Citation and Reference Verification Report

GenAI-RAG-EEG: A Novel Hybrid Deep Learning Architecture with Retrieval-Augmented Generation for Explainable EEG-Based Stress and Cognitive Workload Classification

Verification Date: December 24, 2025

Verification Summary

Metric	Value
Total Citations in Paper	40
Total Bibliography Entries	40
Missing References	**0**
Orphan References (Uncited)	**0**
Verification Status	**PASSED**

Result: All citations are correctly linked to their corresponding bibliography entries.

Detailed Citation-Reference Mapping

#	Citation Key	Cited at Lines	Bib Line	Status
1	who2023stress	115	1221	OK
2	hassard2018cost	115	1224	OK
3	cohen1983pss	115	1227	OK
4	lovibond1995dass	115	1230	OK
5	teplan2002fundamentals	119	1233	OK
6	mcewen2007physiology	119	1236	OK
7	klimesch1999alpha	119	1239	OK
8	ray1985eeg	119	1242	OK
9	harmony2009eeg	119	1245	OK
10	davidson2004well	119	1248	OK
11	subhani2017machine	123, 911	1251	OK
12	sharma2012objective	123, 912	1254	OK
13	healey2005detecting	123	1257	OK
14	alshargie2016mental	125	1260	OK
15	arsalan2019classification	125	1263	OK
16	hou2015eeg	125	1266	OK

#	Citation Key	Cited at Lines	Bib Line	Status
17	alhagry2017emotion	129, 916	1269	OK
18	schirrmeister2017deep	129	1272	OK
19	lawhern2018eegnet	131, 918	1275	OK
20	li2019hierarchical	131	1278	OK
21	tripathi2017using	131, 915	1281	OK
22	chen2021accurate	133, 917	1284	OK
23	zhang2020spatial	133	1287	OK
24	song2020eeg	133, 919	1290	OK
25	tao2020eeg	137	1293	OK
26	wang2022transformers	137	1296	OK
27	li2023bihemisphere	137	1299	OK
28	gonzalez2024deep	139	1302	OK
29	hwang2020learning	139	1305	OK
30	tonekaboni2019clinicians	143	1308	OK
31	holzinger2019causability	143	1311	OK
32	cui2020eeg	143	1314	OK
33	lewis2020rag	145	1317	OK
34	zhang2024medical	145	1320	OK
35	rudin2019stop	152	1323	OK
36	schmidt2018wesad	154	1326	OK
37	lotte2018review	156	1329	OK
38	gal2016dropout	158	1332	OK
39	wang2023evidence	160	1335	OK
40	koelstra2012deap	193	1338	OK

Full Reference Details

#	Key	Full Reference
1	who2023stress	World Health Organization, "Mental health: Strengthening our response," WHO Fact Sheet, 2023.
2	hassard2018cost	J. Hassard et al., "The cost of work-related stress to society: A systematic review," J. Occup. Health Psychol., vol. 23, no. 1, pp. 1–17, 2018.
3	cohen1983pss	S. Cohen, T. Kamarck, and R. Mermelstein, "A global measure of perceived stress," J. Health Soc. Behav., vol. 24, pp. 385–396, 1983.
4	lovibond1995dass	S. H. Lovibond and P. F. Lovibond, "Manual for the Depression Anxiety Stress Scales," Psychology Foundation, Sydney, 1995.
5	teplan2002fundamentals	M. Teplan, "Fundamentals of EEG measurement," Meas. Sci. Rev., vol. 2, no. 2, pp. 1–11, 2002.
6	mcewen2007physiology	B. S. McEwen, "Physiology and neurobiology of stress and adaptation," Physiol. Rev., vol. 87, no. 3, pp. 873–904, 2007.

#	Key	Full Reference
7	klimesch1999alpha	W. Klimesch, "EEG alpha and theta oscillations reflect cognitive and memory performance," Brain Res. Rev., vol. 29, pp. 169–195, 1999.
8	ray1985eeg	W. J. Ray and H. W. Cole, "EEG alpha activity reflects attentional demands," Science, vol. 228, pp. 750–752, 1985.
9	harmony2009eeg	T. Harmony, "The functional significance of delta oscillations in cognitive processing," Front. Integr. Neurosci., vol. 7, p. 83, 2009.
10	davidson2004well	R. J. Davidson, "Well-being and affective style: Neural substrates and biobehavioural correlates," Phil. Trans. R. Soc. B, vol. 359, pp. 1395–1411, 2004.
11	subhani2017machine	A. R. Subhani et al., "Machine learning framework for the detection of mental stress at multiple levels," IEEE Access, vol. 5, pp. 13545–13556, 2017.
12	sharma2012objective	N. Sharma and T. Gedeon, "Objective measures, sensors and computational techniques for stress recognition," Comput. Methods Programs Biomed., vol. 108, pp. 1287–1301, 2012.
13	healey2005detecting	J. A. Healey and R. W. Picard, "Detecting stress during real-world driving tasks using physiological sensors," IEEE Trans. Intell. Transp. Syst., vol. 6, no. 2, pp. 156–166, 2005.
14	alshargie2016mental	F. Al-shargie et al., "Mental stress assessment using simultaneous measurement of EEG and fNIRS," Biomed. Opt. Express, vol. 7, no. 10, pp. 3882–3898, 2016.
15	arsalan2019classification	A. Arsalan et al., "Classification of perceived mental stress using a commercially available EEG headband," IEEE J. Biomed. Health Inform., vol. 23, no. 6, pp. 2257–2264, 2019.
16	hou2015eeg	X. Hou et al., "EEG based stress monitoring," IEEE Int. Conf. Syst. Man Cybern., pp. 3110–3115, 2015.
17	alhagry2017emotion	S. Alhagry, A. A. Fahmy, and R. A. El-Khoribi, "Emotion recognition based on EEG using LSTM recurrent neural network," Int. J. Adv. Comput. Sci. Appl., vol. 8, no. 10, pp. 355–358, 2017.
18	schirrmeister2017deep	R. T. Schirrmeister et al., "Deep learning with convolutional neural networks for EEG decoding and visualization," Hum. Brain Mapp., vol. 38, no. 11, pp. 5391–5420, 2017.
19	lawhern2018eegnet	V. J. Lawhern et al., "EEGNet: A compact convolutional neural network for EEG-based brain-computer interfaces," J. Neural Eng., vol. 15, no. 5, p. 056013, 2018.

#	Key	Full Reference
20	li2019hierarchical	Y. Li et al., “A bi-hemisphere domain adversarial neural network model for EEG emotion recognition,” IEEE Trans. Affect. Comput., vol. 12, no. 2, pp. 494–504, 2019.
21	tripathi2017using	S. Tripathi et al., “Using deep and convolutional neural networks for accurate emotion classification on DEAP dataset,” Proc. AAAI Conf. Artif. Intell., pp. 4746–4752, 2017.
22	chen2021accurate	J. Chen et al., “Accurate EEG-based emotion recognition on combined CNN-LSTM with attention mechanism,” Neural Networks, vol. 143, pp. 485–496, 2021.
23	zhang2020spatial	T. Zhang et al., “Spatial-temporal recurrent neural network for emotion recognition,” IEEE Trans. Cybern., vol. 49, no. 3, pp. 839–847, 2020.
24	song2020eeg	T. Song et al., “EEG emotion recognition using dynamical graph convolutional neural networks,” IEEE Trans. Affect. Comput., vol. 11, no. 3, pp. 532–541, 2020.
25	tao2020eeg	W. Tao et al., “EEG-based emotion recognition via channel-wise attention and self attention,” IEEE Trans. Affect. Comput., 2020.
26	wang2022transformers	Z. Wang et al., “Transformers for EEG-based emotion recognition: A hierarchical spatial information learning model,” IEEE Sens. J., vol. 22, pp. 4359–4368, 2022.
27	li2023bihemisphere	Y. Li et al., “Bi-hemisphere discrepancy for cross-session EEG emotion recognition,” IEEE Trans. Affect. Comput., vol. 14, pp. 1068–1080, 2023.
28	gonzalez2024deep	H. Gonzalez et al., “Deep learning for EEG-based stress detection: A comprehensive benchmark,” IEEE Trans. Neural Syst. Rehabil. Eng., 2024.
29	hwang2020learning	S. Hwang et al., “Learning subject-independent representation for EEG-based drowsiness detection,” IEEE Access, vol. 8, pp. 86736–86746, 2020.
30	tonekaboni2019clinicians	S. Tonekaboni et al., “What clinicians want: Contextualizing explainable machine learning for clinical end use,” Proc. Mach. Learn. Healthc. Conf., pp. 359–380, 2019.
31	holzinger2019causability	A. Holzinger et al., “Causability and explainability of artificial intelligence in medicine,” WIREs Data Min. Knowl. Discov., vol. 9, no. 4, e1312, 2019.
32	cui2020eeg	H. Cui et al., “EEG-based emotion recognition: A review of recent progress,” IEEE Trans. Cogn. Dev. Syst., vol. 12, no. 2, pp. 217–231, 2020.
33	lewis2020rag	P. Lewis et al., “Retrieval-augmented generation for knowledge-intensive NLP tasks,” Proc. NeurIPS, vol. 33, pp. 9459–9474, 2020.

#	Key	Full Reference
34	zhang2024medical	S. Zhang et al., "Medical RAG: Retrieval-augmented generation for clinical decision support," Nature Digit. Med., 2024.
35	rudin2019stop	C. Rudin, "Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead," Nature Mach. Intell., vol. 1, pp. 206–215, 2019.
36	schmidt2018wesad	P. Schmidt et al., "Introducing WESAD, a multimodal dataset for wearable stress and affect detection," Proc. ICMI, pp. 400–408, 2018.
37	lotte2018review	F. Lotte et al., "A review of classification algorithms for EEG-based brain-computer interfaces," J. Neural Eng., vol. 15, no. 3, p. 031005, 2018.
38	gal2016dropout	Y. Gal and Z. Ghahramani, "Dropout as a Bayesian approximation: Representing model uncertainty in deep learning," Proc. ICML, pp. 1050–1059, 2016.
39	wang2023evidence	S. Wang et al., "Evidence-grounded neural network explanations for healthcare," Nature Comput. Sci., 2023.
40	koelstra2012deap	S. Koelstra et al., "DEAP: A database for emotion analysis using physiological signals," IEEE Trans. Affect. Comput., vol. 3, no. 1, pp. 18–31, 2012.

Verification Script

The following Python script can be used to re-verify citations at any time:

```
import re
with open('eeg-stress-rag.tex', 'r') as f:
    content = f.read()
    lines = content.split('\n')

citations = set()
bibitems = set()

for line in lines:
    for m in re.findall(r'\\cite\{([^}]+)\}', line):
        citations.update(m.split(','))
    m = re.match(r'\\bibitem\{([^}]+)\}', line)
    if m: bibitems.add(m.group(1))

missing = citations - bibitems
orphan = bibitems - citations
print(f"Missing refs: {missing or 'None'}")
print(f"Orphan refs: {orphan or 'None'}")
```