic trends) when rating their personality traits across time. In other words, compared to younger adults, older adults view themselves as more static across time. Importantly, our temporal self-compression findings remained significant even when controlling for age. Nonetheless, the aging results are interesting in light of other research demonstrating that older adults generate fewer specific details (or more high-level construals) during both retrospection and prospection (48, 49). Aging is further associated with changes in default network function (75–77). On the one hand, this lack of perceived change in the self with time could be due to changes in temporal simulation skills with aging. On the other hand, lack of perceived self-change could reflect motivational changes in self-perception with age. For example, people may be motivated to stabilize their self-views with age if they perceive limited avenues for change; thus, considering the self 1 year out into the past and future, as we did in our studies, may not be distant enough to detect strong self-compression effects in older populations. Relatedly, we replicated findings from the affective aging literature suggesting that older adults display a positivity bias (78, 79). In our studies, older adults appraised themselves better compared to younger adults across positive traits. One direction for future research could be to further unpack the representational structure of temporal selves in older adults in the default network and the extent to which this may have consequences for behavior.

In summary, we provide behavioral and neural evidence to suggest that past and future selves are temporally compressed. Just as the details of physical objects farther out in space are difficult to see, distant past and future selves may be similarly blurry. These findings add insight into questions of self-continuity over time that have perplexed philosophers and psychologists alike for centuries. Indeed, David Hume—who inspired Parfit’s own thoughts on identity over time (80)—suggested that when we lack access to perceptions, self-continuity breaks down (81). Consistent with Hume’s account, our results suggest that we may struggle to treat our distant past and future selves as part of our own identity, in part because they are in less-clear view.

## Materials and Methods

### Studies 1 through 3.

**Participants and procedures.** For Studies 1a, 2, and 3, Amazon Mechanical Turk (MTurk) participants completed an online survey in which they were asked to rate themselves on positive personality traits (0, not at all to 100, extremely) across various time points. Positive personality traits were selected to be consistent with past social psychology research, which consistently shows that individuals appraise their past self less positively than their present self and their future self more positively than their present self. Trait presentation was fully randomized across time points. Further, we built in attention checks (i.e., prompting participants to move the sliding scale to 60 instead of rating a trait characteristic). All participants across studies provided informed consent and were paid \$4.00 for their time and effort. This study was approved by the Dartmouth College Institutional Review Board.

**Personality trait norming.** Personality traits were selected from the Dumas person-descriptive word list (47) and normed for perceived change using ratings from an independent MTurk sample. Participants who normed the stimuli ( $n = 62$ , 37% female, mean age = 34.8; SD 9.6) were instructed to rate 150 positive and negative trait adjectives on a 0 to 100 scale according to how they perceive the average person changing on that trait in 1 year. For each trait, an average change score was calculated and then z-scored. For Studies 1a, 2, and 3, positive traits were selected such that traits from across the perceived change spectrum were sampled and controlled for likability using scores from the Dumas word list. In Study 1a, 20 traits were selected, whereas in Studies 2 and 3, 10 traits were selected due to the fact that we were asking participants



to rate each trait for the self and Merkel (versus solely the self in Study 1), and we wanted to ensure participants could complete the tasks in a reasonable amount of time (~30 min).

**Trait ratings.** For Studies 1a and 2, each trait was rated across nine time points, up to 1 year in the future and 1 year in the past; every time point was spaced 3 months apart and included the present (Fig. 1A). Studies 2 and 3 prompted participants to rate both the self and German chancellor Angela Merkel. Study 3 prompted participants to respond across uneven time scales in the future only (today, tomorrow, 1 week, 1 month, 3 months, 6 months, 9 months, and 1 year).

**Dynamic temporal self-continuity task.** For Study 1b, participants moved a yellow circle symbolizing a future or past self at various temporal distances (i.e., 3 months, 6 months, 9 months, and 1 year) toward a gray circle symbolizing the current self. Similarity between the two selves was measured by calculating the overlap between the two circles on a 0 to 100 scale. Disconnection, the dependent variable, was then calculated by subtracting the overlap score by 100.

**Participants.** In Study 1, 196 participants were recruited from MTurk. In Study 2, 186 participants were recruited from MTurk. In Study 3, 202 participants were recruited from MTurk. For demographic information for all three studies, refer to *SI Appendix, Table 2*.

**Data Analysis.** After assessing data quality via attention checks, 178 subjects remained in Study 1a, 172 subjects remained in Study 1b, 174 subjects remained in Study 2, and 192 subjects remained in Study 3. For each study, linear mixed models using the R package *lme4* were constructed to assess how time affected the trait ratings or dynamic circle overlap (82). Linear, quadratic, and cubic terms for time were added as fixed effects to the models in Study 1a and 2. *P* values were calculated for mixed model fits by Satterthwaite's degrees of freedom method for Study 1a, 1b, 2, and 3. Adding quadratic and cubic terms to the linear-only models in Studies 1a and 2 significantly improved model fits based on BIC (lowered by 51 and 9 in Study 1a and 2 respectively). In Study 1b, we also measured how temporal distance affected disconnection to the present self. Because there was no motivational component, a logarithmic transformation of time, collapsed across past and future, was added as the compression term to the model.

In Study 3, we were interested in assessing the arbitrary self-improvement hypothesis, with the hypothesis that when earlier and unevenly spaced time points were assessed, perceived change would be linear (rather than compressed). Thus, the primary model in Study 3 assessed the linear relationship with time. The models all included random intercepts, and slopes for participants and in Studies 1a, 2, and 3 random intercepts for item-level traits were included to account for variability within the population and among traits selected and better ensure generalizability (83).

Because Studies 2 and 3 included both self and Merkel as target conditions, target was added as a fixed effect for those models. In order to identify a compression effect that is preferential to the self in Study 2, the interactive effects of both 1) linear time and target and 2) cubic time and target were added to the model. For the primary model in Study 3, we first added solely the interactive effect of linear time and target to see whether there was a linear trend on a compressed time scale. Then, to confirm that closer time points are not compressed, we assessed another model for Study 3 with fixed effects of linear, quadratic, and cubic time, target, and the interaction terms between linear and cubic time and target, respectively. This latter model including temporal compression terms did not have a statistically better model fit (*P* value = 0.8696) compared to the model containing solely a linear time term.

Given that age impacts temporal self-appraisal, we also constructed models for each study adding log-transformed age (to account for skewness in the data) as a fixed effect. For Studies 1 through 3, we included the interaction between age and time (both linear and cubic for Studies 1a and 2, logarithmic for Study 1a, and just linear for Study 3) to assess whether participants who varied in age displayed the self-compression effect differently.

#### Study 4.

**Participants and procedures.** A total of 43 right-handed Dartmouth College undergraduates (women 62.8%, mean age = 19.1; SD = 0.88; racial breakdown: 41.9% White, 39.5% Asian, 9.3% African American, and 9.3% Hispanic) were recruited for the present study and screened for any MRI contraindications (e.g., metal in body, claustrophobia, and pregnancy). All participants provided informed consent and either received extra credit for a course or cash in exchange for their participation. This study was approved by the Dartmouth College Institutional Review Board. Three participants ended their scanning session early due to technical difficulties or

scanner-induced claustrophobia. Another subject responded to only 61% of trials and was therefore removed from analysis, bringing the total analysis to 39 subjects.

In the scanner portion of Study 4, we asked participants to choose which of two traits either self or Merkel embodied more across nine different time scales (the same time points as in Study 1a and 1c; Fig. 1C). Subjects used a button box in the scanner to select which trait they most identified with at that point in time.

One-third of the scanner task trials showed two positive trait options (e.g., charming and wise), two negative trait options (e.g., insecure and lazy), or a combination of positive and negative traits (e.g., charming and insecure). Including positive and negative traits helps ensure that neural results reflect a compressed self-representation as opposed to changes in similarity in valence more generally. As is the case for the positive traits, negative traits were normed on perceived change and controlled for likeability using the Dumas word list. Each subject was presented with seven positive-positive valence, seven negative-negative valence, and seven positive-negative valence trials for their scans for a total of 21 trials per condition. Trait pairings were counter-balanced between self and Merkel targets to help ensure participant engagement. Each trait was presented for 5 s.

**fMRI data acquisition.** Brain imaging took place on a Siemens Prisma 3T scanner. Four functional runs in response to the task were acquired using a T2\*-weighted echo-planar imaging sequence (2.5-mm voxels, repetition time [TR] = 1,000 ms, time to echo [TE] = 30 ms, 2.5-mm slice thickness, field-of-view [FOV] = 24 cm, matrix = 96, flip angle = 59, and simultaneous multislice = 4). A T2-weighted structural image was acquired coplanar with the functional images (0.9-mm voxels, TR = 2,300 ms, TE = 2.32 ms, 0.9-mm slice thickness, FOV = 24 cm, matrix = 256 256, and flip angle = 8). Sequence optimization was obtained using optseq2 (84) and included 30% jittered trials of fixation for measuring a baseline estimation of neural activity.

**Brain-imaging data preprocessing and beta estimates.** Results included in this manuscript come from preprocessing performed using *fMRIPrep* 1.4.0 (refs. 85, 86; Research Resource Identifier [RRID]: SCR\_016216), which is based on *Nipype* 1.2.0 (refs. 87, 88; RRID: SCR\_002502). Per recommendations from the software developers, we report the exact text generated from the boilerplate below.

For each of the four blood-oxygen-level-dependent (BOLD) runs found per subject, the following preprocessing was performed. First, a reference volume and its skull-stripped version were generated using a custom methodology of *fMRIPrep*. The BOLD reference was then coregistered to the T1w reference using *cbregister* (FreeSurfer), which implements boundary-based registration (89). Coregistration was configured with nine degrees of freedom to account for distortions remaining in the BOLD reference. Head-motion parameters with respect to the BOLD reference (transformation matrices and six corresponding rotation and translation parameters) are estimated before any spatiotemporal filtering using *mclirt* (FMRIB Software Library 5.0.9) (90). BOLD runs were slice-time corrected using *3dTshift* from Analysis of Functional Neuroimages (AFNI 20160207) (ref. 91; RRID: SCR\_005927). The BOLD time series were resampled into standard space, generating a preprocessed BOLD run in ["MNI152NLin2009cAsym"] space. First, a reference volume and its skull-stripped version were generated using a custom methodology of *fMRIPrep*. Several confounding time series were calculated based on the preprocessed BOLD: framewise displacement, the derivative of frame-to-frame head motion variance across voxels (DVARS), and three region-wise global signals. FD and DVARS are calculated for each functional run, both using their implementations in *Nipype* (following the definitions by ref. 92). The three global signals are extracted within the cerebrospinal fluid, the white matter, and the whole-brain masks. The head-motion estimates calculated in the correction step were also placed within the corresponding confounds file. The confound time series derived from head-motion estimates and global signals were expanded with the inclusion of temporal derivatives and quadratic terms for each (93). Frames that exceeded a threshold of 0.5 mm FD or 1.5 standardized DVARS were annotated as motion outliers. All resamplings can be performed with a single interpolation step by composing all the pertinent transformations (i.e., head-motion transform matrices, susceptibility distortion correction when available, and coregistrations to anatomical and output spaces). Gridded (volumetric) resamplings were performed using *antsApplyTransforms*, configured with Lanczos interpolation to minimize the smoothing effects of other kernels (94).

Images that estimated each time period's task-conditioned effects for both self and other were calculated by modeling the events of interest convolved with the canonical hemodynamic response function in a general linear model. This model included nuisance regressors for the six motion parameters (*x*, *y*, and *x* directions and roll, pitch, and yaw rotations), each motion parameter's derivative and square of the derivative, linear drift, and run constants. We

additionally regressed out TRs in nonsteady state and TRs that exhibited spikes of motion found from global signal outliers and outliers derived from frame differencing (each 3 SDs).

**RSA (Whole Brain).** Multivariate analyses were all conducted using Python packages, including ntools 0.3.14 (95) and Nilearn (96). After constructing these representational structures, for each participant, we conducted Spearman rank correlations between each structure and each region of interest in the Yeo parcellation scheme (97) that exceeded 5 voxels, for self and other (i.e., Merkel) beta images separately. The Yeo parcellation scheme was chosen because 1) it is based on functional divisions determined in a large sample (1,000 participants) and 2) includes default network regions that are anatomically very similar to known divisions determined by task-based fMRI studies investigating the neural correlates of social cognition, including self-reflection (32, 98, 99). We calculated a one-sample *t* test on the Fisher *z*-transformed correlation values in order to assess which ROIs yielded a correlation consistently above 0. Thresholded maps were generated using a FDR of 0.05 to correct for multiple comparisons.

**ROI-based pattern similarity analysis.** To next assess whether voxels previously associated with the self demonstrate temporal compression, we employed an ROI approach using a Neurosynth-derived (100) MPFC mask

using the search term “self.” This ROI has been used in prior work on self-representation (32, 33, 57, 58). Voxels in the association map test were restricted to Brodmann Area 10, a region particularly associated with self-representation (32, 33, 57). Consequently, the MPFC ROI was restricted from –18 to 18 in the *x* dimension, 30 to 80 in the *y* dimension, and –12 to 22 in the *z* dimension, for a final mask size of 404 voxels (Fig. 4A).

For every contiguous time point for both the self and other (e.g., Self-Today and Self-3 Months in the Future), similarity between the two masked beta images was calculated via Spearman rank correlations within each subject. We then constructed a linear mixed model with target, the logarithmic time, and the interaction between target and logarithmic time as fixed effects predicting similarity (*R* values). We also included random intercepts and slopes for participants.

**Data Availability.** Anonymized behavioral and ROI data have been deposited in Open Science Framework (<https://osf.io/m458tu>).

**ACKNOWLEDGMENTS.** We thank Matthew Lieberman, Naomi Eisenberger, and Mark Thornton for feedback on this manuscript and Frances Sperry for assistance with data collection.

1. B. W. Roberts, D. Mroczek, Personality trait change in adulthood. *Curr. Dir. Psychol. Sci.* **17**, 31–35 (2008).
2. B. W. Roberts, K. E. Walton, W. Viechtbauer, Patterns of mean-level change in personality traits across the life course: A meta-analysis of longitudinal studies. *Psychol. Bull.* **132**, 1–25 (2006).
3. S. Srivastava, O. P. John, S. D. Gosling, J. Potter, Development of personality in early and middle adulthood: Set like plaster or persistent change? *J. Pers. Soc. Psychol.* **84**, 1041–1053 (2003).
4. A. E. Wilson, M. Ross, The frequency of temporal-self and social comparisons in people's personal appraisals. *J. Pers. Soc. Psychol.* **78**, 928–942 (2000).
5. A. E. Wilson, M. Ross, From chump to champ: People's appraisals of their earlier and present selves. *J. Pers. Soc. Psychol.* **80**, 572–584 (2001).
6. J. Quoidbach, D. T. Gilbert, T. D. Wilson, The end of history illusion. *Science* **339**, 96–98 (2013).
7. S. E. Taylor, E. Neter, H. A. Wayment, Self-evaluation processes. *Pers. Soc. Psychol. Bull.* **21**, 1278–1287 (1995).
8. D. Oyserman, L. James, “Possible identities” in *Handbook of Identity Theory and Research*, S. J. Schwartz, K. Luyckx, V. L. Vignoles, Eds. (Springer New York, 2011), pp. 117–145.
9. R. Buehler, C. McFarland, V. Spyropoulos, K. C. H. Lam, Motivated prediction of future feelings: Effects of negative mood and mood orientation on affective forecasts. *Pers. Soc. Psychol. Bull.* **33**, 1265–1278 (2007).
10. D. A. Armor, S. E. Taylor, “When predictions fail: The dilemma of unrealistic optimism” in *Heuristics and Biases: The Psychology of Intuitive Judgment*, T. Gilovich, Ed. (Cambridge University Press, 2002), pp. 334–347.
11. P. C. Regan, M. Snyder, S. M. Kassir, Unrealistic optimism: Self-enhancement or person positivity? *Pers. Soc. Psychol. Bull.* **21**, 1073–1082 (1995).
12. N. D. Weinstein, Unrealistic optimism about future life events. *J. Pers. Soc. Psychol.* **39**, 806–820 (1980).
13. D. Parfit, Personal identity. *Philos. Rev.* **80**, 3–27 (1971).
14. G. T. Fechner, “Elements of psychophysics, 1860” in *Readings in the History of Psychology*, W. Dennis, Ed. (Appleton-Century-Crofts, 1948), pp. 206–213.
15. M. W. Howard, Memory as perception of the past: Compressed time in mind and brain. *Trends Cogn. Sci.* **22**, 124–136 (2018).
16. R. N. Shepard, D. W. Kilpatrick, J. P. Cunningham, The internal representation of numbers. *Cognit. Psychol.* **7**, 82–138 (1975).
17. A. Nieder, D. J. Freedman, E. K. Miller, Representation of the quantity of visual items in the primate prefrontal cortex. *Science* **297**, 1708–1711 (2002).
18. S. Dehaene, The neural basis of the Weber-Fechner law: A logarithmic mental number line. *Trends Cogn. Sci.* **7**, 145–147 (2003).
19. M. R. Longo, S. F. Lourenco, Spatial attention and the mental number line: Evidence for characteristic biases and compression. *Neuropsychologia* **45**, 1400–1407 (2007).
20. S. Dehaene, J. Mehler, Cross-linguistic regularities in the frequency of number words. *Cognition* **43**, 1–29 (1992).
21. M. Piazza, V. Izard, P. Pinel, D. Le Bihan, S. Dehaene, Tuning curves for approximate numerosity in the human intraparietal sulcus. *Neuron* **44**, 547–555 (2004).
22. A. E. G. F. Arnold, G. Iaria, A. D. Ekstrom, Mental simulation of routes during navigation involves adaptive temporal compression. *Cognition* **157**, 14–23 (2016).
23. S. Michelmann, B. P. Staresina, H. Bowman, S. Hanslmayr, Speed of time-compressed forward replay flexibly changes in human episodic memory. *Nat. Hum. Behav.* **3**, 143–154 (2019).
24. O. Jeunehomme, A. Folville, D. Stawarczyk, M. Van der Linden, A. D'Argembeau, Temporal compression in episodic memory for real-life events. *Memory* **26**, 759–770 (2018).
25. C. J. Waksal, S. Nussbaum, N. Liberman, Y. Trope, Representations of the self in the near and distant future. *J. Pers. Soc. Psychol.* **95**, 757–773 (2008).
26. E. Pronin, L. Ross, Temporal differences in trait self-ascription: When the self is seen as an other. *J. Pers. Soc. Psychol.* **90**, 197–209 (2006).
27. S. Nussbaum, Y. Trope, N. Liberman, Creeping dispositionism: The temporal dynamics of behavior prediction. *J. Pers. Soc. Psychol.* **84**, 485–497 (2003).
28. C. K. Soderberg, S. P. Callahan, A. O. Kochersberger, E. Amit, A. Ledgerwood, The effects of psychological distance on abstraction: Two meta-analyses. *Psychol. Bull.* **141**, 525–548 (2015).
29. Y. Trope, N. Liberman, Construal-level theory of psychological distance. *Psychol. Rev.* **117**, 440–463 (2010). Correction in: *Psychol. Rev.* **117**, 1024 (2010).
30. G. Northoff et al., Self-referential processing in our brain—A meta-analysis of imaging studies on the self. *Neuroimage* **31**, 440–457 (2006).
31. R. L. Buckner, J. R. Andrews-Hanna, D. L. Schacter, The brain's default network: Anatomy, function, and relevance to disease. *Ann. N. Y. Acad. Sci.* **1124**, 1–38 (2008).
32. B. T. Denny, H. Kober, T. D. Wager, K. N. Ochsner, A meta-analysis of functional neuroimaging studies of self- and other judgments reveals a spatial gradient for mentalizing in medial prefrontal cortex. *J. Cogn. Neurosci.* **24**, 1742–1752 (2012).
33. M. D. Lieberman, M. A. Straccia, M. L. Meyer, M. Du, K. M. Tan, Social, self, (situational), and affective processes in medial prefrontal cortex (MPFC): Causal, multivariate, and reverse inference evidence. *Neurosci. Biobehav. Rev.* **99**, 311–328 (2019).
34. K. N. Ochsner et al., The neural correlates of direct and reflected self-knowledge. *Neuroimage* **28**, 797–814 (2005).
35. P. Fossati et al., In search of the emotional self: An fMRI study using positive and negative emotional words. *Am. J. Psychiatry* **160**, 1938–1945 (2003).
36. T. T. J. Kircher et al., The neural correlates of intentional and incidental self processing. *Neuropsychologia* **40**, 683–692 (2002).
37. K. N. Ochsner et al., Reflecting upon feelings: An fMRI study of neural systems supporting the attribution of emotion to self and other. *J. Cogn. Neurosci.* **16**, 1746–1772 (2004).
38. D. A. Gusnard, E. Akbudak, G. L. Shulman, M. E. Raichle, Medial prefrontal cortex and self-referential mental activity: Relation to a default mode of brain function. *Proc. Natl. Acad. Sci. U.S.A.* **98**, 4259–4264 (2001).
39. E. B. Falk et al., Self-affirmation alters the brain's response to health messages and subsequent behavior change. *Proc. Natl. Acad. Sci. U.S.A.* **112**, 1977–1982 (2015).
40. C. N. Cascio et al., Self-affirmation activates brain systems associated with self-related processing and reward and is reinforced by future orientation. *Soc. Cogn. Affect. Neurosci.* **11**, 621–629 (2016).
41. N. Cooper, S. Tompson, M. B. O'Donnell, E. B. Falk, Brain activity in self- and value-related regions in response to online antismoking messages predicts behavior change. *J. Media Psychol.* **27**, 93–109 (2015).
42. A. D'Argembeau et al., Self-reflection across time: Cortical midline structures differentiate between present and past selves. *Soc. Cogn. Affect. Neurosci.* **3**, 244–252 (2008).
43. D. I. Tamir, J. P. Mitchell, The default network distinguishes construals of proximal versus distal events. *J. Cogn. Neurosci.* **23**, 2945–2955 (2011).
44. H. Ersner-Hershfield, M. T. Garton, K. Ballard, G. R. Samanez-Larkin, B. Knutson, Don't stop thinking about tomorrow: Individual differences in future self-continuity account for saving. *Judgm. Decis. Mak.* **4**, 280–286 (2009).
45. D. R. Addis, L. Pan, M.-A. Vu, N. Laiser, D. L. Schacter, Constructive episodic simulation of the future and the past: Distinct subsystems of a core brain network mediate imagining and remembering. *Neuropsychologia* **47**, 2222–2238 (2009).
46. D. L. Schacter, D. R. Addis, R. L. Buckner, Remembering the past to imagine the future: The prospective brain. *Nat. Rev. Neurosci.* **8**, 657–661 (2007).
47. J. E. Dumas, M. Johnson, A. M. Lynch, Likableness, familiarity, and frequency of 844 person-descriptive words. *Pers. Individ. Dif.* **32**, 523–531 (2002).

48. B. Levine, E. Svoboda, J. F. Hay, G. Winocur, M. Moscovitch, Aging and autobiographical memory: Dissociating episodic from semantic retrieval. *Psychol. Aging* **17**, 677–689 (2002).
49. D. R. Addis, A. T. Wong, D. L. Schacter, Age-related changes in the episodic simulation of future events. *Psychol. Sci.* **19**, 33–41 (2008).
50. A. Aron, E. N. Aron, D. Smollan, Inclusion of other in the self scale and the structure of interpersonal closeness. *J. Pers. Soc. Psychol.* **63**, 596–612 (1992).
51. H. E. Hershfield, Future self-continuity: How conceptions of the future self transform intertemporal choice. *Ann. N. Y. Acad. Sci.* **1235**, 30–43 (2011).
52. F. M. Krienen, P.-C. Tu, R. L. Buckner, Clan mentality: Evidence that the medial prefrontal cortex responds to close others. *J. Neurosci.* **30**, 13906–13915 (2010).
53. R. E. Nisbett, T. D. Wilson, Telling more than we can know: Verbal reports on mental processes. *Psychol. Rev.* **84**, 231–259 (1977).
54. N. Kriegeskorte, M. Mur, P. Bandettini, Representational similarity analysis - Connecting the branches of systems neuroscience. *Front. Syst. Neurosci.* **2**, 4 (2008).
55. H. Ersner-Hershfield, G. E. Wimmer, B. Knutson, Saving for the future self: Neural measures of future self-continuity predict temporal discounting. *Soc. Cogn. Affect. Neurosci.* **4**, 85–92 (2009).
56. D. R. Addis, A. T. Wong, D. L. Schacter, Remembering the past and imagining the future: Common and distinct neural substrates during event construction and elaboration. *Neuropsychologia* **45**, 1363–1377 (2007).
57. M. L. Meyer, M. D. Lieberman, Why people are always thinking about themselves: Medial prefrontal cortex activity during rest primes self-referential processing. *J. Cogn. Neurosci.* **30**, 714–721 (2018).
58. A. L. Courtney, M. L. Meyer, Self-other representation in the social brain reflects social connection. *J. Neurosci.* **40**, 5616–5627 (2020).
59. G. Ainslie, Specious reward: A behavioral theory of impulsiveness and impulse control. *Psychol. Bull.* **82**, 463–496 (1975).
60. K. Albrecht, K. G. Volz, M. Sutter, D. I. Laibson, D. Y. von Cramon, What is for me is not for you: Brain correlates of intertemporal choice for self and other. *Soc. Cogn. Affect. Neurosci.* **6**, 218–225 (2011).
61. M. A. Thornton, M. E. Weaverdyck, J. N. Mildner, D. I. Tamir, People represent their own mental states more distinctly than those of others. *Nat. Commun.* **10**, 2117 (2019).
62. S. E. Taylor, *Positive Illusions: Creative Self-Deception and the Healthy Mind* (Basic Books, 1989).
63. E. Pronin, C. Y. Olivola, K. A. Kennedy, Doing unto future selves as you would do unto others: Psychological distance and decision making. *Pers. Soc. Psychol. Bull.* **34**, 224–236 (2008).
64. R. S. Chavez, T. F. Heatherton, D. D. Wagner, Neural population decoding reveals the intrinsic positivity of the self. *Cereb. Cortex* **27**, 5222–5229 (2017).
65. G. Northoff, D. J. Hayes, Is our self nothing but reward? *Biol. Psychiatry* **69**, 1019–1025 (2011).
66. K. C. McLean et al., The empirical structure of narrative identity: The initial Big Three. *J. Pers. Soc. Psychol.* **119**, 920–944 (2020).
67. D. P. McAdams, “First we invented stories, then they changed us”: The evolution of narrative identity. *Evol. Stud. Imagin. Cult.* **3**, 1–18 (2019).
68. J. M. Adler et al., Variation in narrative identity is associated with trajectories of mental health over several years. *J. Pers. Soc. Psychol.* **108**, 476–496 (2015).
69. D. P. McAdams, C. Zapata-Gietl, “Three strands of identity development across the human life course: Reading Erik Erikson in full” in *The Oxford Handbook of Identity Development*, K. C. McLean, M. Syed, Eds. (Oxford University Press, 2015), pp. 81–94.
70. E. H. Erikson, *Childhood and Society* (W. W. Norton & Company, 1993).
71. J. Sui, G. W. Humphreys, The integrative self: How self-reference integrates perception and memory. *Trends Cogn. Sci.* **19**, 719–728 (2015).
72. J. Sui, A. Yankouskaya, G. W. Humphreys, Super-capacity me! Super-capacity and violations of race independence for self- but not for reward-associated stimuli. *J. Exp. Psychol. Hum. Percept. Perform.* **41**, 441–452 (2015).
73. C. S. Symons, B. T. Johnson, The self-reference effect in memory: A meta-analysis. *Psychol. Bull.* **121**, 371–394 (1997).
74. J. Okuda et al., Thinking of the future and past: The roles of the frontal pole and the medial temporal lobes. *Neuroimage* **19**, 1369–1380 (2003).
75. J. S. Damoiseaux et al., Reduced resting-state brain activity in the “default network” in normal aging. *Cereb. Cortex* **18**, 1856–1864 (2008).
76. J. R. Andrews-Hanna et al., Disruption of large-scale brain systems in advanced aging. *Neuron* **56**, 924–935 (2007).
77. R. N. Spreng, G. R. Turner, Structural covariance of the default network in healthy and pathological aging. *J. Neurosci.* **33**, 15226–15234 (2013).
78. L. L. Carstensen, J. A. Mikels, At the intersection of emotion and cognition: Aging and the positivity effect. *Curr. Dir. Psychol. Sci.* **14**, 117–121 (2005).
79. M. Mather, L. L. Carstensen, Aging and motivated cognition: The positivity effect in attention and memory. *Trends Cogn. Sci.* **9**, 496–502 (2005).
80. D. Parfit, *Reasons and Persons* (OUP Oxford, 1984).
81. D. Hume, *A Treatise on Human Nature* (Clarendon Press, 1739).
82. D. Bates, M. Mächler, B. Bolker, S. Walker, Fitting linear mixed-effects models using lme4. *J. Stat. Softw.*, 10.18637/jss.v067.i01 (2015).
83. C. M. Judd, J. Westfall, D. A. Kenny, Treating stimuli as a random factor in social psychology: A new and comprehensive solution to a pervasive but largely ignored problem. *J. Pers. Soc. Psychol.* **103**, 54–69 (2012).
84. A. M. Dale, Optimal experimental design for event-related fMRI. *Hum. Brain Mapp.* **8**, 109–114 (1999).
85. O. Esteban et al., fMRIPrep: A robust preprocessing pipeline for functional MRI. *Nat. Methods.* **16**, 111–116 (2019).
86. O. Esteban et al., Data from “fMRIPrep.” Zenodo. <https://doi.org/10.5281/zenodo.2851559>. Accessed 24 November 2021.
87. K. J. Gorgolewski et al., Nipype: A flexible, lightweight and extensible neuroimaging data processing framework in Python. *Front. Neuroinform.* **15**, 10.3389/fninf.2011.00013 (2011).
88. K. J. Gorgolewski et al., Nipype. <https://doi.org/10.5281/zenodo.2685428>. Accessed 24 November 2021.
89. D. N. Greve, B. Fischl, Accurate and robust brain image alignment using boundary-based registration. *Neuroimage* **48**, 63–72 (2009).
90. M. Jenkinson, P. Bannister, M. Brady, S. Smith, Improved optimization for the robust and accurate linear registration and motion correction of brain images. *Neuroimage* **17**, 825–841 (2002).
91. R. W. Cox, J. S. Hyde, Software tools for analysis and visualization of fMRI data. *NMR Biomed.* **10**, 171–178 (1997).
92. J. D. Power et al., Methods to detect, characterize, and remove motion artifact in resting state fMRI. *Neuroimage* **84**, 320–341 (2014).
93. T. D. Satterthwaite et al., An improved framework for confound regression and filtering for control of motion artifact in the preprocessing of resting-state functional connectivity data. *Neuroimage* **64**, 240–256 (2013).
94. C. Lanczos, Evaluation of noisy data. *SIAM J. Numer. Anal.* **1**, 76–85 (1964).
95. L. Chang et al., cosanlab/nitools: 0.3.14. <https://doi.org/10.5281/zenodo.3251172>. Accessed 20 June 2019.
96. A. Abraham et al., Machine learning for neuroimaging with scikit-learn. *Front. Neuroinform.* **8**, 14 (2014).
97. B. T. T. Yeo et al., The organization of the human cerebral cortex estimated by intrinsic functional connectivity. *J. Neurophysiol.* **106**, 1125–1165 (2011).
98. D. M. Amodio, C. D. Frith, Meeting of minds: The medial frontal cortex and social cognition. *Nat. Rev. Neurosci.* **7**, 268–277 (2006).
99. R. Saxe, N. Kanwisher, People thinking about thinking people. The role of the temporo-parietal junction in “theory of mind”. *Neuroimage* **19**, 1835–1842 (2003).
100. T. Yarkoni, R. A. Poldrack, T. E. Nichols, D. C. Van Essen, T. D. Wager, Large-scale automated synthesis of human functional neuroimaging data. *Nat. Methods* **8**, 665–670 (2011).