

Standardization of Measurement and Imaging Protocols in Magnetic Resonance: An Overview of Current Initiatives, Challenges, and Perspectives

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Abstract: Magnetic resonance imaging (MRI) is one of the most important imaging modalities in clinical diagnostics and biomedical research; however, its usability is significantly limited by the high technical and methodological variability across sites, scanners, and acquisition protocols. This lack of uniformity affects quantitative measurements, reduces their reproducibility, and complicates multicenter studies. In recent years, numerous initiatives and technical approaches have emerged, focusing on acquisition standardization, data harmonization, signal quality assessment, and validation of quantitative methods. This review summarizes current knowledge on neuroimaging data harmonization (e.g., ComBat), inter-scanner variability, radiomic feature repeatability, standardized QA procedures, and the challenges associated with integrating artificial intelligence into clinical workflows. Metrological frameworks such as the Quantitative Imaging Biomarker Alliance (QIBA) further emphasize the need for clearly defined measurands, reference methods, and reproducible acquisition conditions. Special attention is given to large dataset initiatives, preclinical standardization platforms, and open tools for MRI quality assessment. The review highlights the need for unified methodologies, transparent protocols, and robust validation frameworks that are essential for the reliable clinical translatability of MRI.

Keywords: imaging protocols, standardization, measurement, magnetic resonance

1. INTRODUCTION

Magnetic resonance imaging (MRI) represents one of the most versatile imaging technologies in modern medicine. Its ability to provide detailed anatomical, functional, and quantitative information without ionizing radiation makes it suitable for broad clinical and research applications. Nevertheless, MRI suffers from a fundamental limitation — high variability across scanners, vendors, sites, and acquisition protocols. This variability can substantially affect quantitative parameters, such as relaxation times, diffusion metrics, and perfusion measures, thereby limiting their clinical interpretability and usability in multicenter studies. In recent literature, this variability is increasingly recognized not only as a technical challenge but also as a conceptual barrier to reliable quantification and clinical translatability. Wijnen et al. emphasize that differences in hardware, pulse sequences, and reconstruction pipelines can lead to divergent interpretations of identical clinical indications, complicating longitudinal follow-up and multicenter studies [1]. At the same time, the authors caution that overly rigid standardization may slow technological progress, highlighting the need for a balanced approach.

Beyond technical variability, several authors emphasize that a substantial portion of inconsistency in MRI practice arises from workflow-related and organizational factors, such as heterogeneous protocol management, site-specific preferences, and insufficient communication among radiologists, physicists, and technologists [2]. These non-technical barriers often amplify scanner-related variability and complicate the implementation of standardized acquisition strategies.

Fortin et al. demonstrated that interscanner differences can significantly influence cortical thickness measurements, while harmonization methods such as ComBat can reduce unwanted scanner effects [3]. Similarly, Mirzaalian et al. showed that diffusion MRI data exhibit substantial intersite variability, which can be partially mitigated using harmonization algorithms [4]. Multicenter studies, such as the work by Grech-Sollars et al., confirm that even when identical protocols are used, differences persist due to hardware configuration, coil performance, and reconstruction pipelines, underscoring the need for harmonization procedures [5].

Variability, however, is not limited to acquisition but extends to reconstruction as well. Knoll et al. in the fast MRI challenge demonstrated that different reconstruction algorithms — including deep neural networks — can yield distinct image characteristics, directly affecting quantitative measurements and radiomic features [6]. Radiomics is extremely sensitive to variability in acquisition and preprocessing, as shown by Martin et al., who reported low test–retest reliability for many diffusion and perfusion radiomic features [7].

Over the past two decades, substantial progress has been made in understanding biochemical and physiological processes in human tissues. However, despite intensive efforts toward unifying quantitative imaging biomarkers, the field has long suffered from inconsistent terminology, heterogeneous methodological practices, and the absence of a common metrological framework. To address these issues, the Radiological Society of North America established the Quantitative Imaging Biomarker Alliance (QIBA), which provides a consensus-driven platform to improve the value, reproducibility, and interpretability of quantitative imaging biomarkers.

QIBA develops so-called QIBA Profiles — standardized, claim-driven documents that define the acquisition, reconstruction, and processing steps required to achieve a specified quantitative performance. A key contribution of the QIBA Metrology Working Group is the clarification of fundamental measurement concepts, including the requirement that quantitative biomarkers must be expressed on ratio or interval scales, the need for clearly defined reference methods, and the distinction between repeatability and reproducibility as components of precision. These metrological principles form the basis for evaluating bias, linearity, and measurement uncertainty, and they enable the use of different scanner types within a single study, provided that appropriate test–retest procedures are implemented [8].

Standardization is equally essential in preclinical research. Pennati et al. emphasized the need for unified preclinical protocols that enable comparability of biomarkers across laboratories [9]. Similarly, Botta et al. highlighted variability in BOLD signal during language mapping in pediatric patients, underscoring the need for standardized methodologies even in clinical fMRI applications [10].

An important trend is the emergence of open tools for MRI quality assessment. Montin et al. introduced MR Optimum — a cloud-based platform for standardized SNR evaluation that enables comparison of different sequences, reconstruction methods, and coil configurations [11]. Likewise, Haueise et al. showed that even basic metrics, such as visceral fat quantification, are sensitive to acquisition differences and require unified protocols [12].

Large dataset initiatives also play a crucial role. Luu et al. analyzed 54 public datasets and demonstrated substantial heterogeneity in resolution, intensity distributions, and preprocessing, complicating the development of generalizable models [13]. In a related review, Li emphasized that without unified protocols and transparent datasets, the clinical translatability of AI methods remains limited [14].

Standardization is also essential for integrating artificial intelligence into clinical practice. Pellegrino et al. and Friebe

pointed out that AI models are highly sensitive to variability in acquisition and preprocessing, which may lead to reduced generalization and unreliable clinical outputs [15], [16]. Tiwary et al. and other studies show that even in the field of contrast agents and nanomaterials, methodological standardization is necessary to ensure comparability across studies [17].

A common theme across all these works is clear: without standardization of acquisition, reconstruction, preprocessing, and quality assessment, reliable quantification and clinical translatability of MRI cannot be achieved. This review, therefore, summarizes current initiatives, technical approaches, and challenges shaping the future of MRI standardization.

2. LITERATURE OVERVIEW

Standardization and harmonization in MRI rely on a set of methodological approaches that help reduce inter-scanner variability, ensure acquisition quality control, and create the conditions necessary for the reliable use of quantitative metrics and artificial intelligence methods. Metrological principles defined by QIBA provide a general framework for assessing bias, precision, and reproducibility in quantitative MRI [8].

Harmonization employs statistical and algorithmic techniques that correct differences caused by hardware, protocols, or reconstruction methods. Quality control is based on regular monitoring of scanner stability, evaluation of signal parameters, and the use of phantoms. In the fields of artificial intelligence and radiomics, methods are applied that minimize model sensitivity to technical variability and ensure the reproducibility of quantitative measurements. Together, these methodological approaches form the foundation for data comparability across sites and for the clinical translatability of modern imaging techniques.

3. CURRENT STATE OF THE FIELD

Harmonization represents a key step in reducing unwanted variability caused by differences between scanners, vendors, sites, or acquisition protocols. Fortin et al. demonstrated that ComBat can effectively remove scanner effects in cortical thickness measurements [3]. Mirzaalian et al. extended this approach to diffusion MRI, showing that harmonization can reduce intersite variability without suppressing true biological differences [4].

The multicenter study by Grech-Sollars et al. confirmed that even when identical protocols are used, differences persist due to hardware configuration, coil performance, and reconstruction pipelines [5]. Luu et al. showed that public MRI datasets exhibit substantial heterogeneity in resolution, intensity distributions, and preprocessing, complicating the development of generalizable models [13].

AI-based harmonization methods have emerged as a promising direction, employing generative models or deep learning to map image distributions across scanners. Knoll et al. demonstrated that reconstruction algorithms based on deep learning can significantly influence image properties, supporting the need for harmonization not only at the level of acquisition but also reconstruction [6].

The quality of MRI data is fundamentally influenced by the long-term operational stability of the measurement system, the configuration and behavior of the coils, the level of noise, and the reconstruction algorithms used. Phantoms — objects with precisely defined physical properties — serve as stable reference standards for assessing signal homogeneity, SNR, CNR, geometric accuracy, temporal stability, and coil performance.

QA protocols define how frequently these measurements should be performed, which phantoms and metrics should be used, and how long-term trends should be evaluated. Modern QA systems often include automated software tools that continuously track measured parameters and assess scanner stability.

Montin et al. introduced MR Optimum, a cloud-based platform for standardized SNR assessment that integrates multiple noise-estimation methods and enables comparison of sequences, reconstruction methods, and coil configurations [11]. Haueise et al. demonstrated that even basic quantitative metrics, such as visceral fat volume, are sensitive to acquisition differences and require unified protocols [12].

Pennati et al. emphasized that preclinical MRI systems often exhibit greater variability than clinical scanners, and without consistent QA procedures, it is not possible to ensure comparability of biomarkers across laboratories [9]. In functional MRI, Bottan et al. highlighted substantial variability in the BOLD signal during language-mapping tasks, underscoring the need for standardized QA procedures [10].

Radiomics and artificial intelligence are extremely sensitive to variability in acquisition, reconstruction, and preprocessing. Martin et al. showed that many diffusion- and perfusion-based radiomic features exhibit low test–retest reliability [7]. Li emphasized that without unified protocols and transparent datasets, the clinical translatability of AI methods remains limited [14].

Pellegrino et al. and Friebe pointed out that AI models are highly sensitive to variability in acquisition and preprocessing, which can lead to reduced generalization and unreliable clinical outputs [15], [16]. Luu et al. demonstrated that even after standardized preprocessing, substantial covariate shifts persist between datasets [13].

In the field of contrast agents and nanomaterials, Tiwary et al., Karati et al., and Mensah et al. showed that experimental imaging protocols require standardization to enable meaningful comparison of results and ensure reproducibility [17]–[19].

Standardization is not limited to acquisition parameters or harmonization algorithms; it also requires structured organizational frameworks that ensure consistent protocol deployment across scanners and clinical sites. Sharma and Saindane describe a multi-layered institutional strategy in which radiologists, MR physicists, and technologists collaboratively develop, review, and maintain protocol libraries [2]. Their experience highlights that protocol variability often originates from inconsistent local practices, insufficient communication, and a lack of centralized oversight. Establishing formal protocol committees, naming conventions, and feedback mechanisms can, therefore, significantly reduce operational variability and improve reproducibility, even before technical harmonization methods are applied.

4. KEY FINDINGS

This review synthesizes findings from recent studies addressing MRI standardization across acquisition, reconstruction, preprocessing, and quality assurance. The literature analyzed consistently demonstrates that technical variability remains one of the primary barriers to the clinical translation of quantitative MRI, radiomics, and AI-based methods. Similar observations have been reported in large radiology enterprises, where protocol inconsistency across scanners and sites leads to workflow inefficiencies, acquisition errors, and reduced image quality, underscoring that organizational variability can be as impactful as hardware-related differences [2].

Across harmonization studies, ComBat-based statistical approaches [3], [4] and multicenter reproducibility analyses [5] show that scanner- and site-related differences significantly affect quantitative metrics. Reconstruction-related variability, highlighted by Knoll et al. [6], further contributes to inconsistencies in image characteristics and downstream quantitative features.

Radiomic and AI-focused studies reveal that model performance is highly sensitive to acquisition and preprocessing differences, with substantial covariate shifts persisting even after standardized pipelines [7], [13]–[16]. QA research demonstrates that standardized SNR evaluation [11] and unified acquisition procedures [12] are essential for ensuring reproducibility. Preclinical studies further emphasize that variability in experimental imaging protocols can hinder translational research [9].

Collectively, the reviewed evidence confirms that meaningful progress in MRI standardization requires coordinated efforts across acquisition, reconstruction, preprocessing, QA, and dataset curation.

5. FUTURE DEVELOPMENTS

Future developments in MRI standardization will be shaped by advances in vendor-neutral acquisition, AI-based harmonization, automated quality assurance, and large-scale data initiatives. Vendor-neutral pulse sequences and open reconstruction frameworks are expected to reduce differences between scanners from different manufacturers, enabling more consistent deployment of quantitative protocols across clinical sites. This direction is supported by findings from Knoll et al. [6], who demonstrated that reconstruction algorithms can substantially influence image characteristics and the quantitative metrics derived from them.

AI-based harmonization methods represent another major trend. While statistical approaches such as ComBat effectively reduce scanner-related differences at the parameter level [3], [4], modern deep-learning methods operate directly on image data and can model complex relationships between scanners. These approaches aim to remove technical variability while preserving clinically relevant information, which is increasingly important as reconstruction algorithms become more sophisticated.

Automated quality assurance is also gaining importance. Cloud-based tools such as MR Optimum [11] demonstrate how standardized SNR evaluation and noise characterization can support long-term monitoring of scanner performance. As MRI systems become more complex, automated QA solutions will be essential for maintaining consistent data quality across sites and over time.

Preclinical imaging will also require clearer standardization. Pennati et al. [9] emphasize that variability in preclinical protocols can hinder translational research, underscoring the need for reproducible procedures that ensure comparability of biomarkers across laboratories.

Large-scale data initiatives will continue to influence standardization efforts. Luu et al. [13] showed that public MRI datasets remain highly heterogeneous in resolution, intensity distributions, and preprocessing pipelines, complicating the development of generalizable AI models. Future datasets will need unified acquisition protocols, transparent preprocessing, and thorough documentation to support robust algorithm development.

Finally, the integration of AI into clinical practice will require new standards for validation, monitoring, and regulatory oversight. Studies by Pellegrino et al. [15] and Friebe [16] highlight that AI models are sensitive to acquisition and preprocessing variability, reinforcing the need for harmonized data and standardized evaluation frameworks.

Overall, future progress in MRI standardization will depend on coordinated efforts across acquisition, reconstruction, preprocessing, QA, and data curation to enable reliable quantitative biomarkers and clinically trustworthy AI systems.

6. DISCUSSION AND CONCLUSION

The reviewed literature demonstrates that despite major technological advances, MRI remains one of the most variable imaging modalities in clinical and research practice. Differences in scanner hardware, vendor-specific implementations, acquisition protocols, reconstruction pipelines, and preprocessing workflows continue to introduce substantial non-biological variability into quantitative measurements.

Harmonization methods such as ComBat and its extensions have shown strong potential for reducing scanner- and site-related differences, while multicenter reproducibility studies highlight the persistent impact of hardware and reconstruction variability. AI-based harmonization approaches represent a promising direction, particularly as modern reconstruction algorithms increasingly influence image characteristics.

Quality assurance remains a cornerstone of standardization. Cloud-based tools such as MR Optimum demonstrate how automated SNR evaluation and noise characterization can support consistent long-term monitoring of scanner performance. Preclinical imaging studies further emphasize that without unified protocols, translational research risks being undermined by methodological inconsistencies.

Large-scale dataset analyses reveal that heterogeneity in resolution, intensity distributions, and preprocessing pipelines continues to challenge the development of generalizable AI models. Future progress will therefore depend on coordinated efforts to establish transparent, vendor-neutral acquisition protocols, standardized reconstruction and preprocessing workflows, and robust QA frameworks.

Recent harmonization and QA studies consistently confirm that acquisition- and reconstruction-related variability remains one of the major obstacles for quantitative MRI. This observation aligns with Golay's arguments, who emphasizes

that without a certain degree of protocol standardization, many advanced MRI methods will not transition into routine clinical use [1]. Conversely, Seiberlich highlights that overly rigid standardization may limit technological progress and reduce flexibility in patient-specific imaging workflows [1]. Together, these contrasting viewpoints underscore the need for a balanced approach that supports innovation while ensuring reproducibility and comparability across sites.

The conceptual structure proposed by QIBA illustrates that technical standardization requires not only protocol unification but also rigorous metrological definitions of measurands, reference methods, and precision metrics [8].

In addition to technical harmonization, institutional experience shows that sustainable standardization also depends on organizational structures that support protocol governance. Sharma and Saindane demonstrate that without coordinated protocol management, even technically identical scanners may produce inconsistent results due to divergent local practices, user preferences, or insufficient training [2]. These findings complement the conceptual debate between Seiberlich and Golay by illustrating that the balance between innovation and standardization must be maintained not only at the level of pulse sequences and reconstruction methods, but also within clinical workflows and institutional processes.

Overall, MRI standardization is a multi-layered process that requires collaboration among clinicians, physicists, engineers, data scientists, and regulatory bodies. Achieving reliable, reproducible, and clinically translatable MRI will depend on the integration of harmonized acquisition, reconstruction, preprocessing, QA, and data-curation strategies.

Current literature and expert commentaries indicate that MRI standardization is essential for reliable quantification, data harmonization, and the integration of AI into clinical workflows. At the same time, standardization must remain sufficiently flexible to avoid hindering technological progress. As highlighted by Sharma and Saindane, effective MRI standardization requires not only technical harmonization but also structured institutional processes, including protocol governance, cross-disciplinary collaboration, and continuous feedback mechanisms [2]. These organizational components are essential for translating standardized protocols into consistent clinical practice. As emphasized by Wijnen, Seiberlich, and Golay, the future of MRI will depend on the community's ability to find an appropriate balance between uniformity and innovation [1].

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REFERENCES

- [1] Wijnen, J. P., Seiberlich, N., Golay, X. (2023). Will standardization kill innovation? *Magnetic Resonance Materials in Physics, Biology and Medicine*, 36, 525-528. <https://doi.org/10.1007/s10334-023-01115-w>
- [2] Sharma, P. S., Saindane, A. M. (2020). Standardizing magnetic resonance imaging protocols across a large radiology enterprise: Barriers and solutions. *Current Problems in Diagnostic Radiology*, 49 (5), 312-316. <https://doi.org/10.1067/j.cpradiol.2020.01.012>

- [3] Fortin, J.-P., Cullen, N., Sheline, Y. I., Taylor, W. D., Aselcioglu, I., Cook, P. A., Adams, P., Cooper, C., Fava, M., McGrath, P. J., McInnis, M., Phillips, M. L., Trivedi, M. H., Weissman, M. M., Shinohara, R. T. (2018). Harmonization of cortical thickness measurements across scanners and sites. *NeuroImage*, 167, 104-120.
<https://doi.org/10.1016/j.neuroimage.2017.11.024>
- [4] Mirzaalian, H., Ning, L., Savadjiev, P., Pasternak, O., Bouix, S., Michailovich, O., Grant, G., Marx, C. E., Morey, R. A., Flashman, L. A., George, M. S., McAllister, T. W., Andaluz, N., Shutter, L., Coimbra, R., Zafonte, R. D., Coleman, M. J., Kubicki, M., Westin, C. F., Stein, M. B., Shenton, M. E., Rath, Y. (2016). Inter-site and inter-scanner diffusion MRI data harmonization. *NeuroImage*, 135, 311-323.
<https://doi.org/10.1016/j.neuroimage.2016.04.041>
- [5] Grech-Sollars, M., Hales, P. W., Miyazaki, K., Raschke, F., Rodriguez, D., Wilson, M., Gill, S. K., Banks, T., Saunders, D. E., Clayden, J. D., Gwilliam, M. N., Barrick, T. R., Morgan, P. S., Davies, N. P., Rossiter, J., Auer, D. P., Grundy, R., Leach, M. O., Howe, F. A., Peet, A. C., Clark, C. A. (2015). Multi-centre reproducibility of diffusion MRI parameters for clinical sequences in the brain. *NMR in Biomedicine*, 28 (4), 468-485. <https://doi.org/10.1002/nbm.3269>
- [6] Knoll, F., Murrell, T., Sriram, A., Yakubova, N., Zbontar, J., Rabbat, M., Defazio, A., Muckley, M. J., Sodickson, D. K., Zitnick, C. L., Recht, M. P. (2020). Advancing machine learning for MR image reconstruction with an open competition: Overview of the 2019 fastMRI challenge. *Magnetic Resonance in Medicine*, 84 (6), 3054-3070.
<https://doi.org/10.1002/mrm.28338>
- [7] Martin, P., Holloway, L., Metcalfe, P., Koh, E.-S., Aly, F., Chan, E., Brighi, C. (2025). Repeatability of diffusion and perfusion MRI derived radiomic features in glioblastoma: A test-retest study. *Physical and Engineering Sciences in Medicine*, 48, 1691-1702.
<https://doi.org/10.1007/s13246-025-01613-2>
- [8] Sullivan, D. C., Obuchowski, N. A., Kessler, L. G., Raunig, D. L., Gatsonis, C., Huang, E. P., Kondratovich, M., McShane, L. M., Reeves, A. P., Barboriak, D. P., Guimaraes, A. R., Wahl, R. L.; RSNA-QIBA Metrology Working Group. (2015). Metrology standards for quantitative imaging biomarkers. *Radiology*, 277 (3), 813-825.
<https://doi.org/10.1148/radiol.2015142202>
- [9] Pennati, F., Buccardi, M., Aliverti, A., Ferrini, E., Stellari, F. F. (2026). Multidimensional lung imaging: Integrated preclinical platforms enabling the identification of translational biomarkers for pulmonary research. *Respiratory Research*, 27, 73.
<https://doi.org/10.1186/s12931-025-03472-7>
- [10] Botta, J. S., Ragguett, R. M., Tang, L., Zuljevic, M., Andrade, A., Duerden, E. G., Eagleson, R., de Ribaupierre S., Nabavi Nouri, M. (2026). Noninvasive imaging techniques to map language areas using BOLD signal fluctuations in pediatric epilepsy: A review. *Child's Nervous System*, 42 (1), 61.
<https://doi.org/10.1007/s00381-026-07150-x>
- [11] Montin, E., Nguyen, X. T., Lattanzi, R. (2026). MR Optimum: A web-based open-source tool for standardized signal-to-noise ratio evaluation in MRI. *Computer Methods and Programs in Biomedicine Update*, 9, 100235.
<https://doi.org/10.1016/j.cmpbup.2026.100235>
- [12] Haueise, T., Schick, F., Stefan, N., Grune, E., von Itter, M. N., Kauczor, H. U., Nattenmüller, J., Norajitra, T., Nonnenmacher, T., Rospleszcz, S., Maier-Hein, K. H., Schlett, C. L., Weiss, J. B., Fischer, B., Jöckel, K. H., Krist, L., Niendorf, T., Peters, A., Sedlmeier, A. M., Willich, S. N., Bamberg, F., Machann, J. (2026). Refining visceral adipose tissue quantification: Influence of sex, age, and BMI on single slice estimation in 3D MRI of the German National Cohort. *Zeitschrift für Medizinische Physik*, 36 (1), 114-124.
<https://doi.org/10.1016/j.zemedi.2025.02.005>
- [13] Luu, M. S. K., Benedichuk, M. V., Roppert, E. I., Kenzhin, R. M., Tuchinov, B. N. (2025). A structured review and quantitative profiling of public brain MRI datasets for foundation model development. *Journal of Imaging*, 11 (12), 454.
<https://doi.org/10.3390/jimaging11120454>
- [14] Li, X. (2025). Functional, structural, and AI-based MRI analysis: A comprehensive review of recent advances. *Diagnostics*, 15 (24), 3212.
<https://doi.org/10.3390/diagnostics15243212>
- [15] Pellegrino, G., Arnone, F., Girlando, M. F., Berloco, D., Perazzo, C., Triggiani, S., Carrafiello, G. (2026). Artificial intelligence in prostate MRI: Redefining the patient journey from imaging to precision care. *Applied Sciences*, 16 (2), 893.
<https://doi.org/10.3390/app16020893>
- [16] Friebe, M. (2026). AI in radiology and interventions: A structured narrative review of workflow automation, accuracy, and efficiency gains. *International Journal of Computer Assisted Radiology and Surgery*, 21, 1-10.
<https://doi.org/10.1007/s11548-025-03547-2>
- [17] Tiwary, P., Oswal, K., Varghese, R., Gupta, P. (2026). Solid lipid nanoparticles in imaging, diagnostics and theranostics: A review of a decade of innovations and clinical applications. *Colloids and Surfaces B: Biointerfaces*, 257, 115122.
<https://doi.org/10.1016/j.colsurfb.2025.115122>
- [18] Karati, D., Meur, S., Roy, S., Mukherjee, S. (2026). Gadolinium based nanoplateform as drug delivery approach for targeted therapy. *Journal of Drug Delivery Science and Technology*, 115, 107807.
<https://doi.org/10.1016/j.jddst.2025.107807>
- [19] Mensah, E. A., Faiyaz, A., Schifitto, G., Uddin, M. N. (2025). Chemical exchange saturation transfer imaging in neuroinflammation: Methods, challenges, and recommendations. *International Journal of Molecular Sciences*, 26 (22), 11059.
<https://doi.org/10.3390/ijms262211059>

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