Theory and Practice of Science and Technology
2026, VOL. 7, NO. 3, 26-29
DOI: 10.47297/taposatWSP2633-456905.20260703

Business Model Innovation and Implementation Challenges in the Cross-disciplinary Integration of Artificial Intelligence and Brain-Computer Interfaces

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ABSTRACT
The convergence of artificial intelligence and brain-computer interface technologies is reshaping the landscape of the technology industry. Against this backdrop, this paper explores the development trajectory of this convergence. It provides an in-depth analysis of the key aspects of business model innovation and practical implementation when these two fields are integrated. By analysing the technological breakthrough requirements in core areas such as computing power adaptation, large-scale electrode manufacturing, and the refinement of legal and regulatory frameworks, this paper proposes a comprehensive industrial upgrading plan encompassing technological R&D, talent cultivation, and capital investment. The aim is to provide a theoretical foundation for transforming cutting-edge scientific and technological achievements into real productive capacity, to promote the formation of a new business ecosystem within a global collaborative framework, and to facilitate high-quality transformation of the real economy.

KEYWORDS
Artificial intelligence; Brain-computer interface; Business model; Technological evolution; Industrial upgrading

1 Introduction

Driven by the new wave of technological revolution, breakthroughs in neuroscience are transforming human interaction patterns. As a vital link between the brain and external devices, brain-computer interface (BCI) technology—having transitioned from medical rehabilitation to the consumer electronics market—has gradually expanded its applications into a wider range of fields. Leveraging its powerful nonlinear data-processing capabilities, artificial intelligence holds significant potential to optimise core technologies such as neural signal decoding, feature extraction, and intent recognition. The convergence of these two fields has overcome the technical bottlenecks of traditional computing architectures, successfully achieving high-precision analysis of neuronal impulse information and efficient command generation. This technological synergy has not only spawned new product forms but also fundamentally disrupted the existing value-creation network. From upstream EEG acquisition chips to downstream application software ecosystems, the universalisation of hardware devices, accompanied by cost reductions and efficiency gains, is inevitable. Simultaneously, neural data itself is gradually being treated as an asset, forming a high-value-added circulation model. The precise matching mechanism of closed-loop application models drives the transition of high-tech innovations from the R&D stage to large-scale commercialisation. Theoretical research must go beyond superficial phenomena to explore the core elements of technological development, systematically elucidating the fundamental laws and intrinsic mechanisms of industrial transformation.

2 Construction of the Theoretical Framework

2.1 Underlying Logic of Artificial Intelligence-Enabled Collaborative Brain-Computer Interfaces

The underlying neural impulse discharge signals are non-linear and non-stationary; traditional signal processing methods cannot achieve high-precision decoding. The incorporation of artificial intelligence, particularly deep learning architectures, has reshaped the underlying decoding logic. Convolutional neural networks can extract information from multi-dimensional spatiotemporal neural features, whilst recurrent neural networks exhibit high robustness towards time-series EEG signals. The collaborative mechanism enables the faithful extraction of subtle potential changes in the cerebral cortex, transforming them into executable machine instructions [1]. After filtering and denoising, neuronal signals are fed into a pre-trained multi-layer perceptron network; the dynamic adjustment of weights between network nodes effectively approximates human brain intent with precision. Breakthroughs in this underlying logic not only increase the upper limit of information transmission bandwidth but also facilitate the transition from unidirectional command output to bidirectional closed-loop feedback. Intelligent algorithms rely on unsupervised learning from vast amounts of neural

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data to automatically adjust decoding parameters, thereby establishing a human-machine interaction hub system with adaptive evolutionary capabilities, which forms the technological foundation for commercial implementation.

2.2 Evolutionary Mechanisms of Cross-Domain Convergence Technology

Cross-domain convergence is not a simple superposition of two technologies, but rather a vigorous chemical reaction occurring along a specific evolutionary trajectory. In the early stages of technological evolution, the approach primarily involved non-implantable EEG data acquisition combined with basic machine learning algorithms, limited to the classification and recognition of specific commands. The primary driving force behind this evolution is a breakthrough in algorithmic computing power, which, in turn, broadens the scope of application. With the iteration of computing architectures, the evolutionary path has gradually shifted towards high-throughput, low-latency implantable flexible microelectrode arrays combined with large-scale model architectures [2]. This evolutionary process aligns with the principle of information entropy reduction, in which the system continuously refines hardware and software interface protocols to minimise information loss during neural signal decoding. The evolution mechanism is also driven by breakthroughs in materials science; the application of biocompatible materials extends the stable operational duration of devices within the body, making the continuous acquisition of long-sequence neural data feasible. From a fundamental technical perspective, the evolution at the algorithmic level involves a transition from small-sample supervised learning to self-supervised representation learning, with each technological iteration exponentially expanding the boundaries of commercial application scenarios.

2.3 Evaluation of Core Drivers for Business Model Transformation

The reshaping of business models relies on improvements in the structure of core elements. The primary driver is the increased conversion rate of data assets, namely the compliant transformation of vast amounts of EEG time-series data into production factors with a commercial pricing basis. Secondly, there is the driving force of hardware terminal proliferation; the high cost of customised equipment limits the reduction in marginal costs, making the mass production of standardised, modular brain-computer interfaces a crucial pathway to breaking down cost barriers. The platformisation of algorithmic services is also a key factor. Efficient neural signal decoding APIs based on cloud computing can lower the technical barriers for downstream application developers, fostering a thriving ecosystem of third-party applications [3]. Changes in the value proposition should not be overlooked either; the shift from medical auxiliary tools to cognitive-enhancing immersive interactions has broadened the scope of the target audience. The evaluation of core driving factors must rely on multi-dimensional quantitative indicators. User acquisition costs, the data value per user over their lifetime, and the efficiency of collaboration across the upstream and downstream of the industrial chain can all serve as evaluation metrics, thereby identifying the key focal points for business model restructuring.

3 Key Breakthroughs for Practical Implementation

3.1 Solutions for Improving the Accuracy of Core Algorithm-Computing Power Adaptation

To address the stringent demands placed on underlying computing power by the real-time decoding of massive amounts of neural data, the primary challenge is to resolve the high computational requirements of such real-time decoding. Existing general-purpose computing architectures are prone to bottlenecks characterised by excessive power consumption and uncontrollable latency when processing high-frequency, concurrent, multi-channel EEG signals. Solutions to improve adaptation accuracy must focus on the development of specialised neuromorphic chips. These chips mimic the firing mechanisms of biological neural networks, enabling integrated storage and computation at very low power consumption. The algorithm architecture must also undergo lightweight pruning, quantisation and restructuring to ensure that complex models can be deployed on resource-constrained edge devices. A collaborative computing power allocation mechanism between edge and cloud is a key strategy for enhancing system robustness. Basic signal denoising, pre-processing and feature extraction are performed at the edge, whilst intention prediction requiring significant computational power is handled by cloud computing clusters. This architecture ensures real-time interaction whilst significantly improving the recognition accuracy of extremely faint intentions, laying the computational foundation for high-frequency commercial-grade applications.

3.2 Scalable Mass Production of Implantable High-Throughput Electrodes

Breakthroughs at the hardware level are constrained by the production capacity and yield rates of high-throughput microelectrode arrays. The purely manual manufacturing approach used in the laboratory phase cannot meet the

requirements for initial market deployment during the commercialisation phase. The key to overcoming this bottleneck lies in the use of semiconductor wafer-level manufacturing processes, employing mature photolithography and etching technologies to achieve batch production of micro- and nano-scale electrode arrays [4]. During mass production, the issue of uniform adhesion of biocompatible coating materials must be resolved to ensure that each batch of electrodes exhibits consistent impedance stability and anti-immune rejection performance when implanted. The establishment of an automated packaging and testing production line is essential, utilising precision machine vision systems to perform micron-level defect detection on hundreds to thousands of electrode contacts. Once mass production is achieved, unit manufacturing costs plummet, and the product transforms from a bespoke scientific instrument into a standardised, consumer-grade medical electronic device, thereby establishing the physical pathway for a closed-loop business model.

3.3 Blueprint for Building a Regulatory Framework for Neural Privacy Compliance

The successful implementation of a business model requires a robust regulatory framework to serve as a foundation of trust. Neural data encompasses information on fundamental human cognitive preferences, emotional states and subconscious activity, making it more sensitive than traditional biometric data. The blueprint for constructing a compliance and regulatory framework must establish a foundational data isolation barrier based on federated learning and differential privacy technologies. During model training, this ensures that raw EEG signals remain within local devices, with only encrypted gradient parameters being exchanged, thereby fundamentally severing the physical chain of data leakage. The regulatory framework must establish standards for the classification, categorisation and ownership of neural data, defining the boundaries of data ownership, usage rights and revenue rights. It must also establish a traceable blockchain evidence network to record every instance of data access authorised by smart contracts. The blueprint must further incorporate a dynamic review committee with medical ethics constraints to ensure that the process of commercialising technological R&D does not violate the principle of human autonomy, thereby shaping a sustainable ecosystem of commercial trust.

4 Pathways for Optimising Industrialisation to Enhance Quality and Efficiency

4.1 Strategic Approach to Achieving Self-Reliance in Core Technologies

This involves the industrialisation process of core underlying technologies operating entirely under independent control. The strategic approach should focus on the R&D and tape-out of dedicated core acquisition chips for brain-computer interfaces, thereby overcoming the performance compromises caused by generic bioelectric amplification chips. Chip design must delve into the physical fundamentals, refining the structure of low-noise amplifiers to significantly improve the common-mode rejection ratio, thereby enabling the capture of extremely faint microvolt-level brain electrical activity even in complex electromagnetic interference environments [5]. The development of an autonomous operating system is of the utmost urgency; it is essential to create a low-level operating system specifically designed for neural interaction scenarios, unifying hardware abstraction layer interface standards and breaking down the silos between different manufacturers' device ecosystems. The strategic approach involves training large language models using high-quality neural data from a large local population, thereby creating multimodal neural decoding models with independent intellectual property rights. Strengthening the technological foundation will impart significant resilience to the industrial chain, preventing critical upstream nodes from being affected by the risk of external supply chain disruptions.

4.2 Mechanisms for Cultivating a Tiered Workforce of Interdisciplinary Professionals

The sustained driving force behind quality improvement and efficiency gains lies in the continuous supply of high-calibre interdisciplinary talent. Professionals with a single-discipline background struggle to meet the industry's demands for a combination of neuroscientific knowledge, integrated circuit design skills, and the application of artificial intelligence algorithms. Cultivation mechanisms must break down traditional departmental barriers by establishing interdisciplinary brain-computer interface experimental classes within the higher education system and reshaping the curriculum framework. Theoretical instruction must integrate the fundamentals of neurobiology with large-scale matrix computing architectures, whilst practical training must directly align with frontline engineering demands in the industry, leading to the establishment of enterprise-level joint innovation laboratories for brain-computer interfaces [6]. A tiered training mechanism is required to cover all stages: breakthroughs in underlying hardware R&D, optimisation of mid-level algorithm models, and the definition of top-level commercial products. A dual-mentor system, involving leading academics and senior industry experts, should be established to facilitate the shift from research-oriented thinking to engineering-oriented product development. The depth of the talent pipeline determines the speed at which the

industrial technology innovation cycle can be shortened.

4.3 Designing a Long-Term, Self-Sustaining Investment Cycle in the Capital Markets

The brain-computer interface industry is characterised by long cycles, high investment requirements and high barriers to entry; efficient capital market support serves as a powerful engine for the industrialisation process. A long-term empowerment mechanism must establish a patient capital investment cycle that aligns with the development patterns of hard technology. Early-stage venture capital should establish a phased funding model focused on breakthroughs in technical metrics, ensuring that core technology R&D is not compromised in the pursuit of short-term commercialisation. The design of the investment cycle must encompass the entire process, from seed-stage proof of concept, through growth-stage engineering iterations, to commercial deployment in the maturity phase. Government-led cross-sectoral industrial funds should be established to leverage their impact and attract private capital. Regarding exit strategies, in addition to opening up channels for public offerings on secondary markets, diversified pathways such as industrial mergers and acquisitions and the securitisation of intellectual property must be created. A well-structured investment cycle ensures that technical teams receive stable and ample financial support whilst tackling highly challenging core technical hurdles, thereby fostering a virtuous cycle of industry-finance integration.

5 Conclusion

The emergence of AI-driven brain-computer interfaces has completely broken down the physical boundaries of human-machine interaction, giving rise to new business models. Improvements in underlying computing power mechanisms and the maturation of microelectrode mass production processes have accelerated the commercialisation of this technology ecosystem. The industrialisation drive, aimed at enhancing quality and efficiency across the entire value chain, must rely on the establishment of a core technology independent innovation system, the formation of a multi-disciplinary engineering talent pipeline, and the long-term support of patient capital networks. The establishment of a regulatory framework that complies with neuroprivacy and security requirements is the cornerstone for ensuring the healthy development of the industry. Looking back at the history of technological evolution, business models will continue to advance along the path of widespread adoption at the end-user level and the deepening of data value, ultimately forming a new industrial ecosystem characterised by high adaptability and global interconnected co-creation.

Funding

2025 China Disabled Persons' Federation Research Proje c(NO: 2025CDPFBF-07)2025 Project of the China Disabled Persons' Federation - 2025CDPFBF-07

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