Self-Referential Neuroimaging Cognitive Ontology Dataset

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Abstract

Self-reference (or self-referential processing) refers to the cognitive process by which individuals process information related to themselves. The field of cognitive neuroscience has conducted extensive research on "self-reference" to understand the neural underpinnings of human self-cognition. However, a fundamental question that has received scant attention is whether the term "self-reference" denotes the same psychological process across different studies. This study attempts to preliminarily establish an ontological dataset of self-reference to examine this issue. Employing a standardized procedure to systematically search and screen literature, two independent coders then encoded and standardized the operational definitions of self-reference at both behavioral and neural levels from the included articles, thereby forming the "Neuroimaging Cognitive Ontology Dataset of Self-Reference" . This dataset, derived from 66 neuroimaging papers, comprises operational definitions of self-reference at behavioral and neural levels (saved in CSV format), coordinate data of brain regions activated under different operational definitions of self-reference (saved in BrainMap format), and a manual. Consistency analysis of the data encoding demonstrates reliable coding results. Compared with the automated meta-analysis database Neurosynth, this dataset offers more precise paper screening and enables comparison of similarities and differences in brain regions activated by different operational definitions of self-reference, thus providing more refined results for understanding the neural basis of self-reference. This dataset not only provides a foundation for deepening our understanding of the neural mechanisms underlying human self-cognition, but also serves as a reference for creating other similar meta-research datasets, thereby advancing research in cognitive ontology.

Full Text

Preamble

A Cognitive Ontology Dataset of Neuroimaging Studies on Self-Reference

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Abstract

Self-reference (or self-referential processing) refers to the cognitive processes involved when people process information related to themselves. Cognitive neuroscience has conducted numerous studies on "self-reference" to understand the neural basis of human self-cognition. However, a fundamental question has received little attention: Does the term "self-reference" represent the same psychological process across different studies? This study attempts to preliminarily establish an ontological dataset for self-reference to examine this issue. Using a standardized protocol, we systematically searched the literature and screened articles. Two independent coders then coded and standardized the operational definitions of self-reference at both behavioral and neural levels, resulting in the "Cognitive Ontology Dataset of Neuroimaging Studies on Self-Reference." This dataset comprises 66 neuroimaging articles, including operational definitions of self-reference at behavioral and neural levels (saved in CSV format), coordinate data of brain regions activated under different operational definitions (saved in BrainMap format), and codebooks. Inter-rater reliability analysis demonstrated robust coding consistency. Compared with automated meta-analytic databases such as Neurosynth, our dataset offers more precise article selection and enables comparison of brain activation patterns across different operationalizations of self-reference, providing more accurate results for understanding the neural basis of self-reference. This dataset lays a foundation for in-depth understanding of the neural mechanisms of human self-cognition, provides a reference for creating similar metascience datasets, and promotes research on cognitive ontology.

Keywords: neuroimaging; self-referential processing; metascience; open data; cognitive ontology

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Dataset Profile

Title: A Cognitive Ontology Dataset of Neuroimaging Studies on Self-Reference
Data Corresponding Author: Chuanpeng Hu (hu.chuan-peng@nnu.edu.cn)
Data Authors: Shuting Sun, Nan Wang, Jiahui Wen, Chuanpeng Hu
Time Range: 1990–2021
Data Volume: 28.8 MB
Data Format: *.txt,* .csv, *.Rmd,* .xlxs, *.nii,* .docx, *.html
Data Service System URL: http://doi.org/10.57760/sciencedb.j00001.00469

Dataset Composition:
In addition to the "README.txt" documentation file, the dataset comprises four components: (1) information on included papers and their codebooks, (2) operational definitions of self-reference and their codebooks, (3) neuroimaging coordinate data, and (4) supplementary materials for methods and results in this paper. The dataset includes 66 articles (72 experiments, 2,056 human participants). "Self_{{{Ref}}*{{Article}}*}{Info}.csv" (Chinese version: "自我参照 _ 文章信息.csv") contains article information including authors, publication year, journal, sample size, etc., with the codebook "Codebook_{{{Self}}*{{Ref}}*}{{{Article}}*{{Info}}}.csv" (Chinese version:* "手册 _ 自我参照 _ 文章信息*.csv"). "Self*{{{Ref}}*{{Operationalization}}}.csv" (Chinese version:* "自我参照 _ 操作化定义*.csv") contains information on operational definitions of self-reference, including experimental stimuli, design, and tasks, with the codebook " Codebook*{{{Self}}*{{Ref}}*}{Operationalization}.csv" (Chinese version: "手册 _ 自我参照 _ 操作化定义.csv"). The folder "Self_{{{Ref}}*{{Foci}}*}{Raw}" includes 72 TXT files corresponding to activation coordinate information from 72 experiments reported in 66 articles. The "Suppl_{Materials}" folder contains supplementary materials for this paper.

Introduction

Self-reference (or self-referential processing) is a widely used concept in cognitive science and cognitive neuroscience, typically referring to the cognitive processes involved when people process self-related information [1]. Previous studies have found that when humans process self-related information, brain regions such as the ventromedial prefrontal cortex (vmPFC) and posterior cingulate cortex (PCC) show specific activation patterns [2-3]. Self-reference is considered an important function of the brain' s default mode network (DMN) [4-5]. Neuroimaging research in psychiatric disorders has also indicated that functional abnormalities in brain regions related to self-reference are associated with various mental illnesses, including depression [6], schizophrenia [7], and autism [8]. Therefore, understanding the neural mechanisms of self-reference represents a crucial question in cognitive neuroscience.

Notably, neuroimaging results for self-reference are influenced by experimental manipulations. For example, comparing self to close others elicits stronger activation in the right lateral prefrontal cortex (rLPFC), whereas comparing self to non-close others yields stronger activation in the medial prefrontal cortex (MPFC) [9]. Information content may also affect the brain regions activated during self-reference: processing physical self-information is closely related to lateral regions of the right hemisphere, while processing psychological self-information primarily activates midline cortical structures [10]. The sensory modality through which self-related information is presented also impacts activation patterns: auditory presentation of self-information activates the posterior precuneus cortex (PCC) more extensively [11], whereas visual presentation leads to greater activation in the dorsolateral prefrontal cortex (DLPFC) and posterior parahippocampal gyrus (PPHG) [12]. Additionally, Zhu Ying and colleagues found that brain regions activated by close-other reference and self-reference are modulated by participants' cultural backgrounds [13].

These studies point to an ontological commitment problem with the concept of "self-reference" —namely, whether this concept represents an objectively existing entity, such as a specific psychological processing mechanism or a particular pattern of brain activity. Current research on cognitive ontology suggests that cognitive science and cognitive neuroscience generally lack rigorous examination of concepts, with substantial variation in the operational definitions of the same concept across studies [14]. Inconsistent operationalization of the same concept may compromise measurement validity and could represent an important contributor to reproducibility issues in psychological and cognitive neuroscience research [15-17]. In exploring the neural mechanisms of self-reference, differences in operational definitions mean researchers struggle to establish stable relationships between self-reference and brain regions/networks. Automated meta-analytic platforms/databases cannot resolve ontological commitment problems. For instance, the Neurosynth database automatically extracts data points and keywords from neuroimaging papers for automated meta-analysis, but its algorithmic search for terms in abstracts cannot extract relevant details about operational definitions of cognitive processes [18]. Recently, researchers developed the NeuroQuery database using supervised learning, which searches full texts to identify semantic similarities and then weighted combines activation coordinates from closely related terms to predict brain regions that different terms might activate [19]. However, NeuroQuery does not consider experimental operationalizations, and the vocabulary used to establish semantic similarity includes paper introductions and discussions, which may reflect researchers' beliefs more than the actual similarity of cognitive processes. Therefore, no current database can help researchers explore the ontological commitment problem of the self-reference concept.

To address this issue, this study adopts a metascience perspective, rigorously examining and standardizing operational definitions of self-reference to establish a neuroimaging ontology dataset for self-reference. The core of this study involves organizing operational definitions that may affect self-referential processing, establishing standardized classification indices, and saving relevant information in common data formats. Meta-analytic results based on this dataset will reveal differences arising from different operationalizations of self-reference, advancing theoretical construction and understanding of human self-cognition.

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1. Data Collection and Processing

1.1 Data Collection

Following the "Standardized Checklist for Open Meta-Analysis Reporting" [20], we conducted systematic literature searches in PubMed and Web of Science (last search date: December 4, 2021). Specifically, we used the keyword "self-referen*" for self-reference literature and combined it with "fMRI" and "PET" using "AND" to search for papers containing these keyword combinations in titles, keywords, and abstracts. To ensure comprehensive inclusion of all relevant literature on self-reference, we also consulted relevant meta-analyses [21-23] and review articles [5,24-28].

We applied the following inclusion criteria when screening all retrieved literature: (1) Studies must have used fMRI or PET scanning; (2) Studies must be empirical research, not meta-analyses or literature reviews; (3) Articles must be written in English and formally published in academic journals or deposited on preprint platforms; (4) Experiments must use healthy adults as participants. Studies including only participants with neurological disorders, other psychiatric abnormalities, or physical diseases were excluded. If studies included both healthy and clinical participants, only data from healthy participants were retained. The primary participant population consisted of young and middle-aged adults (mean age 18–59 years) to avoid abnormalities in self-related information processing due to age changes [29]; (5) Studies reporting spatial coordinates using standard brain spaces (Talairach or MNI) were included. Studies must report complete activation coordinates; if coordinate data were incomplete, authors were contacted via email, and those who did not respond were excluded. To address conversion between the two standard coordinate spaces, we used the Lancaster conversion algorithm [30] to transform Talairach coordinates to MNI space; (6) Studies must include whole-brain analysis results; studies reporting only partial brain regions or region-of-interest (ROI) analyses were excluded; (7) If results from different articles came from the same group of participants, only one article was included in the meta-analysis.

Literature screening followed PRISMA guidelines [31], with the specific screening process adapted from previous work [20,31] (see Figure 1 [Figure 1: see original paper]).

1.2 Data Processing

Coding of included articles involved four stages. In Stage 1, we developed the coding manual. Two coders and the corresponding author collaboratively created a preliminary coding manual. The two coders then independently performed pilot coding on a small number (3-5) of articles based on this preliminary manual, compared results, and discussed improvements with the corresponding author. This stage underwent multiple iterations to produce the final coding manual. In Stage 2, the two coders independently extracted data according to the final coding manual. In Stage 3, the two coders independently rated the consistency of extracted data using a 0/1 scoring system and then aggregated and unified the extracted content. In Stage 4, all included articles were re-examined and aggregated according to the final coding manual. To ensure accuracy in brain imaging data extraction, collection of brain activation coordinate data also involved three stages: independent extraction by two coders, independent verification, discussion of discrepancies, and final integration and classification of all coordinates.

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2. Dataset Description

2.1 Naming Conventions

The dataset comprises four components (excluding the "README" documentation file). The first component records article information in the file "Self_{{{Ref}}*{{Article}}}*{Info}.csv" (Chinese version: "自我参照 _ 文章信息.csv") in CSV format, including basic information such as authors, journal, and sample size. Its codebook is "Codebook_{{{Self}}*{{Ref}}}*{{{Article}}*{{Info}}}.csv" (Chinese version: "手册 _ 自我参照 _ 文章信息.csv"). The second component contains organized operational definition information for self-reference in CSV format, named " Self*{{{Ref}}*{{Operationalization}}}.csv" (Chinese version: "自我参照 _ 操作化定义.csv"), with the codebook "Codebook*{{{Self}}*{{Ref}}}*{Operationalization}.csv" (Chinese version: "手册 _ 自我参照 _ 操作化定义.csv"). The third component includes fMRI activation coordinate data, uniformly stored in the "Self_{{{Ref}}*{{Foci}}}*{Raw}" folder using the same file format as the BrainMap database [32], saved as TXT files named "FirstAuthor_{{{Year}}*{{JournalAbbreviation}}}.txt" , where FirstAuthor represents the surname of the first author, Year represents the publication year, and JournalAbbreviation represents the abbreviated journal name. For example, " Hornung*{{{2019}}*{{FrontBehavNenurosci}}}.txt" indicates an article published in 2019 with first author Hornung in Frontiers in Behavioral Neuroscience. The fourth component contains supplementary materials for methods and results of this paper, stored in the " Suppl*{Materials}" folder.

2.2 Data Sample

The main dataset comprises 66 articles, including 72 experiments and 2,056 participants. Data files include 8 CSV files and 72 TXT files. The 8 CSV files contain Chinese and English versions of article information and operational definitions of self-reference, along with their corresponding codebooks. TXT files contain activation coordinate data. Article IDs are uniformly used across both components. Additionally, the online version of the dataset includes a README.txt file explaining the folder structure (see Figure 2 [Figure 2: see original paper]).

Article information data includes article ID, first author surname, publication year, journal, sample size, gender, age, and other participant-related information (see Figure 2B). Operational definition data includes article ID, experimental design, experimental tasks, etc. (see Figure 2C). This section codes the details of how each article operationalized self-referential processing. Activation coordinate data uses text files (TXT) in BrainMap format (also known as "Sleuth format") to record brief experimental information and brain imaging coordinate data. A single text file records coordinate information from only one article, grouped by whole-brain analysis results. The Sleuth format uses "//" as line separators. Typically, the first line records the brain imaging coordinate template used ("// Reference=MNI" for MNI template); the second line records experimental information; the third line contains additional marker information, where this dataset records the name of the standardized control condition (contrast) corresponding to the coordinate information to preserve the neural-level operational definition of self-reference; the fourth line records sample size ("// Subjects=14" indicates 14 participants underwent brain imaging scanning). Starting from the fifth line, coordinate information is recorded, with each line representing one coordinate point (x, y, z values separated by wildcards). Multiple whole-brain analysis results within a single experiment are separated by blank lines (see Figure 2D).

The data codebooks cover variables used in recording article information and operational definitions, including variable names in Chinese and English, variable values, variable categories, and explanations of specific variable meanings (see Figure 3 [Figure 3: see original paper]A and 3B).

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3. Data Quality Control and Assessment

Following recommendations by Liu et al. [20], coding for this dataset was completed by two independent researchers to reduce subjectivity. After independent coding, the two researchers jointly verified results and scored coding consistency using a 0/1 system. Inter-rater reliability was then calculated (code for consistency scoring and reliability coefficient calculation is available in online supplementary materials).

As a metascience-based dataset, its core quality lies in the accuracy and consistency of the coding process. We used Gwet' s AC1 coefficient [33] to quantify inter-rater reliability, which is more robust than the classic Kappa coefficient [34]. The specific formula is:

$$AC1 = \frac{p_a - p_e}{1 - p_e}$$

where p_a is the overall agreement probability including chance and non-chance agreement, and p_e is the chance agreement probability. The AC1 coefficient was calculated using the R package irrCAC [35]. Results showed an AC1 coefficient of 0.871 for data coding, exceeding 0.8 and indicating high consistency [34].

Coding of experimental details across articles revealed variability in operational definitions of self-reference across experimental design, materials, and data analysis steps (see Figure 4 [Figure 4: see original paper]). These results preliminarily indicate substantial variability in operational definitions of self-reference across studies: sensory modalities include visual, auditory, and mixed presentations; stimulus types include trait words, sentences, and pictures; required participant responses range from judging whether trait words describe oneself (or others) to making no response; control conditions used in statistical analysis to obtain specific activation patterns for self-reference can be standardized into four categories: close others, celebrities, non-person conditions, and strangers. These preliminary analyses demonstrate that the ontological commitment of self-reference is indeed a neglected issue, and its impact on the neural basis of self-reference requires further investigation.

Compared with existing automated meta-analytic databases, this dataset offers two advantages. First, it provides more refined and accurate literature selection, overcoming limitations of automated meta-analytic databases [18-19]. When searching Neurosynth using the closest English term "self-referential," 166 articles were retrieved, with only 14 overlapping with our dataset. Similarly, searching "self-referential" in NeuroQuery yielded 72 associated terms and 30 relevant articles, with only 11 overlapping with our dataset. Differences in article selection lead to different ALE meta-analytic results. Comparing Neurosynth results (Figure 5A) with ALE meta-analysis results from our dataset (Figure 5B; methodological details in supplementary materials) shows similar overall patterns, but our ALE results show more focused activation patterns and exclude temporal regions, consistent with previous manual meta-analyses [10,21].

Second, this dataset can reveal effects of variability in operational definitions. As a demonstration, we classified literature and performed ALE meta-analysis based on one dimension of self-reference operationalization: control conditions in statistical analysis. As noted, current literature can be divided into four operationalization categories based on control conditions: self vs. close others (e.g., family or friends), self vs. celebrities (e.g., politicians or entertainment stars), self vs. non-person conditions (e.g., font or semantic judgments), and self vs. strangers. Due to insufficient literature for the last category (n = 5) to meet ALE meta-analysis requirements, we performed meta-analysis only on the first three categories and conducted contrast analyses. Results showed that differences in control conditions significantly affected the brain network for self-reference effects (see Figure 5 [Figure 5: see original paper] C, D, E and Table 1).

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4. Data Value

This dataset systematically reviews fMRI and PET studies on self-reference, analyzing in detail how self-reference is operationalized in existing literature. By uniformly describing the details of self-reference operationalizations in neuroimaging research and distinguishing several types of operationalizations that may affect self-reference, this dataset helps researchers recognize the importance of operational definitions and the ontological commitment problem of the "self-reference" concept, promoting more standardized use of the concept.

Second, this dataset provides more refined meta-analytic data for self-reference, facilitating comparison of how different operationalizations affect self-reference and improving understanding of the relationship between psychological constructs and their operational definitions. How a psychological process is operationalized inherently reflects researchers' theoretical assumptions about that process. Comparing different operationalizations will help researchers more clearly articulate their theoretical assumptions about self-reference, promoting theoretical construction regarding self-referential processing. Fine-grained distinctions among operationalizations will also enhance precise understanding of brain regions activated by self-reference, advance comprehension of the cognitive neural mechanisms of self-reference, and provide a basis for cross-psychiatric diagnosis and treatment. Finally, establishing this dataset provides a reference for constructing similar cognitive ontology datasets in the future.

As the first neuroimaging cognitive ontology dataset targeting a single psychological construct, this dataset still has considerable room for improvement in terms of data volume and format. In terms of quantity, future work should incorporate more neuroimaging studies on self-information processing, such as research on self-face recognition [10] and autobiographical memory [22]. Regarding data format, future versions may integrate technologies that facilitate machine readability and automated meta-analysis, such as integration with DataLad [36].

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5. Data Usage Methods and Recommendations

This dataset includes operational definitions of self-reference and fMRI/PET activation coordinate results in formats commonly used for ALE neuroimaging meta-analysis. Researchers can use software such as GingerALE, MATLAB, and Python to read and analyze the data. Future research can classify self-referential processing of interest based on operational definitions and perform coordinate-based neuroimaging meta-analysis or Activation Network Mapping [37] analyses to generate new hypotheses or compare results with meta-analyses of other cognitive processes. Specifically, researchers can combine their research interests with operational definition information in the dataset to perform secondary classification and screening of studies included in the dataset, then extract activation coordinate data from each experiment for neuroimaging meta-analysis [10,38-40].

6. Data Availability Statement

This dataset consists of publicly available data from published journal articles and can be obtained from the Science Data Bank. Specifically, the dataset is accessible at http://doi.org/10.57760/sciencedb.j00001.00469. If you use this dataset in your research, please cite it appropriately in your references. Commercial use of this dataset is prohibited.

Author Contributions

Shuting Sun (1998-), female, from Fuzhou, Fujian Province, Master' s student. Research interests: metascience, social cognition, and mental health. Primary contributions: data collection, data verification, compilation, data analysis, and manuscript writing and revision.

Nan Wang (2000-), female, from Yancheng, Jiangsu Province, undergraduate student. Research interests: metascience and psycholinguistics. Primary contributions: data collection, data verification, compilation, and manuscript writing and revision.

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Chuanpeng Hu (1987-), male, from Jingzhou, Hubei Province, Ph.D., Professor. Research interests: metascience, social cognition, and computational cognitive neuroscience. Primary contributions: overall project design, data verification, project coordination, and manuscript writing and revision.

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