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开放数据的学术影响力：基于 DIRECT 联盟与 REST-meta-MDD 数据库的文献计量证据

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摘要: 重性抑郁障碍 (MDD) 是全球最常见的精神疾病之一, 其复杂的神经生物学机制以及对个体化治疗的迫切需求, 推动了抑郁症脑影像大数据研究的进一步发展。静息态功能磁共振成像作为活体无创的全脑神经影像学技术, 已广泛应用于MDD的脑影像病理特征分析, 但由于小样本和分析方法差异等因素, 研究结果推广性受限。为解决这一问题, 我国学者依托DPARF的国内临床用户网络, 联合全国精神科专家, 牵头建立了抑郁症脑影像大数据 (DIRECT) 联盟, 通过统一标准化预处理, 显著提高了研究结果的可重复性。DIRECT联盟于2020年面向全球公开了REST-meta-MDD数据库, 为研究者提供了一个开放的数据资源。本研究对2019–2025年使用REST-meta-MDD数据库进行研究的103篇文章进行了文献计量学分析。结果发现, REST-meta-MDD不仅加速了抑郁症的脑影像学研究, 还促进了跨国合作和开放科学的发展。通过数据共享, 研究者在MDD的亚型分类、诊断模型优化及脑结构和功能异质性等方向取得了进展, 也为其他精神疾病的诊断提供了重要参考, 增强了不同神经精神疾病之间的诊断差异化。未来, 随着更多样本的加入和数据共享的深入, REST-meta-MDD数据库将在训练多疾病分类模型、实现跨疾病诊断、指导神经调控干预以及针对特定临床问题的人工智能分析等方面发挥更大作用。

关键词: 重性抑郁障碍; DIRECT联盟; REST-meta-MDD; R-fMRI; 神经成像; 开放科学

数据库 (集) 基本信息简介

数据库 (集) 名称	REST-meta-MDD 数据库
数据通信作者	严超赣 (yancg@tsinghua.edu.cn)
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数据收集时间	2017–2019年
数据收集范围	中国
数据量	107.58 GB
数据格式	*.zip, *.nii.gz, *.tsv, *.tif, *.hdr, *.txt
数据服务系统网址	https://doi.org/10.57760/sciencedb.o00115.00013
数据库（集）组成	REST-meta-MDD数据库收集了1128名健康对照者与1300名抑郁症患者的静息态功能磁共振成像数据。数据库共包含三个主要文件：1、DIRECT_REST-meta-MDD_Data_Use_Agreement.pdf为数据使用协议，详细说明了数据访问、使用及引用的相关条款；2、REST-meta-MDD-Phase 1-Sharing.zip内含5个子文件夹：(1) Masks：AutoMasks文件夹下储存了基于功能图像自动生成的全脑掩模、(2) PicturesForChkNormalization：储存了用于检查空间标准化质量的图像、(3) QC：质检结果文件夹，包含RawFunImgQC.tsv与RawT1ImgQC.tsv文件，分别记录静息态功能像与T1结构像的质量评估结果、(4) RealignParameter：储存各被试的头动参数信息、(5) Results：储存静息态功能指标的计算结果，包括ALFF、fALFF、ReHo、VMHC、Degree Centrality以及ROI Signals；3、REST-meta-MDD-VBM-Phase1-Sharing.tar.gz中储存了基于体素的形态学分析结果：(1) c1：个体空间中的灰质分割图、(2) c2：个体空间中的白质分割图、(3) c3：个体空间中的脑脊液分割图、(4) wc1：MNI空间中的灰质分割图、(5) wc2：MNI空间中的白质分割图、(6) wc3：MNI空间中的脑脊液分割图、(7) mwc1：MNI空间中的灰质体积、(8) mwc2：MNI空间中的白质体积、(9) mwc3：MNI空间中的脑脊液体积、(10) u_rc1：从个体空间到组模板的变换参数。有关数据结构的详细信息可以参考： http://rfmri.org/RfMRIMapsDataSharingStructure 。

引言

重性抑郁障碍（Major Depressive Disorder, MDD）目前是全球最常见的精神疾病之一，影响着全球约 3 亿人的身心健康^[1]。其核心特征包括持续的情绪低落和认知功能障碍，严重情况下可能伴有自杀行为^[2-3]。近年来，越来越多的研究聚焦于 MDD 生物标志物的探索，旨在实现精准的个性化治疗和更精细的疾病亚型分类，从而推动疾病早期诊断。其中，磁共振成像（magnetic resonance imaging, MRI）技术作为一种重要的客观生物标志物研究工具，受到广泛关注。神经影像学研究发现，MDD 患者在大脑结构和功能上表现出显著异常，例如灰质体积减少和功能网络连通性下降，这些异常可能与其情绪调节障碍和认知缺陷密切相关^[4-5]。此外，MRI 技术具有无创性、采集设备覆盖面广以及高分辨率成像等优势，使其在抑郁症诊断、分型及治疗标志物的探索中展现出巨大潜力。

静息态功能磁共振成像（Resting-state Functional Magnetic Resonance Imaging, R-fMRI）作为探

索 MDD 临床症状背后神经生物学机制的一种神经影像学方法，其应用日益广泛^[6]。尽管大量研究致力于通过 R-fMRI 分析 MDD 的病理特征，然而，迄今为止，仍未发现能够稳定识别 MDD 患者且具有临床应用价值的神经影像标志物^[4]。不仅如此，以往通过 R-fMRI 分析得到的研究结果常常存在不一致，甚至相互矛盾，限制了其向临床应用的转化^[7]。例如，首次关注 MDD 患者默认模式网络（Default Mode Network, DMN）改变的研究发现，DMN 中的功能连接性增加^[8]，然而其他类似的研究却得出了相反的结论^[9-10]，即 MDD 患者默认模式网络中的功能连接减少。导致以上结论冲突的原因是多方面的，包括：首先，不稳定或者矛盾的研究发现是由于多数的 R-fMRI 研究样本量较小^[7]。小样本研究的统计检验力有限，更容易出现假阳性结果，从而导致研究结果的可重复性较低^[11,12]。有研究发现，低于 80 个被试（每组 40 个被试）的小样本量能够反映出真实效应的可能性较低^[13]。最近的一项研究更是指出，想要得到可重复的全脑关联研究结果，其样本量需要达到数千名被试^[14]。这表明，特定的研究领域需要较大的数据库来提高研究结果的可重复性。其次，R-fMRI 研究分析过程中的高度灵活性也会导致结果的不稳定性^[11,13,15]。一项由 70 多个独立团队分别对相同神经影像数据库进行分析的研究结果表明，fMRI 数据的不同预处理流程会产生差异性的研究结果^[16]。这说明，在特定的 R-fMRI 研究领域中，想要得到稳定可重复的真实效应，必须对经过标准化预处理的大型数据库进行分析。

然而，目前在 MDD 研究领域，仍然缺乏具备可重复性的大样本、标准化预处理流程的大型神经影像数据库。为应对这些关键挑战，严超赣教授团队于 2017 年联合臧玉峰教授和赵靖平教授，联络 DPARSF 的国内临床用户，联合全国精神科专家，牵头建立了抑郁症脑影像大数据联盟（Depression Imaging REsearch ConsorTium, DIRECT 联盟）。REST-meta-MDD 是 DIRECT 联盟发起的首个多站点协作项目，旨在构建一个经过标准化预处理流程的大样本 MDD 脑影像数据库。国内共有 17 家医院参与该项目，并共享了 25 个研究数据，包括 1300 名 MDD 患者和 1128 名正常对照的 R-fMRI 数据。REST-meta-MDD 数据库中的 1300 名 MDD 患者包括：(1) 826 名女性和 474 名男性；(2) 562 名首次发作的患者，其中有 318 名首次发作的未服药患者（first episode drug-naïve, FEDN）、160 名服用抗抑郁药的患者、84 名患者服药情况不详；(3) 282 名复发性患者，其中 121 名服用抗抑郁药、76 名未接受药物治疗、85 名患者服药情况不详；(4) 456 名患者的发病类型（首次或复发）和药物治疗情况不详。这些来自不同机构与站点的被试数据，通过统一的 DPARSF 标准化流程进行预处理以减少预处理方法的异质性，并进一步校正了站点效应^[7]。另外，由于 R-fMRI 指标对头部运动等生理因素非常敏感^[17]，研究人员通过 DPARSF 在被试水平和组水平进行回归（Friston-24 模型）来对平均帧位移（Framewise Displacement, FD）校正^[18]。所有通过 REST-meta-MDD 数据库进行分析的研究，都在经过统一的标准化预处理流程后的数据上进行，保证了研究结果的可重复性。

2020 年 1 月 1 日 REST-meta-MDD 数据库（<http://rfmri.org/REST-meta-MDD>）面向全球研究者开放，数据库的开放共享促进了全球科研合作，至今已有包括 Stanford University、Columbia University、New York University、King's College London 和 University of North Carolina 等在内的 522 个国内外知名研究单位申请并获批使用，具体的机构分布如图 1 所示。该数据库提供了大规模、标准化的脑影像数据，可以解决人工智能（Artificial Intelligence, AI）模型训练中的样本异质性问题与小数据瓶颈，进而推动 AI 在抑郁症研究中的应用与创新。截至目前，国内外研究者通过分析 REST-meta-MDD 数据库已经发表了 103 篇经同行评审的研究论文。在本研究中，我们回顾了这些已发表的文章，发现这些研究基于迁移学习和深度学习开发的 MDD 诊断模型，不仅提高了模型的

泛化能力和预测准确性，也为 MDD 的精准诊断提供了新的思路。此外，研究者利用 AI 技术从脑影像数据中提取和识别出 MDD 的关键特征，从而推动了 MDD 亚型分类、病程预测及个性化治疗策略的发展。未来，随着更多数据的加入，DIRECT 联盟有望在 AI 赋能的多疾病分类模型的训练、跨疾病诊断、神经调控干预和个性化治疗领域发挥更大作用。



图 1 申请并获批使用 REST-meta-MDD 数据库的机构分布图

Figure 1 Geospatial distribution of institutions authorized to access the REST-meta-MDD database

1 方法

研究根据 PRISMA (Preferred Reporting Items for Systematic Review and Meta Analyses) 指南^[19]进行。由两人独立进行文献检索，比较两次检索的结果后，对不一致的地方进行讨论并达成共识。

1.1 文献检索与纳入标准

本研究通过 Web of Science Core Collection 进行文献检索。Web of Science 核心合集收录了具有高影响力和高质量文章的期刊以及会议论文和书籍等，被认为是文献计量分析领域的领先数据库^[20]。研究者在使用 REST-meta-MDD 数据库撰写文章时，通常会在作者中加入 DIRECT 联盟、在方法中提及 REST-meta-MDD 数据库或引用文章《Reduced default mode network functional connectivity in patients with recurrent major depressive disorder》^[7]。该文为数据库首次公开发表的代表性成果，后续使用数据库的研究通常引用此文以标明数据来源，该文长期处于 ESI 前千分之一高被引论文行列，其引用可作为数据库使用的初步判断依据。因此，本研究首先在该数据库中检索该文章“Reduced

default mode network functional connectivity in patients with recurrent major depressive disorder”，并确定共有 436 篇引文。此外，研究还利用关键词进行检索：TS = (“REST-meta-MDD”) OR TS = (“DIRECT Consortium” or “DIRECT”) AND TS = (“MDD” or “major depressive disorder” or “depressive disorder”) AND TS = (“functional magnetic resonance imaging” or “functional MRI” or “fMRI”)，得到 36 篇引文（文献检索截至日期为 2024 年 12 月 02 日）。将两部分检索内容合并后去掉重复及非英文文献，得到 437 篇文献。

接下来，对检索到的文献进一步筛选，纳入后续分析的文献需符合以下标准：(1) 研究需为实证研究，非实证类研究应予以排除，包括综述、数据论文、会议摘要、预印本以及社论材料等；(2) 研究使用的数据包括 REST-meta-MDD 数据库。最终，纳入 REST-meta-MDD 数据库相关分析的文献共 103 篇，详细的文献检索、纳入及排除流程如图 2 所示，有关使用 REST-meta-MDD 数据库进行研究的 103 篇相关文献，可查阅补充材料附录 1。

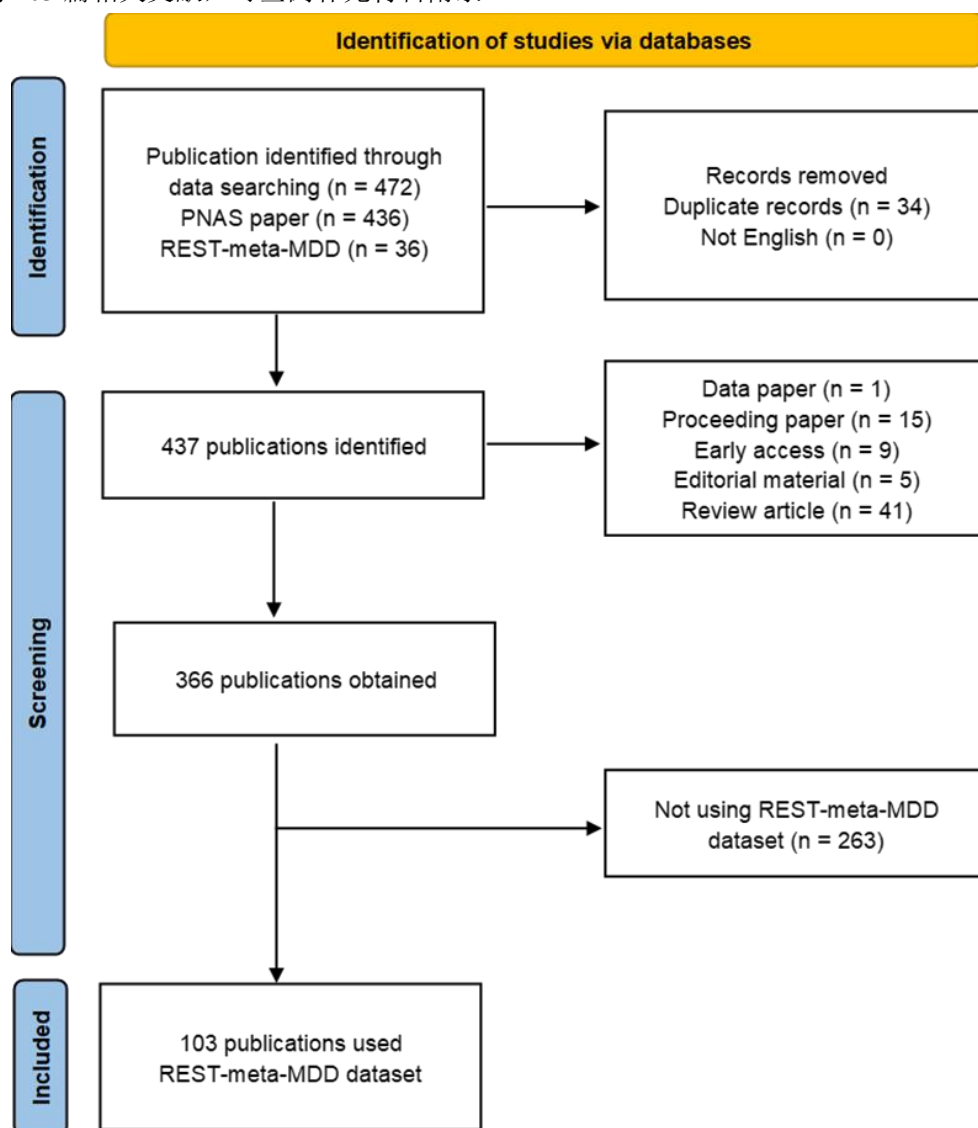


图 2 引用 REST-meta-MDD 数据库文献的检索流程图

Figure 2 Flowchart of the literature retrieval process for studies using the REST-meta-MDD database

注：PNAS paper 代指文章 “Reduced default mode network functional connectivity in patients with recurrent major depressive disorder”

本研究存在以下潜在检索局限：首先，文献来源为 Web of Science 核心数据库收录的高质量期刊文献，可能遗漏部分相关研究；其次，筛选过程中排除了非英文文献，可能引入语言偏倚^[21]；此外，基于现有的筛选标准虽保证了所选文章的质量，但可能遗漏了预印本等尚未正式发表的最新研究。

1.2 研究工具及数据处理过程

本研究结合使用了 CiteSpace (6.3R1) 和 VOSviewer (1.6.20) 等可视化软件进行文献计量分析。CiteSpace 是由美国德雷塞尔大学 Chao-MeiChen 教授团队开发的一款基于 Java 平台的非商业性可视化文献计量软件，也是目前最常用的文献计量分析软件之一^[22]。VOSviewer 由荷兰莱顿大学的 VanEck 教授和 Waltman 教授开发，其核心算法 VOS (Visualization of Similarities) 映射技术可以用来构建和可视化国家/地区的合作网络以及关键词共现网络^[23]。VOS 技术采用一种基于相似性的聚类方法，将频繁共同出现的关键词视为具有潜在主题关联的概念，通过计算其共现频率将关键词分配到不同分类^[24]。如，若“fMRI”“default mode network”和“depression”这些关键词在多篇文献中经常共同出现，VOS 映射会将它们归入同一类别。网络可视化中的每个节点代表一个项目，如国家/地区、机构、作者、期刊或关键词等。节点的不同颜色表示不同的聚类，而节点的大小反映了其出现的次数，节点越大表示出现的次数越多。节点之间的线表示术语之间的联系，线的粗细表示联系的强度^[25]。本研究采用总链接强度 (Total Link Strength, TLS) 来量化节点之间的连接强度。通过 VOS viewer 和 Cite Space 软件分别构建出国家/地区合作网络图、研究主题和术语共现网络图并导入 Photoshop 软件进行调整。此外，研究还通过 R studio (4.4.1) 使用 ggplot2 和 dplyr 等包来进行结果可视化，包括对 REST-meta-MDD 数据库年度应用趋势及其首发文章的引用趋势的可视化分析，以及对收录 REST-meta-MDD 数据库相关文章数量排在前 20 的期刊影响因子进行可视化。

2 研究结果

2.1 REST-meta-MDD数据库的应用趋势

本研究收集了 2019–2025 年使用 REST-meta-MDD 数据库进行研究的已发表文献共计 103 篇。关于全部纳入文献的详细信息，请参阅补充材料。图 3 显示了 REST-meta-MDD 数据库在 2019–2024 年中应用的整体趋势，自 2020 年 DIRECT 联盟将该数据库对全球研究者公开后，申请使用数据库的研究数量逐年增长，其中 2023 年有 36 项研究使用该数据库发表文章。这表明 REST-meta-MDD 数据库对 MDD 领域的相关研究产生了广泛影响。

2.2 REST-meta-MDD数据库的全球影响力

据统计，使用 REST-meta-MDD 数据库发表的 103 篇文献中，共有来自 21 个国家的 243 个研究机构参与。基于 VOSviewer 对 103 篇相关文献的合作国家进行分析，建立了国家间的合作网络，如图 4 所示。网络分析的结果表明，REST-meta-MDD 数据库使得来自不同国家/地区的研究机构产生了紧密的合作联系。其中，中国拥有最强大的国际合作网络 (TLS=53)，其次是美国 (TLS=48)、英国 (TLS=21) 和加拿大 (TLS=18)。根据网络分析中节点之间的联系强度可知，中国和美国之间的联系最为紧密，两者之间拥有较多的合作关系。此外，这两个国家分别作为核心与其他多个国家保持合作关系。上述分析表明，REST-meta-MDD 数据库不仅推动了全球多国间的

科研协作，还积极促进了开放科学的发展，为跨国界的合作研究提供了有力支持。

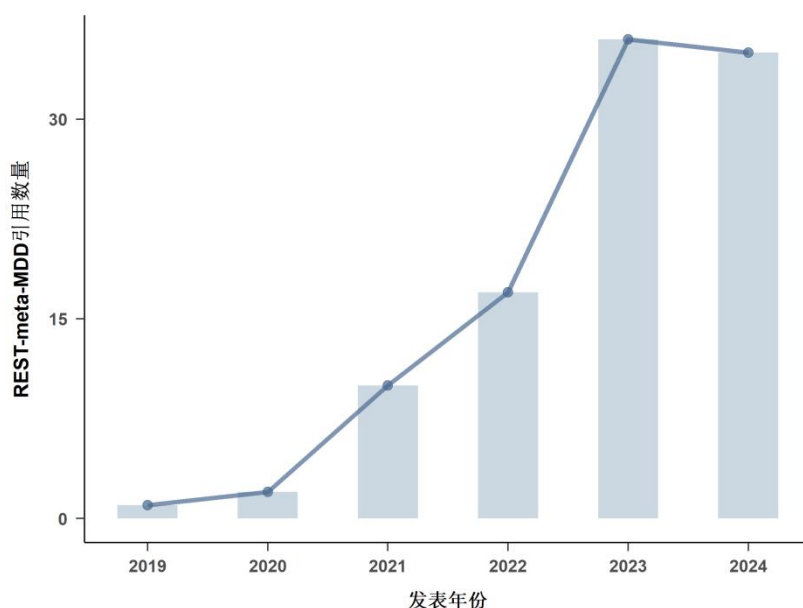


图3 REST-meta-MDD 数据库年度应用趋势

Figure 3 Annual trend in the application of the REST-meta-MDD Database

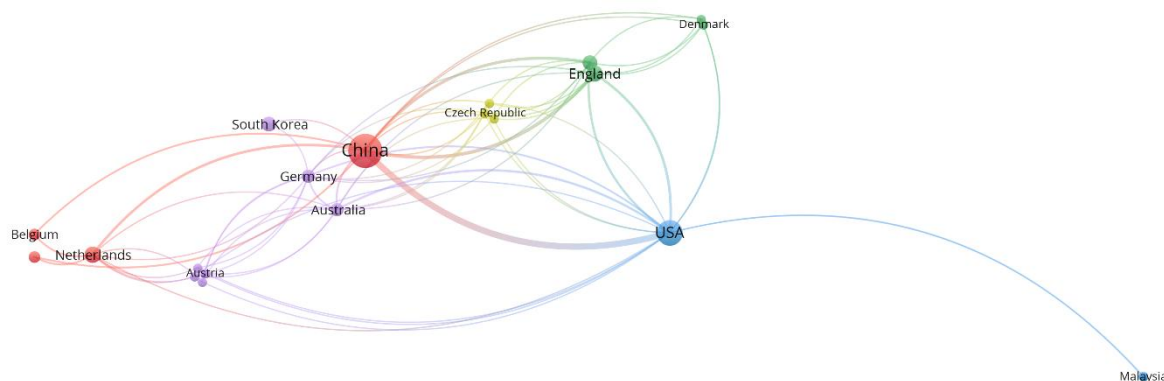


图4 应用 REST-meta-MDD 数据库进行研究的国家/地区合作网络图

Figure 4 International collaboration network of countries and regions conducting studies using the REST-meta-MDD database

2.3 REST-meta-MDD数据库相关研究的期刊分布

本研究统计了所有收录应用 REST-meta-MDD 数据库发表文章的期刊，共 58 种，多数期刊的 JCR（Journal Citation Reports）分区为 SCI 一区。其中影响因子最高的期刊为 *Science Bulletin*（Impact Factor, IF = 18.8），共收录了两篇相关文章。随后，筛选出收录文章数量排名前 20 的期刊及其影响因子，如图 5 所示。*Journal of Affective Disorders*（IF=4.9）收录的文章最多，有 12 篇，其次是 *IEEE Journal of Biomedical and Health Informatics*（IF=6.7）和 *Human Brain Mapping*（IF=3.5），均收录了 6 篇相关文章。此外，*Science Advance*、*Molecular Psychiatry*、*Biological Psychiatry*、*Neuroimage*、*Nature Mental Health* 等神经影像学和精神医学等领域的顶尖期刊也收录了基于 REST-meta-MDD 数据库的相关文章。这些统计结果说明 REST-meta-MDD 数据库对于推进 MDD 领域中的新发现以及开发基于脑影像大数据的新方法学框架均起到了重要作用。

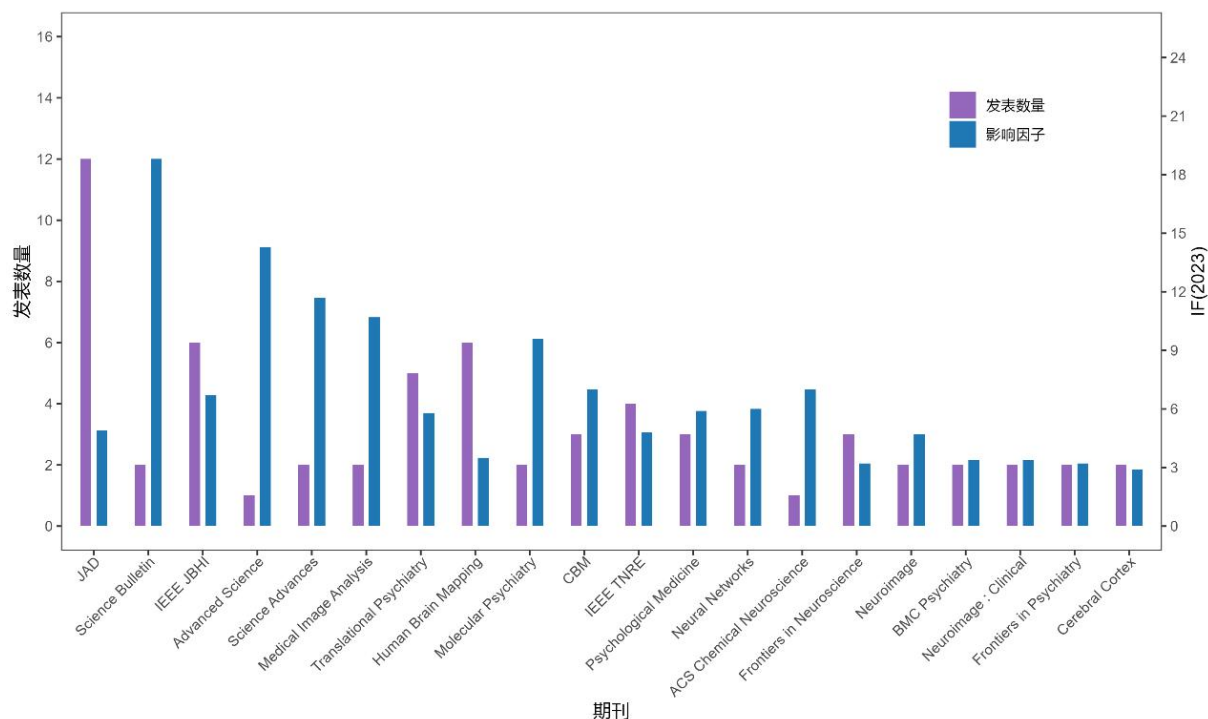


图5 收录 REST-meta-MDD 数据库相关文章数量前 20 的期刊（此外，Science Advance、Molecular Psychiatry、Biological Psychiatry、Neuroimage、Nature Mental Health 等神经影像学和精神医学等领域的顶尖期刊也收录了基于 REST-meta-MDD 数据库的相关文章）

Figure 5 Top 20 journals publishing the most articles related to the REST-meta-MDD Database (Furthermore, top journals in the fields of neuroimaging and psychiatry, such as Science Advances, Molecular Psychiatry, Biological Psychiatry, NeuroImage, and Nature Mental Health, have also published articles based on the REST-meta-MDD database.)

注：JAD = Journal of Affective Disorders; IEEE JBHI = IEEE Journal of Biomedical and Health Informatics; IEEE TNRE = IEEE Transactions on Neural Systems and Rehabilitation Engineering; CBM = Computers in Biology and Medicine; 影响因子数据参考自 Web of Science 2023 年的记录。

2.4 REST-meta-MDD数据库相关研究的期刊分布

本研究通过构建引用 REST-meta-MDD 数据库进行研究的文章关键词聚类图谱，来调查该数据库的应用趋势及研究热点。使用 CiteSpace 软件，将网络节点类型设置为“关键词”，采用前 10% 高频词优选策略（Top 10% terms strategy），筛选出 101 个具有实际研究意义的关键词。随后，调用对数似然比算法（Log-Likelihood Ratio, LLR）为聚类生成标签，并将关键词划分为六个不同的类别，如图 6 所示，图中不同颜色代表各自的类别。第一类（红色）研究聚焦于 MDD 诊断，关键词包括“major depressive disorder”“diagnosis”和“intelligent diagnosis”等。例如，Qin 等人利用图卷积网络（Graph Convolutional Network, GCN）训练的诊断模型，其分类准确率达到 81.5%^[26]。第二类（黄色）关注 MDD 脑结构特征，关键词如“biomarker”“posterior cingulate cortex”“middle temporal gyrus”和“anterior cingulate gyrus”等。此类研究发现，MDD 患者额上回、扣带回等脑区灰质体积显著减小^[26-28]。第三类（绿色）探讨时空动态性变化，关键词包括“temporal-spatial expression specificity”“brain modeling”“heterogeneity”等，这些研究揭示了 MDD 患者脑功能的

时空特征。第四类（浅蓝色）研究聚焦于 MDD 的功能异常，关键词包括“default mode network”“cellular signature”和“brain networks”等。此类研究发现，MDD 患者的默认模式网络连接性改变与临床症状相关^[27-29]。第五类（深蓝色）则涉及其他精神障碍的诊断，关键词涵盖“supervised classification”“psychiatric diagnosis”，例如，有研究采用“震源图法”提高精神分裂症的诊断准确率。该方法最初用于地震学中分析震中位置，在神经影像学中被引入用于识别脑功能异常的核心区域，进而提高疾病识别的空间精度^[30]。最后一类（粉色）关注深度学习 methodology 创新，关键词包括“causal generation”“prototype learning”和“multi-view graph”等。其中，“prototype learning”（原型学习）指的是通过构建具有代表性的原型样本，来概括各类别的核心特征；而“multi-view graph”方法则通过整合结构连接与功能连接等多个特征维度，对大脑网络进行联合建模。此外，研究者还提出了多视图-图神经网络（Multi-View Graph Neural Network, MV-GNN）、多尺度自适应多通道融合深度图卷积网络（multi-scale adaptive multi-channel fusion deep graph convolutional network, MAMF-GCN）等新型深度学习模型，显著提升了 MDD 诊断的准确性和可解释性^[31-32]。分析表明，研究主要集中于开发 MDD 诊断新算法模型、探索 MDD 脑结构与功能异常、相关神经精神疾病诊断等领域。

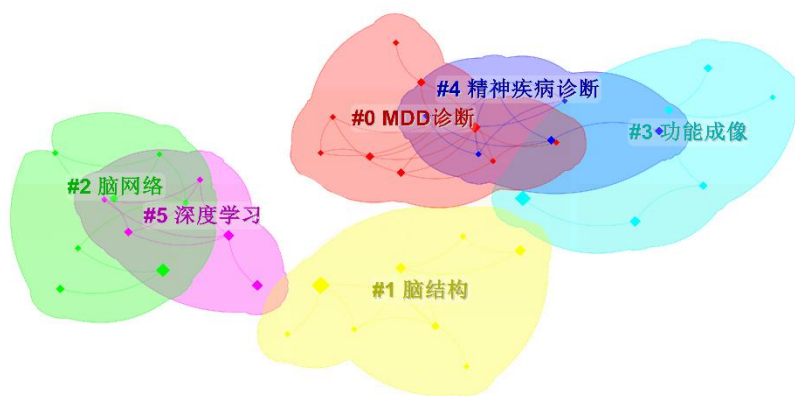


图 6 基于 REST-meta-MDD 数据库进行的研究关键词聚类图谱

Figure 6 Keyword clustering map of research based on the REST-meta-MDD database

3 讨论

REST-meta-MDD 数据库作为一个开放获取的神经成像数据库，凭借其大规模样本量和规范的数据处理模式，已经成为重性抑郁障碍领域的重要研究资源。自 2020 年向全球公开以来，已有 103 项研究基于该数据库展开分析，这些研究不仅提升了 MDD 的诊断准确性与亚组分类精度，推动了 MDD 脑结构与功能异质性的深入探索，还增强了神经精神疾病间的特异性诊断精度。未来，该数据库将继续在基于经颅磁刺激（transcranial magnetic stimulation, TMS）治疗的 MDD 个体化靶点计算领域发挥重要作用。

作为一个大规模、多站点的研究，Rest-meta-MDD 为训练 MDD 诊断与亚组分类模型提供了丰富的数据。许多研究者利用 REST-meta-MDD 数据库来改进 MDD 脑影像诊断模型。比如，Qin 等人使用图卷积网络训练了一个诊断模型，其分类准确率达到 81.5%，并且优于传统的机器学习分类器^[26]。此外，还有研究利用数据库进行 MDD 亚组分类。基于脑萎缩的不同轨迹，研究者发现了三

种高度稳健的 MDD 亚型，这些亚型表现出了不同的临床特征和基因表达模式^[33]。Gallo 等人结合支持向量机（Support Vector Machine, SVM）与图卷积神经网络，训练模型对药物治疗亚组和非药物治疗亚组进行分类，平均准确率为 62%，尽管模型准确性不理想，但研究发现，丘脑的超连接性可以提升模型的分类表现^[34]。除了 GCN，还有一些研究者提出了不同的 MDD 诊断模型框架，如基于脑功能连接的异构图神经网络（Heterogeneous Graph Neural Network based on brain Functional Connectivity, FC-HGNN）、基于差异的无监督跨域 fMRI 适应框架（Unsupervised cross-domain fMRI Adaptation framework, UFA-Net）以及多视图-图神经网络等^[31,35-36]，这些模型在一定程度上提升了基于脑影像的 MDD 诊断准确性，从而推动了 MDD 精准医疗和个性化治疗的发展。

还有相当一部分研究利用 REST-meta-MDD 数据库揭示并验证了重性抑郁障碍患者大脑结构和功能异质性的新发现。在不同亚型的 MDD 患者中，多个脑区的灰质体积显著减小，包括颞上回、扣带回前中部皮层、额下皮层以及楔前皮层等。这些脑区的灰质减少可能与抑郁症的临床症状相关，影响患者的情绪调节、认知功能以及自我意识等方面^[27-29]。不同亚型之间在灰质体积变化上也存在一定差异，提示不同抑郁症亚型可能涉及不同的神经生物学机制^[27,37]。这些研究结果与 Bora 等人基于荟萃分析对 MDD 患者灰质异常的相关脑区的发现相似^[38-39]。此外，部分研究表明 MDD 可能加速大脑的衰老进程。随着年龄的增长，大脑各功能网络的连通性逐渐减弱，特别是默认模式网络和躯体运动网络内的功能连接性显著下降^[40]。与健康对照组相比，MDD 患者的大脑功能网络连通性下降程度更为显著，进一步支持了 MDD 对大脑衰老的加速作用^[41]。除灰质减少和加速衰老外，也有研究关注 MDD 患者的大脑功能网络在动态连接性、拓扑结构和性别差异等方面的异质性^[42-45]。通过对 REST-meta-MDD 数据库的深入分析，研究者不仅揭示了有关 MDD 的新发现，还进一步验证了先前的研究结果。

作为一个大型的重性抑郁障碍患者静息态脑影像数据库，REST-meta-MDD 数据库不仅推动了 MDD 的特异性诊断，还对其他神经精神疾病的诊断起到了重要促进作用。许多研究将该数据库作为验证集，用以评估其开发的诊断方法和新框架。例如，基于脑功能连接的多级融合分类框架（multi-level FC fusion classification framework, MFC）、采用注意力机制的多尺度自适应多通道融合深度图卷积网络（MAMF-GCN）及动态-静态融合图神经网络（Dynamic-Static Fusion Graph Neural Network, DSFGNN）等新型方法，不仅在诊断准确率上超越了传统模型，还显著提高了模型的可解释性^[32,46-47]。此外，REST-meta-MDD 数据库在提高其他相似精神障碍诊断精度方面同样起到了重要推动作用。例如，以往的研究表明，精神分裂症患者在脑结构改变、临床表现和病理机制等方面与其他神经精神疾病存在显著重叠^[48-50]。为了提高精神分裂症的特异性诊断精度，研究者开发了“震源图法”，识别出的精神分裂症神经影像衍生震源，与其他重叠神经精神疾病的常模偏差模式进行比较后发现，该震源具有较高的诊断特异性^[30]。REST-meta-MDD 数据库提供的重性抑郁障碍脑影像常模，对区分其他重叠精神疾病的特异性诊断同样起到了重要作用。

基于 REST-meta-MDD 数据库构建的诊断分类模型可为 MDD 亚型划分及精准治疗提供依据。通过实现疾病亚型分类，临床治疗可据此实施个性化干预策略，从而优化治疗效果^[51]。在现有治疗体系中，经颅磁刺激作为新型非侵入性神经调控技术，其作用机制为诱导神经活动改变，已获 FDA 批准用于药物难治性抑郁障碍治疗^[52]。该技术的精准实施依赖于功能磁共振成像的神经环路定位功能——通过识别特定脑区异常功能连接模式，fMRI 可为个体化 TMS 靶点选择提供客观依据^[53-54]。基于 fMRI 的个性化 TMS 干预在抑郁症治疗中展现出独特优势，如 Liston 团队的研究发现前额叶背外侧皮层与其他脑区的个体化功能连接特征，可有效预测抑郁患者对 rTMS 治疗的反应

性^[55]。这种以神经环路为靶向的调控方法，为传统疗法应答不佳的患者提供了替代性解决方案。REST-meta-MDD 作为大规模 MDD 患者静息态功能磁共振影像数据库，可以为 TMS 靶点计算提供关键数据支撑。未来，随着更多研究通过该数据库探索 TMS 起效的神经回路及导向靶点算法开发，会进一步推进 MDD 神经调控治疗技术发展。

REST-meta-MDD 数据库在跨疾病研究与人工智能应用中展现出广阔前景。当前已有研究者将其与其他大型精神疾病脑影像数据库（如精神分裂症、孤独症、焦虑障碍等）联合使用，结合深度学习、多任务学习、迁移学习等技术，开发具备跨疾病诊断能力的模型，从而提高不同精神疾病之间的鉴别诊断准确率。如，近期有研究提出了一个深度学习框架，结合自适应注意力网络（adaptive attention network）与功能网络关系解码器，实现了个体化特征选择与全局拓扑结构分析，同时引入反条件分析（counter-condition analysis）模拟脑功能连接在健康与病态间的变化路径，以增强模型的可解释性。该框架在 REST-meta-MDD 和 ABIDE 数据库上得到验证，其诊断性能优于现有方法，体现了 REST-meta-MDD 数据库在跨疾病智能诊断和神经机制解释中的应用价值^[56]。除了支持模型开发，该数据库也被用于评估算法在多站点、多疾病条件下的模型泛化能力，助力构建更具临床可行性的智能辅助诊疗系统。具体来说，有研究者提出了少样本合成在线迁移学习框架（Few-shot Synthetic Online Transfer Learning, FSOTL），通过生成式对抗网络进行预训练，并动态适应新样本，有效缓解了多站点数据差异带来的模型泛化难题。该方法同样在由多个站点构成的不同精神疾病脑影像数据库中进行了验证，表现出更优的稳定性与诊断精度^[57]。尽管如此，实现真正意义上的跨疾病智能诊断仍面临诸多挑战，例如不同疾病脑影像数据库标准不统一、标签系统存在差异，以及多模态特征融合的技术障碍。未来，REST-meta-MDD 及类似数据库的建设仍需在数据标准化、语义对齐和跨模态整合等方面持续推进，才能充分发挥其在跨精神疾病智能诊疗中的潜在价值。

4 结论

总体而言，REST-meta-MDD 数据库的建立吸引了全球研究者对重性抑郁障碍领域的关注，并推动了相关研究的进展。基于该数据库的研究为 MDD 神经病理学中存在的不一致结果提供了新的证据。抑郁症脑影像大数据联盟通过汇集多站点脑影像数据，不仅提升了统计效能，揭示了 MDD 领域的细微异常和稳健关联，还促进了基于 AI 的脑影像分析方法、诊断建模和个体化预测技术的发展。数据库的全面公开进一步促进了全球合作，使研究者能够利用机器学习、深度学习等算法，从大规模脑影像数据中提取关键特征、识别潜在生物标志物，并优化 MDD 诊断和预测模型。这不仅加深了我们对 MDD 神经生物学机制的理解，也为临床干预策略提供了科学依据。然而，数据协调、隐私保护和有效共享仍然是当前面临的主要挑战。尽管脑影像数据已脱敏，但在与临床或行为数据联合分析时，仍存在个体识别的风险。同时，如何在确保数据安全的前提下实现有序共享，也是数据库管理的重要挑战。为应对这些问题，DIRECT 联盟正推动统一的数据标准、加强数据加密与伦理审查，并建设“开放有度”的共享机制，以平衡科研开放性与隐私合规性。目前，DIRECT I 期已共享静息态 fMRI 数据处理结果及基于图谱的时间序列。随着 DIRECT 联盟 II 期合作的推进，联盟将公开基于体素（voxel）和皮层顶点（vertex）水平的时间序列数据。期待在这一更大规模和更深层次的数据共享基础上，研究者能够挖掘出更具临床意义的发现。未来，DIRECT 联盟 III 期拟开展抑郁症 TMS 个体化靶点定位方法临床试验，还将从纵向追踪抗抑郁治疗、反刍思

维和自发思维范式、白质纤维重建技术和中国人脑静息态功能磁共振影像参考常模等方面推动联盟合作，期待通过开放科学模式，推动中国抑郁症的科学合作研究，提升抑郁症的精确诊断和精准治疗水平。

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The academic impact of open data: Bibliometric evidence from the DIRECT consortium and the REST-meta-MDD database

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Abstract: Major depressive disorder (MDD) is one of the most prevalent mental illnesses worldwide. Its complex neurobiological mechanisms, coupled with the urgent need for personalized treatment, have driven the rapid development of neuroimaging and big data research in MDD. Resting-state functional magnetic resonance imaging, a noninvasive whole-brain neuroimaging technique, has been widely used to study MDD-related brain features. However, the generalizability of previous findings has been limited by small sample sizes and methodological inconsistencies. To address this, Chinese researchers, in collaboration with psychiatric experts nationwide, established the Depression Imaging REsearch ConsorTium (DIRECT) based on the national clinical user network of DPARSF. By implementing a unified standardized preprocessing pipeline, the consortium has substantially improved the reproducibility and comparability of research findings. The REST-meta-MDD database, publicly released by the DIRECT team in 2020, provides an open resource for global researchers. This study presents a bibliometric analysis of 103 publications (2019 – 2025) that utilized the REST-meta-MDD database. The results demonstrate that the dataset has accelerated MDD neuroimaging research, facilitated international collaborations, and promoted the development of open science. Through data sharing, researchers have made notable advances in MDD subtype classification, diagnostic model optimization, and the exploration of brain structural and functional heterogeneity. Furthermore, it has provided insights for the diagnosis of other mental disorders, enhancing diagnostic differentiation between neuropsychiatric diseases. In the future, with the inclusion of more samples and the advancement of data sharing, the database is expected to play an increasingly important role in training multi-disease classification, facilitating cross-disease diagnostics, guiding neuromodulation interventions, and enabling AI-based analyses targeting specific clinical problems.

Keywords: major depressive disorder (MDD); DIRECT Consortium; REST-meta-MDD Dataset; R-fMRI; neuroimaging; open science

Dataset Profile

Title	REST-meta-MDD database
Data corresponding author	YAN Chagan (yancg@tsinghua.edu.cn)
Data authors	YAN Chaogan, CHEN Xiao, LI Le, CASTELLANOS Francisco Xavier, BAI Tongjian, BO Qijing, CAO Jun, CHEN Guanmao, CHEN Ningxuan, CHEN Wei, CHENG Chang, CHENG Yuqi, CUI Xilong, DUAN Jia, FANG Yiru, GONG Qiyong, GUO Wenbin, HOU Zhenghua, HU Lan, KUANG Li, LI Feng, LI Tao, LIU Yansong, LIU Zhening, LONG Yicheng, LUO Qinghua, MENG Huaqing, PENG Daihui, QIU Haitang, QIU Jiang, SHEN Yuedi, SHI Yushu, TANG Yanqing, WANG Chuanyue, WANG Fei, WANG Kai, WANG Li, WANG Xiang, WANG Ying, WU Xiaoping, WU Xinran, XIE Chunming, XIE Guangrong, XIE Haiyan, XIE Peng, XU Xiufeng, YANG Hong, YANG Jian, YAO Jiashu, YAO Shuqiao, YIN Yingying, YUAN Yonggui, ZHANG Aixia, ZHANG Hong, ZHANG Kerang, ZHANG Lei, ZHANG Zhijun, ZHOU Rubai, ZHOU Yiting, ZHU Junjuan, ZOU Chaojie, SI Tianmei, ZUO Xinian, ZHAO Jingping, ZANG Yufeng
Time range	2017-2019
Collection scope	China
Data volume	107.58 GB
Data format	*.zip, *.nii.gz, *.tsv, *.tif, *.hdr, *.txt
Data service system	https://doi.org/10.57760/sciencedb.o00115.00013
Database composition	The REST-meta-MDD database comprises resting-state functional magnetic resonance imaging (R-fMRI) data from 1,300 patients with depressive disorder and 1,128 healthy controls. The database consists of three major components as follows. 1. DIRECT_REST-meta-MDD_Data_Use_Agreement.pdf specifies the data use agreement, detailing the terms and conditions for data access, usage, and citation. 2. REST-meta-MDD-Phase 1-Sharing.zip, contains five subfolders: (1) Masks, namely the AutoMasks subfolder, storing the automasks generated based on functional images, (2) PicturesForChkNormalization, containing image files used to visually inspect the quality of spatial normalization, (3) QC: including the quality control ratings for the resting-state functional (RawFunImgQC.tsv) and T1-weighted structural (RawT1ImgQC.tsv) images, (4) RealignParameter: storing the head motion parameters for each participant, (5) Results: containing the R-fMRI indices, including ALFF, fALFF, ReHo, VMHC, Degree Centrality, and ROI Signals. 3. REST-meta-MDD-VBM-Phase1-Sharing.tar.gz includes voxel-based morphometry (VBM) analysis results: (1) c1: Gray matter density in native space, (2) c2: White matter density in native space, (3) c3: Cerebrospinal fluid density in native space, (4) wc1: Gray matter density in MNI space, (5) wc2: White matter density in MNI space, (6) wc3: Cerebrospinal fluid density in MNI space, (7) mwc1: Gray matter volume in MNI space, (8) mwc2: White matter volume in MNI space, (9) mwc3: Cerebrospinal fluid volume density in MNI space, and (10) u_rc1: Transformation from native space to the group template. Further details on the data structure are available at: http://rfmri.org/RfMRIMapsDataSharingStructure.

附录 1 引用 REST-meta-MDD 数据库进行研究的 103 篇相关文献列表(N=103)

(统计截止日期为 2024 年 12 月 2 日)

Appendix 1 Literature index of studies utilizing the REST-meta-MDD database (N=103)

(Data collection cut-off date: December 2, 2024)

Number	Title	Author	Publication Year	Journal	Research Domains
1	Multivariate Machine Learning Analyses in Identification of Major Depressive Disorder Using Resting-State Functional Connectivity: A Multicentral Study	Shi et al.	2021	ACS chemical neuroscience	Diagnosis
2	Gene Expression has Distinct Associations with Brain Structure and Function in Major Depressive Disorder	Liu et al.	2023	Advanced Science	Neurobiological Heterogeneity
3	Functional plasticity abnormalities over the lifespan of first-episode patients with major depressive disorder: a resting state fMRI study	Yang et al.	2021	Annals of Translational Medicine	Neurobiological Heterogeneity
4	The alterations of brain functional connectivity networks in major depressive disorder detected by machine learning through multisite rs-fMRI data	Dai et al.	2022	Behavioural Brain Research	Neurobiological Heterogeneity
5	Capturing the Individual Deviations From Normative Models of Brain Structure for Depression Diagnosis and Treatment	Shao et al.	2024	Biological Psychiatry	Subtyping
6	Episodic Memory-Related Imaging Features as Valuable Biomarkers for the Diagnosis of Alzheimer's Disease: A Multicenter Study Based on Machine Learning	Shi et al.	2023	Biological Psychiatry Cognitive Neuroscience and Neuroimaging	Methodological Innovation
7	Sex Determines Anterior Cingulate Cortex Cortical Thickness in the Course of Depression	Wu et al.	2024	Biological Psychiatry Global Open Science	Neurobiological Heterogeneity
8	Fusing multi-scale fMRI features using a brain-inspired multi-channel graph neural network for major depressive disorder diagnosis	Liu et al.	2024	Biomedical Signal Processing and Control	Diagnosis
9	Impaired robust interhemispheric function integration of depressive brain from REST-meta-MDD database in China	Deng et al.	2022	Bipolar Disorders	Neurobiological Heterogeneity

Number	Title	Author	Publication Year	Journal	Research Domains
10	AI-based dimensional neuroimaging system for characterizing heterogeneity in brain structure and function in major depressive disorder: COORDINATE-MDD consortium design and rationale	Fu et al.	2023	BMC Psychiatry	Diagnosis
11	Gender differences in major depressive disorder at different ages: a REST-meta-MDD project-based study	Tian et al.	2024	BMC Psychiatry	Neurobiological Heterogeneity
12	Impaired topology and connectivity of grey matter structural networks in major depressive disorder: evidence from a multi-site neuroimaging data-set	Long et al.	2024	Br J Psychiatry	Neurobiological Heterogeneity
13	Gene expression and brain imaging association study reveals gene signatures in major depressive disorder	Liu et al.	2024	Brain Communications	Neurobiological Heterogeneity
14	Altered spatio-temporal state patterns for functional dynamics estimation in first-episode drug-naïve major depression	Jing et al.	2022	Brain Imaging and Behavior	Neurobiological Heterogeneity
15	Gray matter volume and corresponding covariance connectivity are biomarkers for major depressive disorder	Hu et al.	2024	Brain Research	Diagnosis
16	Selecting Multiple Node Statistics Jointly from Functional Connectivity Networks for Brain Disorders Identification	Zhang et al.	2022	Brain Topography	Multi-Disease Diagnostics
17	Classification of major depressive disorder using an attention-guided unified deep convolutional neural network and individual structural covariance network	Gao et al.	2023	Cerebral Cortex	Subtyping
18	Maladaptive changes in delay discounting in males during the COVID-19 pandemic: the predictive role of functional connectome	Xiao et al.	2022	Cerebral Cortex	Neurobiological Heterogeneity
19	Sex differences of signal complexity at resting-state functional magnetic resonance imaging and their associations with the estrogen-signaling pathway in the brain	Zhao et al.	2024	Cognitive Neurodynamics	Neurobiological Heterogeneity
20	Transcriptomic decoding of regional cortical vulnerability to major depressive	Zhu et al.	2024	Communications Biology	Neurobiological

Number	Title	Author	Publication Year	Journal	Research Domains
	disorder				Heterogeneity
21	Classification of recurrent major depressive disorder using a residual denoising autoencoder framework: Insights from large-scale multisite fMRI data	Dai et al.	2024	Computer Methods and Programs in Biomedicine	Subtyping
22	MAMF-GCN: Multi-scale adaptive multi-channel fusion deep graph convolutional network for predicting mental disorder	Pan et al.	2022	Computers in Biology and Medicine	Diagnosis
23	Multi-view graph network learning framework for identification of major depressive disorder	Zhang et al.	2023	Computers in Biology and Medicine	Diagnosis
24	Effective hyper-connectivity network construction and learning: Application to major depressive disorder identification	Liu et al.	2024	Computers in Biology and Medicine	Diagnosis
25	Using graph convolutional network to characterize individuals with major depressive disorder across multiple imaging sites	Qin et al.	2022	EBioMedicine	Diagnosis
26	DepressionGraph: A Two-Channel Graph Neural Network for the Diagnosis of Major Depressive Disorders Using rs-fMRI	Xia et al.	2023	Electronics	Diagnosis
27	Age-Related Decrease in Default-Mode Network Functional Connectivity Is Accelerated in Patients With Major Depressive Disorder	Tang et al.	2022	Frontiers in Aging Neuroscience	Neurobiological Heterogeneity
28	The classification of brain network for major depressive disorder patients based on deep graph convolutional neural network	Zhu et al.	2023	Frontiers in Human Neuroscience	Diagnosis
29	Adaptive Multimodal Neuroimage Integration for Major Depression Disorder Detection	Wang et al.	2022	Frontiers in Neuroinformatics	Diagnosis
30	Distinct resting-state effective connectivity of large-scale networks in first-episode and recurrent major depression disorder: evidence from the REST-meta-MDD consortium	Zhu et al.	2023	Frontiers in Neuroscience	Neurobiological Heterogeneity

Number	Title	Author	Publication Year	Journal	Research Domains
31	Intelligent diagnosis of major depression disease based on multi-layer brain network	Long et al.	2023	Frontiers in Neuroscience	Diagnosis
32	Spatial-temporal data-augmentation-based functional brain network analysis for brain disorders identification	Liu et al.	2023	Frontiers in Neuroscience	Methodological Innovation
33	Multi-band network fusion for Alzheimer's disease identification with functional MRI	Guo et al.	2022	Frontiers in Psychiatry	Multi-Disease Diagnostics
34	Ensemble graph neural network model for classification of major depressive disorder using whole-brain functional connectivity	Venkatapathy et al.	2023	Frontiers in Psychiatry	Subtyping
35	Age- and gender-related dispersion of brain networks across the lifespan	Wang et al.	2023	GeroScience	Neurobiological Heterogeneity
36	Addressing multi-site functional MRI heterogeneity through dual-expert collaborative learning for brain disease identification	Fang et al.	2023	Human Brain Mapping	Diagnosis
37	Classification of MDD using a Transformer classifier with large-scale multisite resting-state fMRI data	Dai et al.	2023	Human Brain Mapping	Diagnosis
38	Compressed primary-to-transmodal gradient is accompanied with subcortical alterations and linked to neurotransmitters and cellular signatures in major depressive disorder	Xiao et al.	2023	Human Brain Mapping	Neurobiological Heterogeneity
39	Evaluating test-retest reliability and sex-/age-related effects on temporal clustering coefficient of dynamic functional brain networks	Long et al.	2023	Human Brain Mapping	Methodological Innovation
40	Heterogeneous brain dynamic functional connectivity patterns in first-episode drug-naive patients with major depressive disorder	Jing et al.	2023	Human Brain Mapping	Neurobiological Heterogeneity
41	Unsupervised contrastive graph learning for resting-state functional MRI analysis and brain disorder detection	Wang et al.	2023	Human Brain Mapping	Methodological Innovation

Number	Title	Author	Publication Year	Journal	Research Domains
42	Classification of Adolescent Major Depressive Disorder Via Static and Dynamic Connectivity	Sen et al.	2021	IEEE Journal of Biomedical and Health Informatics	Methodological Innovation
43	Multi-Level Functional Connectivity Fusion Classification Framework for Brain Disease Diagnosis	Liang et al.	2022	IEEE Journal of Biomedical and Health Informatics	Methodological Innovation
44	Enhancing Major Depressive Disorder Diagnosis With Dynamic-Static Fusion Graph Neural Networks	Zhao et al.	2024	IEEE Journal of Biomedical and Health Informatics	Methodological Innovation
45	Graph Autoencoders for Embedding Learning in Brain Networks and Major Depressive Disorder Identification	Noman et al.	2024	IEEE Journal of Biomedical and Health Informatics	Methodological Innovation
46	Graph-Based Conditional Generative Adversarial Networks for Major Depressive Disorder Diagnosis With Synthetic Functional Brain Network Generation	Oh et al.	2024	IEEE Journal of Biomedical and Health Informatics	Methodological Innovation
47	Spectral Graph Neural Network-Based Multi-Atlas Brain Network Fusion for Major Depressive Disorder Diagnosis	Lee et al.	2024	IEEE journal of biomedical and Health Informatics	Methodological Innovation
48	Few-Shot Synthetic Online Transfer Learning for Cross-Site Neurological Disease Diagnosis	Pei et al.	2024	IEEE Transactions on Computational Social Systems	Methodological Innovation
49	A Learnable Counter-Condition Analysis Framework for Functional Connectivity-Based Neurological Disorder Diagnosis	Kang et al.	2024	IEEE Transactions on Medical Imaging	Methodological Innovation
50	Multi-Scale Dynamic Graph Learning for Brain Disorder Detection With Functional MRI	Ma et al.	2023	IEEE Transactions on Neural Systems and Rehabilitation Engineering	Methodological Innovation
51	Cross-Domain Identification of Multisite Major Depressive Disorder Using End-to-End Brain Dynamic Attention Network	Yuan et al.	2024	IEEE Transactions on Neural Systems and Rehabilitation Engineering	Methodological Innovation
52	BrainNPT: Pre-Training Transformer Networks for Brain Network Classification	Hu et al.	2024	IEEE Transactions on Neural Systems and Rehabilitation Engineering	Methodological Innovation

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53	Automated Diagnosis of Major Depressive Disorder With Multi-Modal MRIs Based on Contrastive Learning: A Few-Shot Study	Li et al.	2024	IEEE Transactions on Neural Systems and Rehabilitation Engineering	Methodological Innovation
54	FC-HGNN: A heterogeneous graph neural network based on brain functional connectivity for mental disorder identification	Gu et al.	2025	Information Fusion	Methodological Innovation
55	Disrupted hemispheric connectivity specialization in patients with major depressive disorder: Evidence from the REST-meta-MDD Project	Ding et al.	2021	Journal of Affective Disorders	Neurobiological Heterogeneity
56	Heterogeneous alterations in thalamic subfields in major depression disorder	Hong et al.	2021	Journal of Affective Disorders	Neurobiological Heterogeneity
57	Sleep disturbance-related neuroimaging features as potential biomarkers for the diagnosis of major depressive disorder: A multicenter study based on machine learning	Shi et al.	2021	Journal of Affective Disorders	Diagnosis
58	Biotypes of major depressive disorder identified by a multiview clustering framework	Chen et al.	2023	Journal of Affective Disorders	Subtyping
59	Classification of recurrent major depressive disorder using a new time series feature extraction method through multisite rs-fMRI data	Dai et al.	2023	Journal of Affective Disorders	Diagnosis
60	Abnormal cortical-striatal-thalamic-cortical circuit centered on the thalamus in MDD patients with somatic symptoms: Evidence from the REST-meta-MDD project	Sun et al.	2023	Journal of Affective Disorders	Neurobiological Heterogeneity
61	Disrupted intrinsic functional brain network in patients with late-life depression: Evidence from a multi-site dataset	Tan et al.	2023	Journal of Affective Disorders	Neurobiological Heterogeneity
62	Normative modeling analysis reveals corpus callosum volume changes in early and mid-to-late first episode major depression	Wu et al.	2023	Journal of Affective Disorders	Neurobiological Heterogeneity
63	Understanding the heterogeneity of dynamic functional connectivity patterns in first-	Lin et al.	2023	Journal of Affective Disorders	Neurobiological

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	episode drug naïve depression using normative models				Heterogeneity
64	Abnormal changes of dynamic topological characteristics in patients with major depressive disorder	Zhou et al.	2024	Journal of Affective Disorders	Neurobiological Heterogeneity
65	Distinct effects of first-episode and recurrent major depressive disorder on brain changes related to suicidal ideation: Evidence from the REST-meta-MDD Project	Sun et al.	2024	Journal of Affective Disorders	Neurobiological Heterogeneity
66	Individualized gray matter morphological abnormalities uncover two robust transdiagnostic biotypes	Fang et al.	2024	Journal of Affective Disorders	Multi-Disease Diagnostics
67	The Effect Analysis of Atlas and Global Signal Regression in Classification based on Brain Network for Major Depression Disorders	Long et al.	2022	Journal of Imaging Science and Technology	Subtyping
68	Classification of Major Depressive Disorder Based on Integrated Temporal and Spatial Functional MRI Variability Features of Dynamic Brain Network	Gai et al.	2023	Journal of Magnetic Resonance Imaging	Subtyping
69	An attention-based multi-modal MRI fusion model for major depressive disorder diagnosis	Zheng et al.	2023	Journal of Neural Engineering	Diagnosis
70	Linking inter-subject variability of cerebellar functional connectome to clinical symptoms in major depressive disorder	Lin et al.	2024	Journal of Psychiatric Research	Neurobiological Heterogeneity
71	Specificity-Aware Federated Graph Learning for Brain Disorder Analysis with Functional MRI	Zhang et al.	2024	Machine Learning in Medical Imaging	Methodological Innovation
72	Cross Atlas Remapping via Optimal Transport (CAROT): Creating connectomes for different atlases when raw data is not available	Dadashkari mi et al.	2023	Medical image analysis	Methodological Innovation
73	Unsupervised Cross-Domain Functional MRI Adaptation for Automated Major Depressive Disorder Identification	Fang et al.	2023	Medical image analysis	Diagnosis

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74	Disrupted intrinsic functional brain topology in patients with major depressive disorder	Yang et al.	2021	Molecular Psychiatry	Neurobiological Heterogeneity
75	Functional connectivity signatures of major depressive disorder: machine learning analysis of two multicenter neuroimaging studies	Gallo et al.	2023	Molecular Psychiatry	Subtyping
76	Neurophysiological stratification of major depressive disorder by distinct trajectories	Chen et al.	2023	Nature Mental Health	Subtyping
77	SLG-NET: Subgraph Neural Network with Local-Global Braingraph Feature Extraction Modules and a Novel Subgraph Generation Algorithm for Automated Identification of Major Depressive Disorder	Zhang et al.	2024	Neural Information Processing	Methodological Innovation
78	Preserving specificity in federated graph learning for fMRI-based neurological disorder identification	Zhang et al.	2023	Neural Networks	Methodological Innovation
79	CI-GNN: A Granger Causality-Inspired Graph Neural Network for Interpretable Brain Network-Based Psychiatric Diagnosis	Zheng et al.	2024	Neural Networks	Methodological Innovation
80	Multi-feature concatenation and multi-classifier stacking: An interpretable and generalizable machine learning method for MDD discrimination with rsfMRI	Luo et al.	2024	NeuroImage	Diagnosis
81	BPI-GNN: Interpretable brain network-based psychiatric diagnosis and subtyping	Zheng et al.	2024	Neuroimage	Multi-Disease Diagnostics
82	Altered resting-state dynamic functional brain networks in major depressive disorder: Findings from the REST-meta-MDD consortium	Long et al.	2020	NeuroImage : Clinical	Neurobiological Heterogeneity
83	Biotypes of major depressive disorder: Neuroimaging evidence from resting-state default mode network patterns	Liang et al.	2020	NeuroImage : Clinical	Subtyping
84	Reduced functional connectivity of default mode network subsystems in depression: Meta-analytic evidence and relationship with trait rumination	Tozzi et al.	2021	NeuroImage. Clinical	Neurobiological Heterogeneity

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85	Source-free collaborative domain adaptation via multi-perspective feature enrichment for functional MRI analysis	Fang et al.	2025	Pattern Recognition	Methodological Innovation
86	Reduced default mode network functional connectivity in patients with recurrent major depressive disorder	Yan et al.	2019	PNAS	Neurobiological Heterogeneity
87	Atypical dynamic network reconfiguration and genetic mechanisms in patients with major depressive disorder	Xiao et al.	2024	Progress in Neuro-Psychopharmacology and Biological Psychiatry	Neurobiological Heterogeneity
88	Dimensional subtyping of first-episode drug-naïve major depressive disorder: A multisite resting-state fMRI study	Zhang et al.	2023	Psychiatry Research	Subtyping
89	Brain structural abnormalities in adult major depressive disorder revealed by voxel- and source-based morphometry: evidence from the REST-meta-MDD Consortium	Wang et al.	2023	Psychological Medicine	Neurobiological Heterogeneity
90	Altered topology of individual brain structural covariance networks in major depressive disorder	Ping et al.	2023	Psychological Medicine	Neurobiological Heterogeneity
91	Common and distinct functional brain network abnormalities in adolescent, early-middle adult, and late adult major depressive disorders	Long et al.	2024	Psychological Medicine	Neurobiological Heterogeneity
92	The DIRECT consortium and the REST-meta-MDD project: towards neuroimaging biomarkers of major depressive disorder	Chen et al.	2022	Psychoradiology	Methodological Innovation
93	Astrocyte dysfunction drives abnormal resting-state functional connectivity in depression	Liu et al.	2022	Science Advances	Methodological Innovation
94	Neuroimaging epicenters as potential sites of onset of the neuroanatomical pathology in schizophrenia	Jiang et al.	2024	Science Advances	Methodological Innovation
95	Small p values may not yield robust findings: an example using REST-meta-PD	Jia et al.	2021	Science Bulletin	Methodological

Number	Title	Author	Publication Year	Journal	Research Domains
					Innovation
96	The power of many brains: Catalyzing neuropsychiatric discovery through open neuroimaging data and large-scale collaboration	Lu et al.	2024	Science Bulletin	Methodological Innovation
97	Functional Connectome Prediction of Anxiety Related to the COVID-19 Pandemic	He et al.	2021	The American Journal of Psychiatry	Methodological Innovation
98	Altered Effective Connectivity Among the Cerebellum and Cerebrum in Patients with Major Depressive Disorder Using Multisite Resting-State fMRI	Dai et al.	2022	The Cerebellum	Neurobiological Heterogeneity
99	Accelerated functional brain aging in major depressive disorder: evidence from a large scale fMRI analysis of Chinese participants	Luo et al.	2022	Translational Psychiatry	Neurobiological Heterogeneity
100	Reduced nucleus accumbens functional connectivity in reward network and default mode network in patients with recurrent major depressive disorder	Ding et al.	2022	Translational Psychiatry	Neurobiological Heterogeneity
101	Connectomics-based resting-state functional network alterations predict suicidality in major depressive disorder	Wang et al.	2023	Translational Psychiatry	Neurobiological Heterogeneity
102	Aberrant resting-state co-activation network dynamics in major depressive disorder	An et al.	2024	Translational Psychiatry	Subtyping
103	Transcriptional patterns of amygdala functional connectivity in first-episode, drug-naïve major depressive disorder	Liu et al.	2024	Translational Psychiatry	Neurobiological Heterogeneity