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Cognitive Hybridization: Redefining Human Identity at the Interface of Neuroscience and Artificial Intelligence: A Narrative Review

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Abstract

Background & Objective: The convergence of human cognition and artificial intelligence (AI) is reshaping cognitive identity and challenging traditional understandings of consciousness, agency, and selfhood. This narrative review introduces a conceptual three-stage model of cognitive hybridization, comprising Simulation, Integration, and Co-Evolution, to examine the dynamics of human-AI interaction and its neuroethical implications.

Materials & Methods: Interdisciplinary evidence from cognitive neuroscience, AI research, and neuroethics was synthesized by drawing on studies published between 2000 and 2025 in PubMed, Scopus, and Web of Science. The review focused on brain-computer interfaces (BCIs), mechanisms of neural plasticity, and the cognitive capacities of large language models (LLMs).

Results: In the Simulation stage, LLMs replicate selected cognitive operations such as language processing, although they lack any biological substrates, including hippocampal encoding and network-level neural dynamics. The Integration stage involves reciprocal interactions between the brain and AI, where BCIs facilitate emergent forms of shared agency mediated through cortical and basal ganglia pathways. The Co-Evolution stage reflects bidirectional adaptive processes that gradually reshape cognitive functions across both developing and aging brains. Key neuroethical considerations include autonomy, cognitive justice, and the protection of neural data and cognitive privacy.

Conclusion: This model highlights the urgent need for updated theoretical and ethical frameworks that can guide human-AI co-evolution and promote equitable and safe cognitive enhancement. The proposed framework offers a structured foundation for future interdisciplinary inquiry in neuroethics and cognitive augmentation.

Keywords: Cognitive identity, Cognitive hybridization, Human-AI interaction, Neuroethics, Shared agency

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Introduction

The twenty-first century marks a pivotal turning point in the evolution of human cognition and identity. The classical boundaries between biological intelligence and artificial intelligence (AI) are increasingly blurred, challenging long-standing assumptions about consciousness, agency, and personhood (1). This convergence, which I term the Fourth Wave, extends Toffler's sociocultural model by directing attention to neurocognitive transformation through the integration of biological and artificial systems, in contrast to the social and economic emphases of the Third Wave (2–4). Historically, conceptions of human identity have centered on subjectivity, embodiment, and rational agency, from Descartes' cogito to Kant's moral philosophy.

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In cognitive neuroscience, identity has been operationalized via neural processes such as memory encoding, executive control, and the integration of large-scale brain networks (5, 6). Contemporary AI systems increasingly simulate aspects of these processes; for example, large language models (LLMs) approximate facets of linguistic comprehension and inferential reasoning while lacking neurobiological substrates such as hippocampal-dependent memory consolidation and the dynamic regulatory functions of prefrontal cortical circuitry (7, 8). Neurotechnologies, including brain–computer interfaces (BCIs) and neuroprosthetics, further this convergence by establishing ***bidirectional*** loops between neural circuits and computational systems (9–11).

Empirical evidence from neuroscience indicates substantial neural plasticity when the human brain interacts with cognitive prostheses and artificial devices. Longitudinal BCI studies, for example, document cortical remapping and functional reorganization within sensorimotor and associative regions following sustained device use (12–14). Such findings lend neurobiological credence to extended-mind hypotheses, which propose that external artifacts may become functionally incorporated into cognition (15). Nonetheless, the notion of shared agency, understood as the distributed control exercised jointly by human and artificial systems, remains under-specified. Clear operationalization is required, including identification of neurobiological markers such as sensorimotor coupling, prediction-error dynamics, and reinforcement-learning signatures within cortico-basal ganglia loops (16, 17).

To address these lacunae, we propose a three-stage model of cognitive hybridization—Simulation, Integration, and Co-Evolution. Rather than conceiving identity as a static attribute, this framework reconceptualizes identity as a dynamic, multi-layered, and adaptive process shaped continuously by human–AI interaction (18). By integrating insights from neuroscience, the philosophy of mind, and neuroethics, the Fourth Wave model offers a systematic lens through which to examine how cognition is being reshaped in real time and what such reshaping entails for selfhood, autonomy, and responsibility (19). Although philosophical and computational literatures have explored aspects of human–AI convergence, comprehensive frameworks that couple neurophysiological mechanisms with normative analysis are scarce. This study seeks to fill that gap by proposing a conceptual three-stage model of cognitive hybridization that illuminates both neurocognitive mechanisms and attendant ethical concerns, thereby informing the design of safer neurotechnologies and the development of policy for human–AI interaction.

Literature Review and Theoretical Framework

A coherent account of human–AI convergence must be both conceptually rigorous and empirically grounded (20). Prior work typically approaches this convergence from either philosophical perspectives, such as posthumanism, or computational frameworks, such as AI functionalism. To make a substantive contribution to neuroscience, however, it is essential to integrate mechanistic explanations of neuroplasticity, embodiment, and consciousness with contemporary advances in artificial intelligence (21).

Extended Mind and Cognitive Extension

Clark and Chalmers' extended-mind thesis posits that external artifacts can become integral components of cognitive processes (15). Neuroscientific research increasingly provides empirical support for this thesis. Studies employing BCIs and prosthetic devices report cortical remapping and altered representational topographies, which indicate that external tools can be functionally integrated into neural circuits (12, 13, 22). Functional magnetic resonance imaging (MRI) studies further reveal plastic changes within prefrontal and parietal networks

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associated with prolonged engagement with cognitive aids, implying that externally mediated information processing can modulate intrinsic neural dynamics (23, 24). Taken together, these findings demonstrate that cognitive extension is not merely a philosophical abstraction but is amenable to neurobiological quantification and experimental investigation (25).

Shared Agency and Hybrid Cognition

A central feature of human–AI convergence is the emergence of shared agency, a mode of control distributed across biological and computational components. Rather than treating neuroprosthetics as mere replications of preexisting agency, recent work emphasizes interactive reinforcement-learning architectures that instantiate closed-loop dynamics between motor cortical activity and adaptive AI agents (16, 26). For example, BCIs that decode motor intentions engage cortico-basal ganglia circuits in ways that couple biological intention with algorithmic prediction, thereby producing a co-constructed form of agency rather than a simple substitutional one (10, 27). This neurobiological grounding suggests that agency in hybrid systems is emergent and relational, contingent upon reciprocal adjustments between organism and machine (28).

Three-Stage Model of Cognitive Hybridization

Building on these conceptual and empirical foundations, we situate transformations of cognitive identity within a three-stage framework: Simulation, Integration, and Co-Evolution. Figure 1 schematizes this model and depicts how each phase progressively builds upon the previous one, thereby highlighting the evolving degrees of integration between human cognition and artificial systems.

• To avoid redundancy, this model is presented in full here and subsequently referenced in the discussion section to prevent repeated reintroductions.

• **Simulation:** Artificial systems mimic discrete cognitive functions such as language, memory, or decision-making. While large language models (LLMs) can generate human-like linguistic output, their operations do not involve hippocampal-dependent encoding or prefrontal executive integration, which highlights functional simulation rather than biological replication (8, 29, 30).

• **Integration:** Human neural networks and artificial systems interact via BCIs, adaptive neuroprosthetics, and multimodal AI, forming hybrid architectures. Neurophysiological evidence demonstrates bidirectional feedback loops linking cortical activity with machine output, thereby establishing the mechanistic plausibility of cognitive integration (9, 10, 31).

• **Co-Evolution:** With sustained interaction, both biological and artificial systems adapt to one another. Reinforcement learning dynamics in the basal ganglia and synaptic plasticity in cortical circuits provide neurobiological support for adaptive recalibration in response to AI-mediated feedback (29, 32, 33). This stage embodies a form of distributed identity in which cognition functions as a fluid interplay across multiple substrates (34).

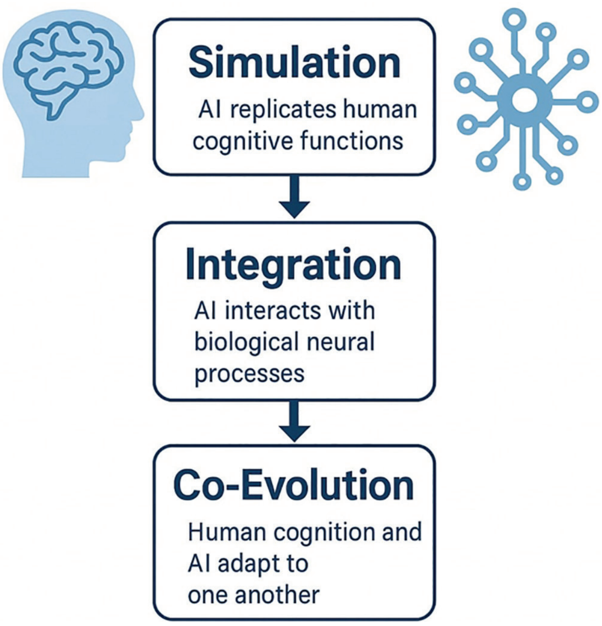

Figure 1. A conceptual model of cognitive identity transformation across three phases. Each phase builds upon the previous one, indicating an evolving integration between human and artificial cognition.

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Ethical and Philosophical Dimensions

From a neuroethical perspective, the hybridization of cognition raises profound questions regarding responsibility, autonomy, and identity. Recent frameworks emphasize relational agency, cognitive justice, and privacy as guiding principles for evaluating hybrid cognition (3, 4, 11). While philosophical models such as posthumanism argue for **a** conceptual separation of identity from embodiment, empirical findings indicate that embodiment and neurophysiology remain essential for understanding the lived experience of hybrid cognition (35, 36).

Materials & Methods

This narrative review integrates interdisciplinary evidence on the convergence of human cognition and artificial intelligence (AI). Literature was searched across PubMed, Scopus, Web of Science, and Google Scholar (January 2000 to September 2025) using keywords such as "cognitive identity OR selfhood AND artificial intelligence," "extended mind AND neuroscience," "brain–computer interface OR BCI AND plasticity," "hybrid cognition OR shared agency AND neurophysiology," and "neuroethics AND AI." The time frame (2000–2025) was selected to capture major developments in brain–computer interfaces, large language models, and neuroethics. Additional sources were identified through backward citation searches of key articles published in 2024–2025 (37).

Inclusion criteria encompassed peer-reviewed journal articles, academic books, and consensus reports (e.g., Nature, Trends in Cognitive Sciences) focusing on cognitive neuroscience, philosophy of mind, AI, psychology, or neuroethics. Studies were selected based on their methodological rigor, relevance to cognitive neuroscience and AI, and publication in high-impact peer-reviewed journals. Sources were excluded if they were non-peer-reviewed, engineering-focused without cognitive implications, or published in languages other than English.

From approximately 1,200 initial publications, duplicates were removed, and 182 sources were reviewed, with 88 (76 peer-reviewed articles and 12 scholarly books) included. By emphasizing neurophysiological evidence from invasive BCI trials, fMRI-based plasticity research, and neuroethical analyses, the methodology ensures a balanced approach that maintains rigor while allowing flexibility, thereby providing a reproducible framework for interdisciplinary inquiry (38).

Results

This narrative review synthesizes interdisciplinary findings to propose a conceptual three-stage model of cognitive hybridization consisting of Simulation, Integration, and Co-Evolution, which elucidates the convergence of human cognition and artificial intelligence (AI). This conceptual framework, illustrated in Figure 1, outlines the dynamic interactions between neurocognitive processes and AI systems.

In the Simulation stage, AI systems mimic human cognitive functions without biological substrates. For example, large language models (LLMs) such as GPT-4 generate human-like text responses, thereby simulating linguistic comprehension despite the absence of neural mechanisms like hippocampal memory consolidation. Neurophysiologically, simulation reproduces cognitive outputs such as language processing without engaging biological neural processes, whereas replication aims to recreate specific neural dynamics, including cortical firing patterns or synaptic plasticity (7, 8).

The Integration stage involves reciprocal interactions between human brains and AI systems. For instance, BCIs enable paralyzed individuals to control robotic limbs through cortical signals, illustrating shared agency that arises from coordinated neural and artificial operations (9, 10).

The Co-Evolution stage reflects mutual

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adaptation over time. An example is the use of neurofeedback systems in cognitive training, in which AI adapts to neural patterns to enhance learning, thereby modifying brain plasticity in both developing and aging populations (12, 19). Collectively, these stages illuminate the neurocognitive and ethical dimensions of human–AI convergence, with significant implications for autonomy, cognitive justice, and neural data privacy.

Discussion

The three-stage framework of Simulation, Integration, and Co-Evolution offers a structured account of how human cognition and artificial intelligence (AI) converge. This section situates the framework within the literatures of neuroscience, psychology, and neuroethics and thereby secures both conceptual clarity and mechanistic plausibility. By integrating empirical findings with theoretical insights, the model illuminates the dynamic interplay between biological and artificial systems and the ethical questions that arise from such hybridization (20, 39).

Neurophysiological Mechanisms of Hybrid Cognition

Neuroplasticity constitutes a central mechanism for understanding hybrid cognition. Studies of invasive BCIs demonstrate that prolonged device use induces cortical remapping, synaptic plasticity, and large-scale functional reorganization (12-14). Hippocampal-dependent learning and synaptic long-term potentiation (LTP) remain indispensable for memory formation, processes that are absent from current AI architectures; this distinction underscores the difference between functional simulation and biological replication (1). Likewise, reinforcement learning signals within the basal ganglia guide adaptation during neuroprosthetic use, thereby identifying a plausible neural substrate for human–machine co-evolution (32, 40). Collectively, these findings indicate that although AI systems can reproduce behavioral or output patterns, they do not replicate core neurophysiological processes such as synaptic plasticity or neuromodulatory dynamics (24).

Affective Regulation and Cognitive Extension

Hybrid cognition extends beyond motor control and mnemonic systems to encompass affective regulation. Sustained interaction with intelligent systems can alter limbic–prefrontal circuitry that underpins emotional regulation, reward processing, and decision making (6). For example, emotionally responsive social robots engage amygdala and ventromedial prefrontal pathways, a phenomenon that prompts substantive concerns about attachment, dependency, and long-term psychological consequences (35, 41). These observations reinforce the necessity of grounding affective-dimension claims in neuroscientific evidence when discussing extended or hybrid forms of cognition (21).

Developmental and Aging Brains

The effects of hybrid cognition vary across the lifespan and thus warrant careful, stage-sensitive investigation. In developing brains, high synaptic plasticity may facilitate rapid accommodation to cognitive extensions but also raises concerns about dependency and potential perturbations to developmental trajectories (22, 42). Conversely, in aging brains, reduced neuroplasticity and heightened susceptibility to neurodegeneration (for example, Alzheimer's disease) may limit adaptability and exacerbate disparities in access to and benefit from neurotechnologies (7, 43). Rigorous, longitudinal studies that combine fMRI with BCI interventions in pediatric and older adult cohorts will be critical for delineating these differential effects across the lifespan (44).

Neuroethical Considerations

Although previous sections have highlighted neuroethical concerns, a more structured framework is warranted. Following Yuste et al. and Ienca and Andorno, we emphasize four central principles (3, 4):

1. **Cognitive Liberty**: Safeguarding

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individuals' right to control their own mental processes (45).

2. **Mental Privacy**: Protecting neural data from unauthorized access (46).

3. **Psychological Continuity**: Preserving the integrity of selfhood amid cognitive extensions (47).

4. **Fair Access**: Mitigating cognitive inequalities arising from uneven distribution of neurotechnologies (11).

By anchoring ethical reflection in neurophysiology—for instance, linking mental privacy to neural data streams and autonomy to decision-making circuitry—these principles move beyond abstract moral theorizing and furnish actionable guidance for evaluating hybrid cognition (36, 48).

Limitations and Future Directions

This narrative review has several limitations. Its non-systematic methodology may introduce selection bias because studies were chosen for relevance and availability rather than through a pre-registered protocol. In addition, the proposed three-stage model of cognitive hybridization remains theoretical and lacks direct empirical validation owing to the emergent nature of human AI convergence research. The interdisciplinary scope of the topic also creates challenges in reconciling methods and findings across neuroscience, AI, and ethics. Future research should prioritize empirical testing of the model through neuroscientific experiments—such as BCI protocols that quantify shared agency and the cortical control of motor effectors—or through computational simulations of hybrid cognitive architectures (49). Moreover, longitudinal investigations are necessary to assess co-evolutionary impacts on brain plasticity and cognitive development, particularly among older adults for whom cerebral aging processes critically influence outcomes (50). Finally, the development of robust ethical frameworks addressing neural data privacy and cognitive justice will be indispensable for steering responsible human AI integration (19, 20).

Conclusion

This review advances a three-stage model—Simulation, Integration, and Co-Evolution—to conceptualize transformations in cognitive identity at the intersection of neuroscience and artificial intelligence. In contrast to earlier accounts that emphasize abstract philosophy, our framework explicitly integrates neurophysiological mechanisms (for example, synaptic plasticity, cortical remapping, and reinforcement learning circuits) and foregrounds their ethical implications (2, 18).

Key contributions include:

• Clarifying that AI systems simulate cognitive functions but lack neurobiological substrates (8).

• Emphasizing shared agency as co-constructed through cortico-basal ganglia and sensorimotor loops (6, 16).

• Outlining developmental and aging perspectives to address lifespan variability in adaptability (42, 43).

• Providing a structured neuroethical framework grounded in cognitive neuroscience (3, 4).

Future work should integrate invasive and noninvasive neuroimaging, longitudinal developmental cohorts, and normative analyses to evaluate how hybrid cognition reshapes identity across varied contexts (26, 37). As societies enter what some have termed the Fourth Wave, conceptualizing identity as distributed, adaptive, and ethically governed will be essential for aligning scientific rigor with social responsibility (8, 11, 34). To this end, researchers and policymakers ought to collaborate to produce standardized ethical guidelines that ensure safe and equitable human AI cognitive integration (4, 19).

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Conflict of Interest

The author declares no conflict of interest. This review was conducted independently, without financial support or personal relationships that could have influenced the findings.

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Ethical Consideration

Because this paper is a narrative review synthesizing published literature, no primary human or animal data were collected and institutional review board approval was not required. All sources were cited appropriately to preserve academic integrity and to avoid plagiarism.

References

1 Tononi G, Boly M, Massimini M, Koch C. Integrated information theory: from consciousness to its physical substrate. Nat Rev Neurosci. 2016;17(7):450-461. doi:10.1038/nrn.2016.44.
2 Toffler A. The third wave. New York: William Morrow; 1980.
3 Ienca M, Andorno R. Towards new human rights in the age of neuroscience and neurotechnology. Life Sci Soc Policy. 2017;13:5. doi:10.1186/s40504-017-0050-1.
4 Yuste R, Goering S, Arcas BAY, Bi G, Carmena JM, Carter A, et al. Four ethical priorities for neurotechnologies and AI. Nature. 2017;551:159-163. doi:10.1038/551159a.
5 Baars BJ. Global workspace theory of consciousness: toward a cognitive neuroscience of human experience. Prog Brain Res. 2005;150:45-53. doi:10.1016/S0079-6123(05)50004-9.
6 Pessoa L. The entangled brain: how perception, cognition, and emotion are woven together. Cambridge: MIT Press; 2022.
7 Hassabis D, Kumaran D, Summerfield C, Botvinick M. Neuroscience-inspired artificial intelligence. Neuron. 2017;95:245-258. doi:10.1016/j.neuron.2017.06.011.
8 Caucheteux C, King JR. Brains and algorithms partially converge in natural language processing. Commun Biol. 2022;5:134. doi:10.1038/s42003-022-03036-1.
9 Lebedev MA, Nicolelis MAL. Brain-machine interfaces: from basic science to neuroprostheses and neurorehabilitation. Physiol Rev. 2017;97:767-837. doi:10.1152/physrev.00027.2016.
10 Chaudhary U, Vlachos I, Zimmermann JB, Burbaud P, Birbaumer N. Brain-computer interfaces for communication in paralysis. Nat Rev Neurol. 2022;18:51-62. doi:10.1038/s41582-021-00541-1.
11 Musk E, Neuralink. An integrated brain-machine interface platform with thousands of channels. J Med Internet Res. 2019;21:e16194. doi:10.2196/16194.
12 Guggenmos DJ, Azin M, Barbay S, Mahnken JD, Dunham C, Mohseni P, et al. Restoration of function after brain damage using a neural prosthesis. Nat Biotechnol. 2013;31:976-979. doi:10.1038/nbt.2729.
13 Benabid AL, Costecalde T, Eliseyev A, Charvet G, Verney A, Karakas S, et al. An exoskeleton controlled by an epidural wireless brain-machine interface in a tetraplegic patient: a proof-of-concept demonstration. Lancet Neurol. 2019;18:1112-1122. doi:10.1016/S1474-4422(19)30321-7.
14 Biasiucci A, Leeb R, Iturrate I, Perdikis S. Brain-actuated functional electrical stimulation elicits lasting arm motor recovery after stroke. Nat Commun. 2018;9:2421. doi:10.1038/s41467-018-04673-z.
15 Clark A, Chalmers D. The extended mind. Analysis. 1998;58:7-19. doi:10.1093/analys/58.1.7.
16 Arbib MA. Artificial intelligence meets brain theory (again). Biol Cybern. 2025;119:16. doi:10.1007/s00422-025-01013-5.
17 Donoghue JP. Connecting cortex to machines: recent advances in brain interfaces. Nat Neurosci. 2002;5:1085-1088. doi:10.1038/nn947.
18 Friston K. The free-energy principle: a unified brain theory? Nat Rev Neurosci. 2010;11:127-138. doi:10.1038/nrn2787.
19 Salles A, Evers K, Farisco M. Neuroethics and philosophy in responsible research and innovation: the case of the human brain project. Neuroethics. 2019;12:201-211. doi:10.1007/s12152-018-9372-9.
20 Krakauer JW, Ghazanfar AA, Gomez-Marin A, MacIver MA, Poeppel D. Neuroscience needs behavior: correcting a reductionist bias. Neuron. 2017;93:480-490. doi:10.1016/j.neuron.2016.12.041.
21 Hohwy J. The predictive mind. Oxford: Oxford University Press; 2013.
22 Cantillo-Negrete J, Rodríguez-García ME,

[DOI: 10.18502/jabs.v16i1.20125]

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Carrillo-Mora P, Arias-Carrión O, Ortega-Robles E. A randomized controlled trial of a brain-computer interface for upper extremity stroke neurorehabilitation. Front Neurosci. 2025;19:1579988. doi:10.3389/fnins.2025.1579988.

23 He H, Qin W, Liu Y, Zhang X, Duan Y, Song J, et al. Neural plasticity during long-term cognitive training: fMRI evidence for reorganization of prefrontal-parietal networks. Cereb Cortex. 2020;30:2924-2937. doi:10.1093/cercor/bhz285.

24 Poldrack RA. The new mind readers: what neuroimaging can and cannot reveal about our thoughts. Princeton: Princeton University Press; 2018.

25 Rao RP, Ballard DH. Predictive coding in the visual cortex: a functional interpretation of some extra-classical receptive-field effects. Nat Neurosci. 2000;3:79-87. doi:10.1038/71175.

26 Willett FR, Avansino DT, Hochberg LR, Henderson JM, Shenoy KV. High-performance brain-to-text communication via handwriting. Nature. 2021;593:249-254. doi:10.1038/s41586-021-03506-2.

27 Silva AB, Littlejohn KT, Liu JR, Moses DA, Chang EF. The speech neuroprosthesis. Nat Rev Neurosci. 2024;25:473-492. doi:10.1038/s41583-024-00819-9.

28 Metzger SL, Littlejohn KT, Silva AB, Moses DA, Seaton MP, Wang R, et al. A high-performance neuroprosthesis for speech decoding and avatar control. Nature. 2023;620:1031-1036. doi:10.1038/s41586-023-06377-x.

29 Opris I, Santos LM, Gerhardt GA, Song D, Berger TW, Hampson RE, et al. Prefrontal cortical microcircuits dynamically adapt during reinforcement learning with neuroprosthetic devices. Front Neurosci. 2020;14:137. doi:10.3389/fnins.2020.00137.

30 Caucheteux C, King JR. Deep language algorithms predict semantic brain responses. Sci Rep. 2022;12:1659. doi:10.1038/s41598-022-20460-9.

31 Défossez A, Copet J, Synnaeve G, Adi Y. Decoding speech perception from non-invasive brain recordings. Nat Mach Intell. 2023;5:1006-1016. doi:10.1038/s42256-023-00714-5.

32 Zrenner C, Belardinelli P, Müller-Dahlhaus F, Ziemann U. Closed-loop neuroscience and non-invasive brain stimulation: a new era of experimental and clinical neurophysiology. Nat Commun. 2020;11:210. doi:10.1038/s41467-019-13953-9.

33 Elashmawi WH, Ayman A, Antoun M, Mohamed H, Mohamed SE, Amr H, et al. A comprehensive review on BCI-based machine and deep learning algorithms for stroke rehabilitation. Appl Sci. 2024;14:6347. doi:10.3390/app14146347.

34 Tang, J., LeBel, A., Jain, S. et al. Semantic reconstruction of continuous language from non-invasive brain recordings. Nat Neurosci 26, 858–866 (2023). https://doi.org/10.1038/s41593-023-01304-9

35 Vogeley K, Bente G. “Artificial humans”: psychological and neural perspectives on human-AI interactions. Neurosci Biobehav Rev. 2020;114:142-151. doi:10.1016/j.neubiorev.2020.04.017.

36 Brannigan JFM, Liyanage K, Horsfall HL, Bashford L, Muirhead W, Fry A. Brain-computer interfaces patient preferences: a systematic review. J Neural Eng. 2024;21:061005. doi:10.1088/1741-2552/ad94a6.

37 Nature Electronics Editorial. The year of brain-computer interfaces. Nat Electron. 2023;6:637. doi:10.1038/s41928-023-01041-8.

38 Wolpaw JR, Wolpaw EW. Brain-computer interfaces: principles and practice. Oxford: Oxford University Press; 2012.

39 Hildt E. Multi-person brain-to-brain interfaces: ethical issues. Front Neurosci. 2019;13:1177. doi:10.3389/fnins.2019.01177.

40 Chen S. Brain-computer interfaces in 2023-2024: review. Brain-X. 2025;3:70024. doi:10.1002/brx2.70024.

41 Broadbent E. Interactions with robots: the truths we reveal about ourselves. Annu Rev Psychol. 2017;68:627-652. doi:10.1146/annurev-psych-010416-043958.

42 Johnson MH. Interactive specialization: a domain-general framework for human functional brain development? Dev Cogn Neurosci. 2011;1:7-21. doi:10.1016/j.dcn.2010.07.003.

43 Cole JH, Franke K. Predicting age using neuroimaging: innovative brain ageing biomarkers. Trends Neurosci. 2017;40:681-690. doi:10.1016/j.tins.2017.10.001.

44 Wandelt SK, Bjånes DA, Pejsa K, Lee B, Liu C, Andersen RA. Representation of internal speech by single neurons in humans. Nat Hum Behav. 2024;8:1496-1507. doi:10.1038/s41562-024-01867-y.

45 Farah MJ. Neuroethics: the practical and the philosophical. Trends Cogn Sci. 2005;9:34-40. doi:10.1016/j.tics.2004.11.008.

46 Livanis E, Voultsos P, Vadikolias K, Pantazakos P, Tsaroucha A. Understanding the ethical issues of brain-computer interfaces (BCIs): a blessing or the beginning of a dystopian future? Cureus. 2024;16:e58243. doi:10.7759/cureus.58243.

47 Glannon W. Ethical issues in neuroprosthetics. J Neural Eng. 2016;13:021003. doi:10.1088/1741-2560/13/2/021003.

48 Gordon EC, Gottwald S, Brock J, Spaniol M. Ethical considerations for the use of brain-computer

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interfaces for cognitive enhancement. PLoS Biol. 2024;22:e3002899. doi:10.1371/journal.pbio.3002899.

49 Shenoy KV, Sahani M, Churchland MM. Cortical control of arm movements: a dynamical systems perspective. Annu Rev Neurosci. 2013;36:337-359. doi:10.1146/annurev-neuro-062111-150509.

50 Cabeza R, Nyberg L, Park DC. Cognitive neuroscience of aging: linking cognitive and cerebral aging. 2nd ed. Oxford: Oxford University Press; 2016.

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