ITC
International Training Centre

ACTION RESEARCH ON THE IMPACT OF NEUROTECHNOLOGY ON LIFELONG LEARNING

AND HOW TO HARNESS IT FOR SOCIAL JUSTICE

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Acknowledgements

The present report was authored by Murielle Popa-Fabre, PhD, under the overall direction and supervision of ITCILO staff.

The diagnostic report is structured into four main parts. In Part I, the field of neurotechnology is positioned within a taxonomy of foundational technologies. In Part II, the major neurotechnological strands are demarcated and selected strands are prioritized for further analysis. In Part III, the impact of the prioritized neurotechnology strands for the future of learning is further assessed with the help of a purpose-built evaluation grid. Part IV presents the findings and conclusions and provides a set of recommendations for capacity development initiatives that empower ILO constituents and other ILO development partners to harness neurotechnology for positive change along just digital transformation pathways.

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EXECUTIVE SUMMARY

Actions for Neurotech & Learning services: Strategic Insights & Future Directions

Enhance lifelong learning and learning with disabilities

The convergence of neurotechnology and education presents transformative opportunities for lifelong learning. While the primary catalyst for neural technology development is currently neurological disorder treatment, a significant secondary pathway is emerging focused on cognitive performance enhancement with some direct applications to learning environments, and for learners with disabilities that deserve careful adaptation. It is fundamental to experimentally establish critical foundations for responsible integration of neurotechnology in educational contexts, and to benefit learners with disabilities.

Adapting Neuro wearables market-ready products to educational settings This action research puts forward that non-invasive Neuro wearable products offering Neurofeedback through neuro-analytics technologies offer viable means to leverage brain data for positive change in e-education by 2030, without the ethical and safety concerns associated with invasive alternatives. Recent experimental results and Neuro wearable market-ready products are increasingly showing that neural signals and brain patterns can be effectively mapped and decoded, providing insights into cognitive processes by monitoring a given set of neuro-analytics during learning activities, such as concentration or workload, etc. The findings presented in this action research support questioning the psychological impact of integrating neuro-analytics into learning environments with appropriate safeguards, transparent data practices and teachers' empowerment.

Pilot classroom neuro-analytics, experiment individual and group educational neuro-markers

Testing if the introduction of consumer-grade neuro-analytic devices into classroom settings can show promises when implemented with a human-centered approach is the main priority. The development of a comprehensive neurotechnology strategy addressing the intersection of human rights, social justice, and educational applications provides an essential ethical framework for experimentation at ITCILO level. The distinction between individual and group-level neuro-markers has proven particularly valuable, enabling both personalized learning interventions and broader pedagogical innovations based on collective cognitive patterns at the level of a class. As innovative capacity building will lie at the nexus between neuroscience, engineering, and educators it is essential to adopt an empirical path and partner with academia and neurotechnology companies to build projects that address social justice since their inception. Two possible sandbox experiment can involve addressing the impact and effectiveness in real conditions of neurotech toolboxes helping to cope with ADHD, and group-level class dynamics in distance learning in a partnership with academia.

Sandbox experiments Controlled sandbox experiments described in this action research will be able to validate at individual-level, group-level and, ecosystem level key variables within defined ethical boundaries, yielding actionable insights for educational practitioners through academia and private sector partnerships. These pilots and experiments should follow a cautious, incremental approach that prioritizes learner wellbeing while systematically evaluating neurotechnology's educational potential by addressing (1) educational validity of marketed neuro-analytics recoded by Neuro wearables, (2) psychological impact of monitoring neuro-analytics for Neuro-feedback and (3) the effectiveness of group level neuro-markers for pedagogical shifts in e-learning.

A neurotech manifesto: learners' autonomy and capacity building in the teacher space

As this research extends beyond immediate educational applications to broader implications for work and society, communication and, advocacy efforts should highlight the nexus between neurotechnology and social justice, acknowledging that these technologies can reshape workforce development and economic participation. As neurotechnology continues to evolve, maintaining the holistic perspective of preserving learner autonomy and dignity **and empowering the teacher space** will be essential for developing policies and practices that harness its potential while mitigating risks, ensuring that human connection remains at the heart of learning. A manifesto would serve as a guiding document for ensuring that neurotechnology deployment respects fundamental rights while advancing educational objectives.

In summary, neurotechnology offers significant potential to enhance lifelong learning experiences, provided its implementation follows rigorous piloting and ethical guidelines that prioritize human-centered approaches. The future direction of this field will require continued collaboration between neuroscientists, educators, ethicists, and policymakers to create sustainable models that advance educational outcomes while preserving human dignity, autonomy for learners and teachers and human connection at the heart of human learning.

Foreword – Neurotechnology, social justice and learning

In an era defined by unprecedented technological acceleration, education and learning are at a critical inflection point. The pace of innovation presents both profound challenges and extraordinary opportunities for advancing social justice through decent work—the core mission that guides the efforts at the International Training Centre of the International Labour Organization (ITCILO).

A systemic perspective. This action research paper emerges from the commitment to be not merely reactive, but proactive and ahead of the curve by approaching technology with a systemic perspective that examines technologies not in isolation, but as products directly landing in society with their complex interconnections and societal implications, to be at the forefront of a realistic positive change.

Objective. If the nexus between technology and social justice needs to be explored in order to be at the forefront of harnessing technology for positive change, the pursuit of social justice through decent work and innovative capacity development solutions deserves careful scrutiny and realism about the ethical challenges of these technologies for autonomy and privacy. This white paper sheds light on this intersection by investigating what neuro-technologies are, how they are bound to be affecting the future of learning and capacity development in a responsible framework. As a commitment to understanding the full spectrum of technological change, we pay particular attention to human rights impact assessments, ensuring that technological advancement serves human dignity rather than diminishing it, in such a distinctive human activity like learning.

Approach. By examining neural technologies that have often been overshadowed by the hype surrounding artificial intelligence, this diagnostic report takes a techno-realist approach by limiting exploration to 2030. It seeks to understand what is genuinely happening now in the neurotech product space and how these developments can reshape the future of learning and capacity development to harness them and experiment for meaningful transformation.

INTRODUCTION

Adult learning is undergoing rapid transformation driven by intersecting social, technological, environmental, economic, and political forces. Demographic shifts are for example increasing demand for a tailored lifelong learning offer, while advancements in neurotechnology research have the potential of revolutionizing workplaces and expanding opportunities for learners with disabilities—yet simultaneously raising critical questions about learner privacy rights and autonomy.

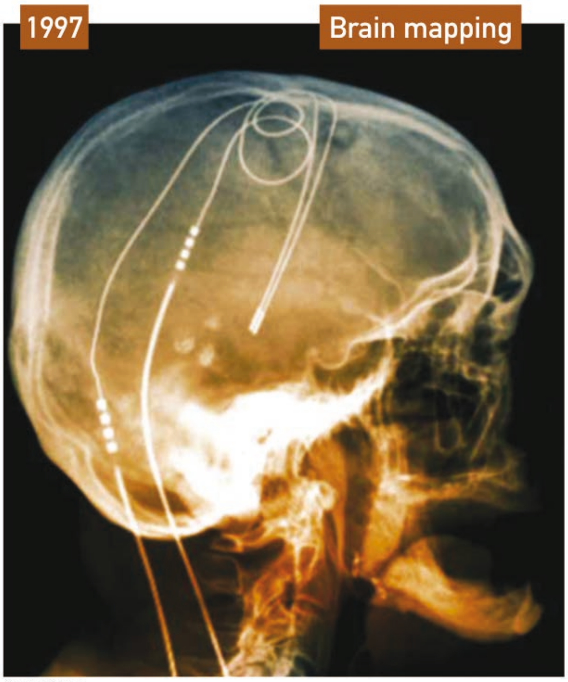
In Part I, the field of neurotechnology is positioned within a taxonomy of foundational technologies, as the compounded impact of technological breakthroughs in artificial intelligence (AI) with neurotechnology can dramatically enhance learning capabilities for knowledge workers, while potentially widening inequalities between education systems across the digital divide. Harnessing these technologies for societal benefit requires new skills, careful ethical consideration, and calls for changes in regulatory landscapes, all of these must be deeply rooted in the awareness and knowledge presented in Part II and III, as prerequisite to make informed policy choices.

This action research aims to foster informed debate and prepare the ground for 'thinking slow' about foundational technologies, viewing technology not as an end itself but to advance human flourishing and social justice. After thoughtfully examining foundational technologies, Part IV prepares to act decisively when technological breakthroughs emerge, identifying potential innovation pilots that test neurotechnology applications in adult learning while supporting just digital transitions through system-level capacity building.

A. Why neurotechnology now?

The year 2023 has witnessed significant breakthroughs in brain decoding of human movements and speech followed by spectacular neurotechnological answers to paralysis and aphasia to proactively question and investigate how neuro-technologies can potentially disrupt on the way adults learn. The preconized approach of this analysis is to remain cognizant that these technologies hold a comparatively higher risk for increasing inequality and to deepen the digital divide between knowledge workers, while on the other hand they could potentially boost inclusion of learners with disabilities and strengthen fundamental educational goals like memory retention or enhance learning. Hence, this action research is focused on the *social* impact of technologies along digital transformation pathways. Analyzing the potential scope of Neuro-technologies' social impact in both positive and negative ways is at the core of this approach.

Figure 1.
X-ray image of the first patient that had a brain stimulation implant in order to alleviate tremors in Parkinson's disease.



Coloured X-ray of
the head of a patient showing the electrodes (light lines) of a deep brain stimulator (DBS) implanted in the brain to treat the symptoms of Parkinson's disease. © Zephyr / Science Photo Library.

B. What is neurotechnology?

An old technology developing its fundamentals in the 18th century

Neurotechnology is a discipline that has a long history as Romans where already using electrical stimulation to cure headaches and some timelines trace it back to ancient Egypt where electric catfish was used to treat arthritis. If Luigi Galvani was the first to show that muscles and brain cells possess electrical force responsible for contraction and conduction in the early 1780s, it is only a hundred years after that electrical impulses are observed at the brain surface of living animals by R. Caton. Early 20th century experimentations will start recording electro-encephalography in animals and humans, to then begin implanting electrodes in the 50s and install the first non-rejected cochlear implant in 1969. The 70s and 80s see the surge of Electro-encephalography (EEG) signal use for controlling external devices and the term Brain Computer Interface (BCI) is coined. In the 90s the first US Federal Drug Administration (FDA) approval of a brain implant to control the tremor symptoms of Parkinson's disease is opening new venues for deep brain stimulator (DBS) to treat dystonia and epilepsy (see Figure 1). 2000s were finally marked by the first tetraplegic patient controlling an artificial hand using a BCI and the Brain Gate project confirmed the control of robot prosthetic limbs in 2013, and the first retinal implant was approved. Later years of 2010 were the stage of an increasing private investment in neurotechnology, thus shifting the paradigm from academic research to translational research, thanks to the miniaturization of implants that can record high-fidelity signals from millions of neurons. These developments bring us to today's state of the art where in parallel to breakthroughs in implant-based neuro-decoding (EcoG), neurotech products like Neuro wearables arrive on the market. Non-invasive brain recording technologies are nowadays being embedded in consumer goods for real-time monitoring of sleep, focus or stress.

Definition and Main Strands

The term "neurotechnology" encompasses nowadays an array of devices and systems that interact with the central nervous system through electrical, magnetic, optogenetic and other means, but it importantly also leverages non-neural data to infer mental states (see Part II Section B 3). Some brain interfaces primarily serve to understand the brain's functioning, while others may consist of methods aimed at directly intervening in mental processes with the purpose of restoring lost functions and enhancing cognitive capabilities[1] or marginally modulating cognitive states. An overview of both invasive and non-invasive recording, stimulating or perception technologies is given in Figure 2.

Neurotechnology is a fast growing and multidisciplinary field encompassing a wide range of techniques and applications that can be listed and grouped into the following major strands, going from more fundamental research to more applied sectors:

1. **Neuroimaging and brain mapping** are the two foundational enablers of the latest advancements in Neurotechnology. Advanced visualization techniques of brain activity and structure are instrumental for a detailed understanding of (1) how **cognitive functions** map onto the brain and what are their **neural signatures** thenceforth **Neuro-markers**, (2) to diagnose neurological disorders, and (3) for locating surgical intervention. Examples for high imaging precision are functional Magnetic Resonance Imaging, Electroencephalography, Magnetoencephalography, Positron Emission Tomography, and Diffusion Tensor Imaging, functional Near-Infrared Spectroscopy (fNIRS) (see Recoding Technologies on Figure 2).

[1] UN Human Rights Council 2024: Impact, opportunities and challenges of neurotechnology with regard to the promotion and protection of all human rights, A/HRC/57/61, p.2.

Importantly, neuroimaging and brain mapping technologies are laying the ground for the whole spectrum of neurotechnology applications from neuroscience fundamental research to clinical diagnostics, and monitoring brain activity in healthy adults and patients with neurological diseases like Alzheimer's, epilepsy, and stroke.

2. **Neural data analysis and computational neuroscience** to model, simulate, and analyze neural data using computational techniques to better understand brain function and develop predictive models. Examples for neural data analysis and computational neuroscience technologies are machine learning algorithms, neural network modeling, and AI applied to neural data processing. Neural data analysis and computational neuroscience research are essential to **decode brain activity in real-time**, **monitor brain functions and neural signatures through neuro-analytics**, identify and track neuro-markers among the brainwaves patterns collected across large populations, and ultimately develop AI systems that can mimic the human brain.

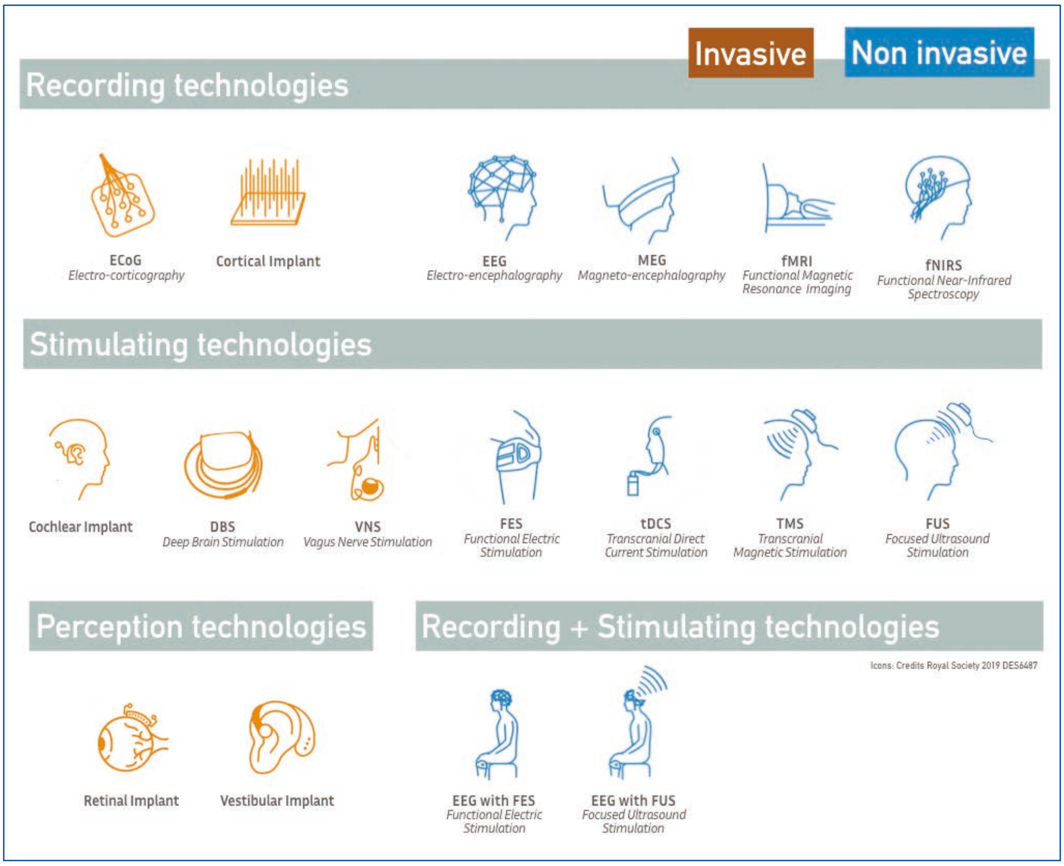
3. **Brain-computer interfaces (BCI)** to establish a direct communication pathway between the brain and an external device, allowing for control of machines or computers or to give Neurofeedback based on neural signals tracking in real-time (henceforth Neuro-analytics). **Examples for BCI are electro-encephalography (EEG) Neuro wearables**, invasive BCIs using intracortical implants, and non-invasive techniques like near-infrared spectroscopy (NIRS). BCI are applied to assist people with disabilities to control prosthetic limbs, communicate, interact with computers or to provide non-invasive brain interfacing **like monitoring cognitive states**. Applications in gaming or virtual reality are starting to arrive on the market, but this strand spans an increasing variety of potential industries and applications – going from gaming to interactive television, everyday computer interactions, hands-free control system, assistive neurotech, smart adaptive environments, art, accessibility design, market research, psychology, learning, medicine, robotics, automotive, transport safety, defense, and security.

4. **Neurostimulation and neuromodulation** to modulate neural activity, either to restore function or enhance cognitive and sensory abilities. Examples for neurostimulation and neuromodulation technologies are deep brain stimulations, Transcranial Magnetic Stimulation, Transcranial Direct Current Stimulation, and going beyond electrical stimulation with Optogenetics and Focused Ultrasound stimulation. A new landscape of non-invasive brain stimulation is emerging where companies are developing approaches to treat illness without surgery, ranging from ablation, to opening the blood-brain barrier, to performing neuromodulation with Focused Ultrasounds. Neurostimulation and neuromodulation technologies are applied to treat neurological and psychiatric disorders (e.g., Parkinson's disease, depression, chronic pain, long lasting addiction), enhancing cognition, or potentially influencing learning and memory, or just influencing moods through music selection or color noise listening. In Neuro wearable devices, providing non-invasive brain interfacing, will see earlier and perhaps wider adoption, their inability to penetrate deeper into the brain will mean they can only access surface-level neural signals, limiting their depth of insight and neuromodulation capabilities.

5. **Neural prosthetics** help restore lost sensory or motor functions by interfacing prosthetic devices directly within the nervous system with perception and stimulating technologies (see Figure 2). The first examples for neural prosthetics technologies were cochlear implants, retinal implants, followed by brain-controlled prosthetic limbs. Late developments of neural prosthetics include brain-controlled limb prosthetics through brain implants or in non-invasive methods (see Part I A 4).

6. **Neuropharmacology and neuromodulators** are nowadays used to influence brain function and neural circuits through drugs and chemical compounds, or with the help of Focused Ultrasound opening the blood-brain barrier to allow focal action of drugs in brain tissues. Examples for neuropharmacology and neuromodulators technologies are the development of drugs targeting neurotransmitter systems, gene therapy for neurological disorders, and precision medicine in neurology. Neuropharmacology and neuromodulators are applied to treat psychiatric disorders (e.g., schizophrenia, anxiety, depression, long lasting addiction), neurodegenerative diseases (e.g., Alzheimer's, Parkinson's), and gradually for cognitive enhancement.

Figure 2.
Neurotechnology can be divided into invasive and non-invasive, and within this main division we have recording technology, stimulating technology, perception technologies. Whether one records at the level of the scalp (non-invasive) or inside the brain, brain mapping and most crucially the decoding of brain patterns are two essential foundational steps in order to know where to target intervention or how to interpret the brain waves signal that is recorded.



PART I.
HORIZON SCANNING OF EMERGING AND ENABLING INNOVATIONS FOR THE FIELD OF NEUROTECHNOLOGY

A. The compounding impact of technologies in Neurotech

The four major enablers driving current developments in neurotechnology

The following section is dedicated to the analysis of the main enablers of the latest developments and growth in neurotechnology industry. The importance of observing the compounding effects of several technologies is here addressed and notably the importance of AI and Machine Learning is propelling progress in the different technologies embedded in neurotech products.

I. Research enablers
A mature and operable research on the mapping of cognitive functions and their neural signatures – **neuro-markers.**

II. Economic and market enablers
The current market dynamics and configuration enabling the development of the neuro-technology industry to answer the therapeutics needs of an increasing global health burden linked to neurological disorder.

III. Technological and AI-driven enablers
AI development and capillarity in science and technology is showing to what extent machine learning can solve fast and real-time decoding of brain patterns, through advanced methods of neuro-data analysis enabling the monitoring of brain activity in **real-time neuro-analytics.**

IV. Experimental and recoding hardware enablers
Recent neuro-decoding achievements through **brain implants or Neuro wearables** show the potential to operationalize neuro-markers identified through research in the brain imaging of cognitive functions to power neuro-prosthetics.

I. A research layer understanding the brain to interface with it: Mature research on the Brain Mapping of Cognitive Functions and their neural signatures

As a scene-setting preliminary consideration, it is essential to set the fact that interfacing with the brain requires a detailed functional understanding of the brain. The human brain is a very complex and efficient system. Some simple numbers can give an initial description of this system encompassing an estimated amount of 85 billion neurons, each one having the possibility to have around 10,000 connections and only consuming an average of 20 Watts. Therefore, one of the most fundamental research strands of Neurotechnology is to lay the ground of a fine-grained cognitive and functional mapping, and understanding of the human brain in order to be able to interface with it. This role has been played in the last 25 years by neuroimaging techniques (see invasive and non-invasive recording techniques on Figure 2). Hence, a technology collecting, interpreting, inferring, learning, and modifying signals from the brain or from the nervous system at large need a preliminary understanding of this system.

The last 20 year of academic research in the field of cognitive neuroscience and neuroimaging have been laying the ground for a more fine-grained mapping of cognitive functions, which is today the first and main enabler of neurotechnology solutions and industry. Its latest developments in decoding neural signals for higher cognitive functions like language[2], have proven to be very successful in the field of neuroprosthetics of waking and speech reconstruction (see Section B IV).

II. An economic and market layer investing in Neurotech development: possible educational developments of the Neurotech industry

Neurotechnology industry growth across several global markets

Has the fundamental research has reached the point of being translated into an answer to neurological disorders and everyday brain monitoring devices? The market dynamics of the ever-growing field of Neurotechnology have been lately under scrutiny because of an increasing annual growth of + 11% to 14% according to the different forecasts and estimations available since 2010 (Neuro Analytics 2022). While Neurotechnology can qualify today as a major industry (see composition in Figure 3), recent estimates suggest that the neurotech devices market may grow at a compounded annual growth rate of 14.4%, going from $11.3 billion in 2021[3] and will reach $17.1 billion in 2026[4] (Figure 4).

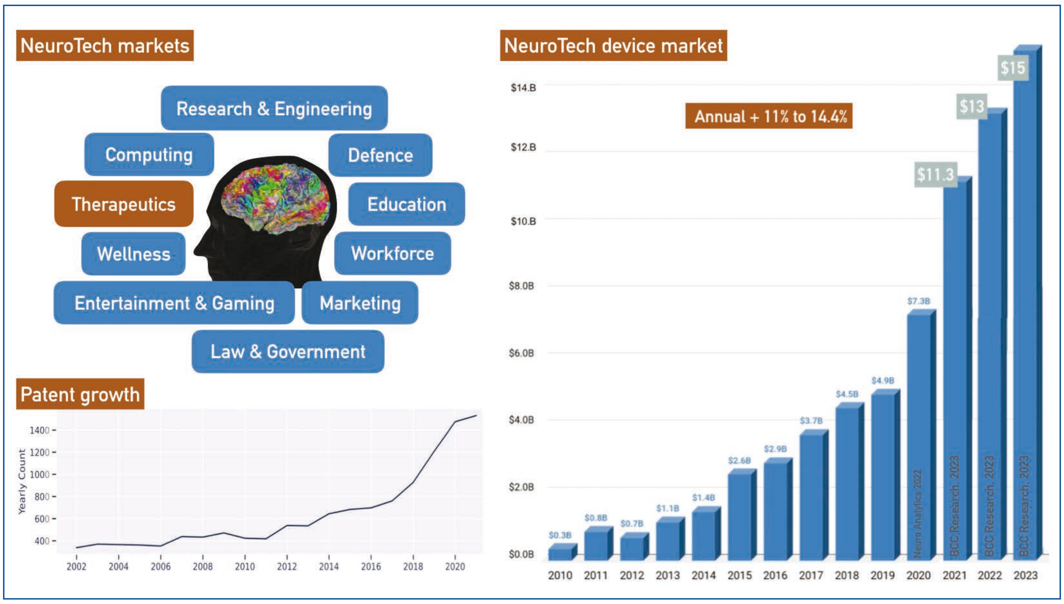
[2] Kemmerer, D. (2022). Cognitive Neuroscience of Language (2nd ed.). Routledge. https://doi.org/10.4324/9781138318427.

[3] Neurotech Devices: Global Market Outlook BCC Research, 2023 https://www.bccresearch.com/market-research/information-technology/neurotech-devices-market.html?srsltid=AfmBOopNl4hQRVpRjxJR4dOyL0ZAdnSVDN3VQkrX6ZFZ7CMZI1BAwDR0.

[4] Neurotech Reports. The Market for Neurotechnology: 2022-2026. https://www.neurotechreports.com/pages/execsum.html.

Figure 3.
The current dimensions and market stands of the neurotechnology industry.

Figure 4.
Investment tracking from 2010 to 2023. Patent growth in the last 20 years, source European Patent Office's Worldwide Patent Statistical Database (PATSTAT) (2000-2020) *analyzed by UNESCO 2023*.



As shown in Figure 3 (top left), neurotech devices are the result of a complex technological assembly that already have some cases of successful products in different sectors of application and markets. However, Consumer neurotech is a market that is hard to define, the best strategy is to look at different proxies like Neurofeedback Market that was evaluated at $1.4 billion in 2023 and is expected to double in 2030. A second important emerging category intersecting the biometric-driven hardware and the traditional neurofeedback market is that of **smart headphones**, with $12 billion market in 2023 expected to grow at a 17% Compound Annual Growth Rate through 2030.

Importantly, private investment in neurotech companies has also been increasing significantly over the last ten years (2010-2020), the amount invested in neurotech companies increased 22 times, from $331 million to $7.3 billion, with total investment reaching $33.2 billion in 2020[5]. If the therapeutics market is currently leading in the neurotech space, the Consumer Neurotech is nonetheless expanding to the Mental Wellness Market, where several businesses target self-improvement and meditation segments, that was valued at $48 billion in 2023 and is projected to grow at an 8% Compound Annual Growth Rate through 2030.

[5] NeuroTech Analytics, 2021, NeuroTech Investment Digest, 2021 Q4. https://analytics.dkv.global/neurotech-investment-digest-q4-2021.pdf.

While the strongest growth projections point to the neurotech devices market, one should add government investment in national brain-research initiatives like the European Human Brain Project (HBP, 2013 to 2023) and the American NIH BRAIN Initiative and China Brain Project. Rough estimates based on data for a subset of countries (Canada, Japan, Korea, Australia, EU, USA, and China) suggest that such investment has totaled $6 billion since 2013[6].

Therapeutics are leading the whole innovation spectrum of neurotechnology

Neurotechnology development and deployment is currently driven by the need to answer to global health care burden and cost of neuro-degenerative and mental health disorder.

In numbers, 43,1% of the global population will of neurological disorder during their lifetime (stoke, epilepsy dementia). It means that statistically, half of the people in one room may end up with a neurological disease and the diagnoses arrives years after the beginning of the disease, but one should also consider PTSD and burnout in this spectrum.

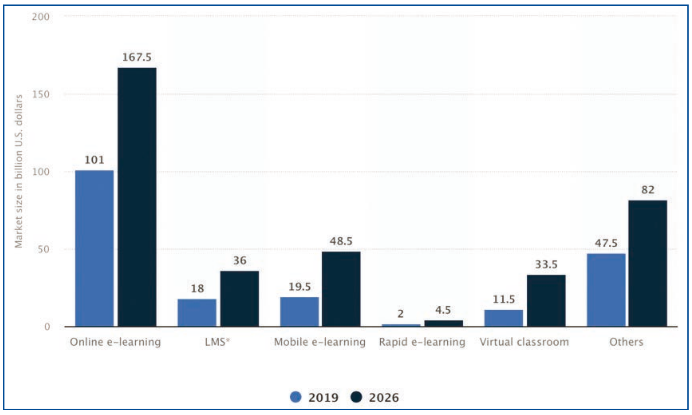
Health priorities are stunning because neurological disorders are identified as the first cause of disability worldwide and second cause of mortality. Most neurological disorders do not have cure and most patients do not have access to basic screening tools for diagnosis. As one can observe on the patent growth in the last 20 years. On Figure 3 one can observe that in 2018 something happened with the number of patents that were globally registered (bottom left).

In summary, the steadily augmenting investment is a response to the following challenges:

1. One in three persons will develop neurological disorders at some point in their life.
2. Neurological disorder is the leading cause of disability (Position paper on optimizing brain health across life, WHO 2022).
3. The Scientific American was titling the $10 trillion disease for Alzheimer and dementia, showing the burden of neurological disorder on the global health ecosystem.

Figure 5.

Size of the global e-learning market in 2019 and 2026, by segment (in billion U.S. dollars). *Source: Statista 2024*.



6 Daniel S. Hain, Roman Jurowetzki, Mariagrazia Squicciarini, Lihui Xu. 'Unveiling the Neurotechnology Landscape: Scientific Advancements Innovations and Major Trends', UNESCO, 2023. https://doi.org/10.54678/OCBM4164.

The current market drive in neurotechnology is to address fundamental therapeutic responses to the neurological disorders that are heavily increasing the health burden across the world. If one focuses on the European expenditure of global health care, neurological disorders count for around $10 billion, which is comparably the same size in Europe of heart disease, diabetes, and cancer all together. Answering to the global neurological expenditure, will we instrumental in democratizing neurotechnology and make it available to other sectors.

Spill over from the medical and wellness domain to consumer market: E-learning market size

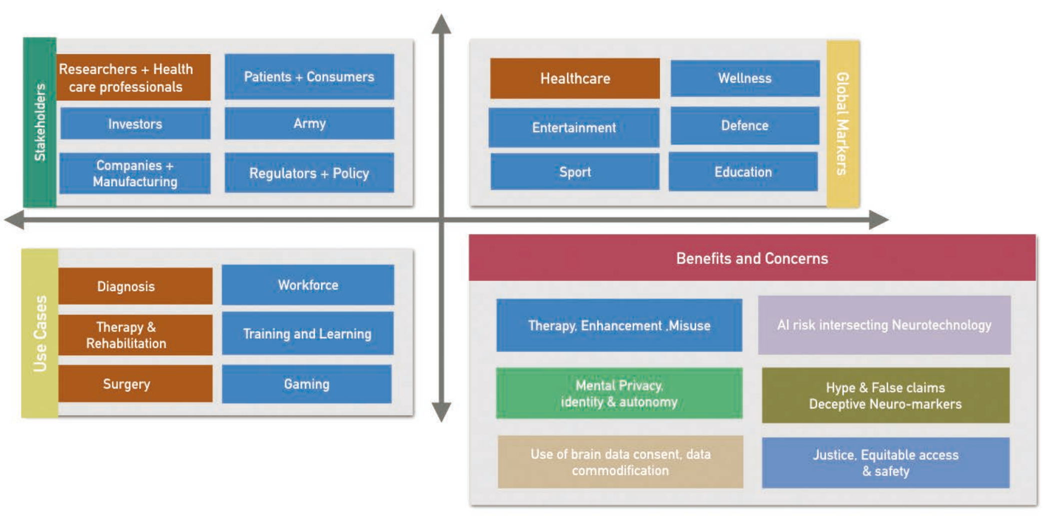
Despite the unknowns and light scientific grounding of neurofeedback and its therapeutical effects, some neuro-technologies – such as wearable headsets or headbands – are spilling over from the medical domain into the consumer market with applications that are labelled as electronic – not medical – claiming to improve different mental states like concentration in learning and wellness settings like mediation and yoga.

Although therapeutics is currently leading the innovation spectrum, it is interesting for the needs of the current action research to observe in parallel the projections of extension in the size of the global e-learning market to have a hint on how the market of e-learning could compound with the development of learning-oriented applications of neuro-technologies and particularly of wearables (see predictions in Figure 5). Such an increasing market growth is thus showing that there is a space, not only in investment, but for making neurotechnology have ripe outcomes and benefits in the educational and workspace ecosystem and market.

A mapping of neurotechnology's benefits and concerns across stakeholders, markets, and use-cases

While discussing the benefits it is also important to note that the healthcare sector driving the neurotechnology development is also the sector that is less involved in the risks mapped in Figure 6. The following table is mapping some of the benefits and concerns of the field of neurotechnology. The concerns are namely linked to use-cases that are mainly out of the health spectrum and the healthcare market, as they involve mental privacy, identity, autonomy, the use of brain data and its consent, the licenses in order to train the algorithms that are decoding the brain. To these concerns on should also add the AI risks that are now globally defined at the policy level (ref. UNESCO Recommendation and UN resolutions in 2024), that are intersecting with neurotechnology solutions, and the perspective of social justice encourages to address the challenges of equitable access to these technologies.

Figure 6.
Neurotechnology mapping of stakeholders, global markets, use-cases together with benefits and concerns raised by neurotech use cases.



Each of these domains of applications of neurotechnology holds potential to transform not only healthcare but a large part of human interaction with a technology, therefore raising new opportunities and challenges for society. Its parallelly calls for the neuro-ethics and tailored neuro-technological policy action, together with legal and regulatory frameworks to address the precise ethical, legal, and societal implications of neurotechnology advancements[7]. Most importantly, issues around privacy[8], consent, identity, and cognitive enhancement[9] are new and emergent concerns that should be systematically assessed together with human rights impacts or deceptive neuro-markers, as described in the Figure 6.

III. A technological layer having AI as the main enabler for real-time brain patterns decoding

AI and Machine Learning (ML), not only enable real-time interpretation of complex neural signals, but serve as the fundamental drivers of innovation across neurotechnology's diverse domains, particularly within the commercial neurotech industry. This centrality of Machine Learning follows a compelling rationale: when integrating material science, neuro-data

[7] United Nations, 'Third Committee Experts Caution that Abuse of Technology Threatens Free Thought, Privacy Rights, as Delegates Call for Dismantling Unjust Laws', UN General Assembly, Third Committee, Seventy-sixth session, 19 October 2021, https://press.un.org/en/2021/gashc4326.doc.htm. See also: First draft of the Recommendation on the Ethics of Neurotechnology, SHS/BIO/AHEG-Neuro/2024/2, UNESCO, 2024.Rommelfanger, Karen, Amanda Pustilnik and Arleen Salles, 'Mind the Gap: Lessons learned from neurorights', Science & Diplomacy, 28 February 2022, www.sciencediplomacy.org/article/2022/mind-gap-lessons-learned-neurorights.

[8] See report for the UN Human Rights Council from Jan 16th 2025 A/HRC/58/58: Foundations and principles for the regulation of neurotechnologies and the processing of neurodata from the perspective of the right to privacy - Report of the Special Rapporteur on the right to privacy, Ana Brian Nougrères https://www.ohchr.org/en/documents/thematic-reports/ahrc5858-foundations-and-principles-regulation-neurotechnologies-and.

[9] Report of the Human Rights Council Advisory Committee by the UN General Assembly, 'Impact, opportunities and challenges of neurotechnology with regard to the promotion and protection of all human rights' (Aug 8th, 2024).

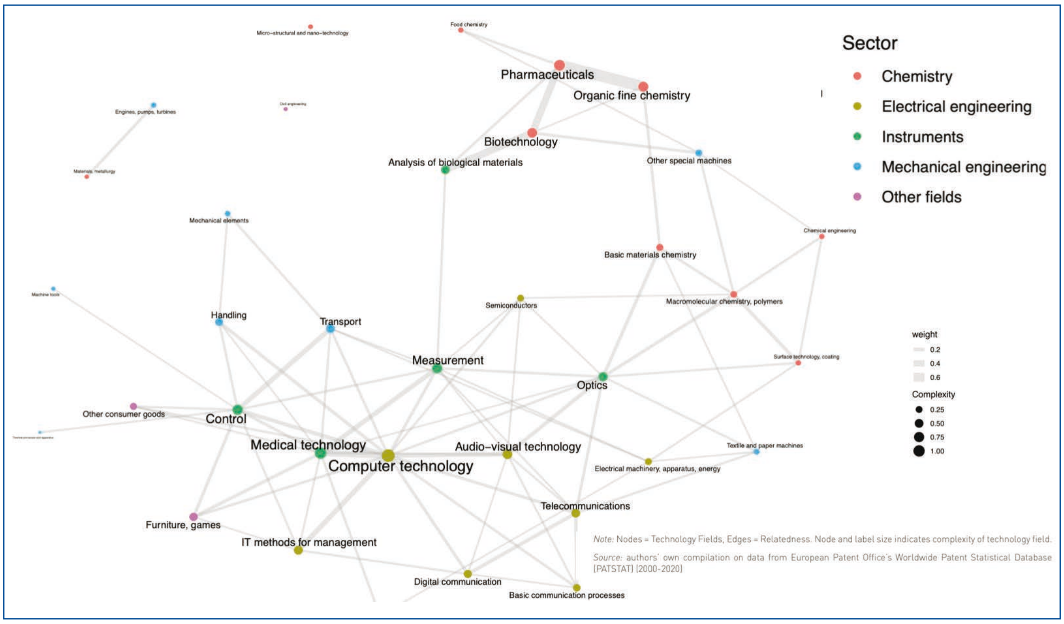
collection, transfer storage, connectivity, analytics, and real-time neural data processing, AI emerges as the essential orchestrator of the complexity and scale of neural data processing and the only way to achieve efficient data processing and automation. This computational layer transforms neurotechnology from isolated technical achievements into integrated systems capable of decoding and responding to the intricate patterns of brain activity that underlie human cognition and behavior.

Namely, as these technologies converge into cohesive products and applications, AI provides the only viable framework for achieving the necessary efficiency, automation, and interpretability required to translate raw neural signals into meaningful insights and actions. The two examples of deep brain stimulation breakthroughs in 2023 described in Section B IV show that AI and specifically Machine Learning is one of the main drivers of this innovation.

To further attest this enabling effect of AI progress over neurotechnology development, Figure 7 shows a graph representing keywords in the neurotech patents registered worldwide in the last 20 years. One of the main bulks of this across different patents is computer technology.

Figure 7.

Keywords in the neurotech patents in the last 20 years. *Source: UNESCO 2023.*[10]



[10] Daniel S. Hain, Roman Jurowetzki, Mariagrazia Squicciarini, Lihui Xu. 'Unveiling the Neurotechnology Landscape: Scientific Advancements Innovations and Major Trends', UNESCO, 2023. https://doi.org/10.54678/OCBM4164.

AI is enabling monitoring of neuro-analytics by identifying neuro-markers' brain patterns

Across both invasive and non-invasive neurotechnology paradigms, the critical challenge remains developing systems capable of real-time neural signal decoding, harnessing the sophisticated computational capabilities that Machine Learning brings to online signal processing. Whether capturing neural activity directly from within brain tissue or recording signals externally, this fundamental bottleneck must be overcome to unlock the full potential of neural interface technologies. (Figure 8).

Neuro-markers are mainly based on neuroimaging brain patters that have been associated by fundamental research in cognitive neuroscience to a given mental state as if different cognitive activities had distinct neural signature or fingerprints. For example, the prefrontal cortex is a key player in stress response regulation, and precise Electroencephalographic (EEG) responses, such as a decrease in frontal alpha waves and an increase in frontal beta power, have been proposed as a neural signature of stress as they reflect stress-related brain activity in prefrontal cortex. These types of neural signatures are called neuro-markers and can be recorded at the level of the scalp in non-invasive settings to help identify stress.

As shown on Figure 8, signal processing and Machine Learning allow extracting features from the raw signal recoded by electrodes. Neural data analysis allows pattern recognition and helps further separate the different bandwidths on Figure 8 that are respectively indicators and markers of the different ongoing cognitive processes. Focusing for example on cognitive load[11], a typical neuro-marker is the suppression of alpha waves (i.e., Alpha suppression). Namely, alpha activity typically becomes visibly suppressed 10 seconds after participants to an experiment open their eyes and engages in a mental arithmetic task. Additionally, Beta waves have been involved in various cognitive abilities, such as working memory, attention, and executive function[12], thus showing to be a more complex neuro-marker.[13]

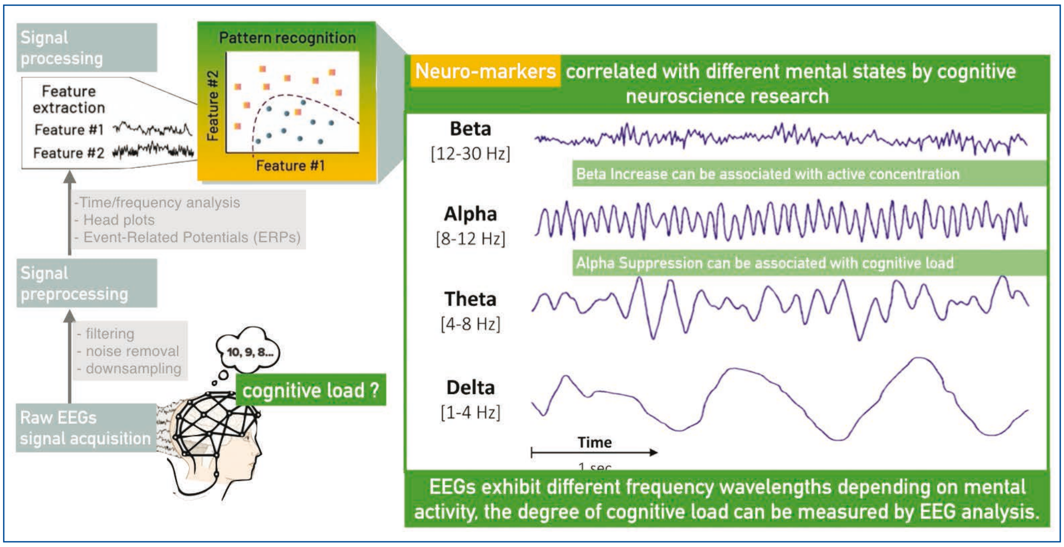
Signal processing of the brainwaves recorded by Neuro-wearables allows to assess mental state based on the relative power distribution in each of these bands Alpha, Beta, Theta, Gamma, Delta (Figure 8), and to monitor them and give the user Neurofeedback through specific Neuro-analytics.

[11] Antonenko, P., Paas, F., Grabner, R., & van Gog, T. (2010). Using electroencephalography (EEG) to measure cognitive load. Educational Psychology Review, 22, 425–438. A careful note on the difference between self-reported measures and neurophysiological measures in Brunken, R., Plass, J. L., & Leutner, D. (2003). Direct measurement of cognitive load in multimedia learning. Educational psychologist, 38(1), 53-61.

[12] For a review on Beta band :https://www.sciencedirect.com/topics/medicine-and-dentistry/beta-wave#:~:text=3.6.&text=Beta%20waves%20may%20be%20involved,power%20%5B37–44%5D.

[13] For a focused scientific article discussing how spatiotemporal patterns of beta bursting implement cognitive control operations underlying goal-directed behavior: https://www.sciencedirect.com/science/article/pii/S1364661324000779.

Figure 8.
Neuro-markers are the association between a given mental state (e.g., cognitive load) and a precise brain pattern decoded from brain recordings (e.g., Alpha suppression, and/or Beta increase). *From bottom left following the arrows:* signal processing and Machine Learning allow extracting features from the raw signal recoded by electrodes, pattern recognition helps further separate the different bandwidths (on the right) that are respectively involved in different cognitive processes. Generic correlations between the different frequency wavelengths with mental activity are as follows: *Beta band* - indicator of cortical transmission and associated with power increases during active concentration. *Delta band* - predominates during deep sleep; *Theta band* - involved in memory encoding and retrieval and associated with power increases during drowsiness; *Alpha band* - involved in motor functions (over the motor cortex) and cognitive functioning.



Given the brainwaves neuro decoding process described above, one can easily understand that to enable brainwaves' patterns monitoring and neuro-analytics in real-time to give Neuro-feedback in real life settings, an efficient decoding of these continuous signals and neuro-markers (micro volts) is needed. Efficient and reliable tracking of these neuro-markers in time is in turn essential to have trusted neuro-analytics that provide scientifically grounded feedback to individuals wearing a neuro-wearable in a learning context.

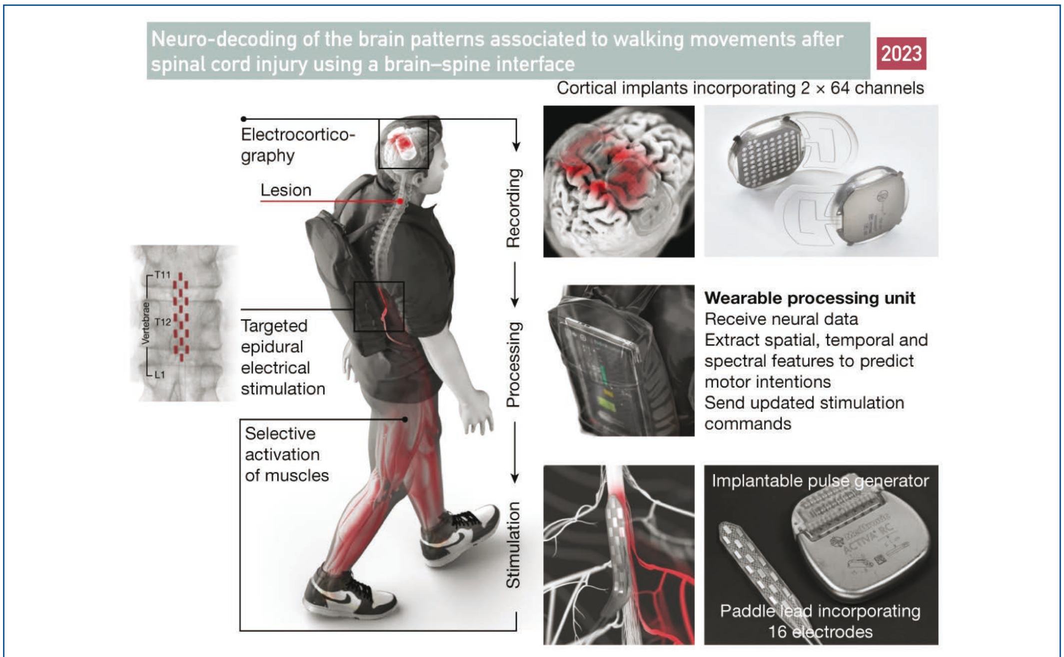
AI enabling to leverage more and diverse data from all types of wearables

As explained in a recent Nature Medicine Perspective paper on the transformative nature of Machine Learning in medicine research[14], wearables in the broad sense are increasingly making research protocols land in peoples' everyday life, thus allowing to leverage on the immerged part of a "data iceberg". An unprecedented amount of noisy and multidomain data can now be leveraged through the democratization of Deep Learning techniques. If this is making medicine more efficient by bringing real-world health data into Cohort studies, into cases studies traditionally performed in very controlled lab settings.

[14] Mahajan, A., Heydari, K. & Powell, D. Wearable AI to enhance patient safety and clinical decision-making. npj Digit. Med. 8, 176 (2025). https://doi.org/10.1038/s41746-025-01554-w.

While fostering the future of medicine and research, AI and wearables can also have a transformative impact on education, as education hardly happens in controlled settings like research labs. Specifically, adult education sometimes doesn't often happen in a classroom. Hence, what is being recorded with wearables is instrumental to transfer cutting-edge research to the society. The future of learning can parallelly benefit of such data-driven approach and from the insights that neuro-wearables can bring to capacity building in the domain of learning for example by bridging the distance gap present in e-learning and remote classrooms.

Figure 9.
Two cortical implants composed of 64 electrodes are positioned epidurally over the sensorimotor cortex to collect ECoG signals. A processing unit predicts motor intentions and translates these predictions into the modulation of epidural electrical stimulation programs targeting the dorsal root entry zones of the lumbosacral spinal cord. Stimulations (BSI) are delivered by an implantable pulse generator connected to a 16-electrode paddle lead. *Source: Lorach et al (2023)*.



IV. Experimental and recoding hardware enablers for Neuro-decoding leading to Neuro-prosthetics achievements

In order to bridge other three main strands of Neurotechnology, namely Neuroimaging and Brain Mapping, Neural Prosthetics and Neuromodulators, the focus will be given in the following to the advancements in Neuroimaging precision, the main enabler for more and more fine-grained interventions in Neuro-prosthetics and neuromodulation.

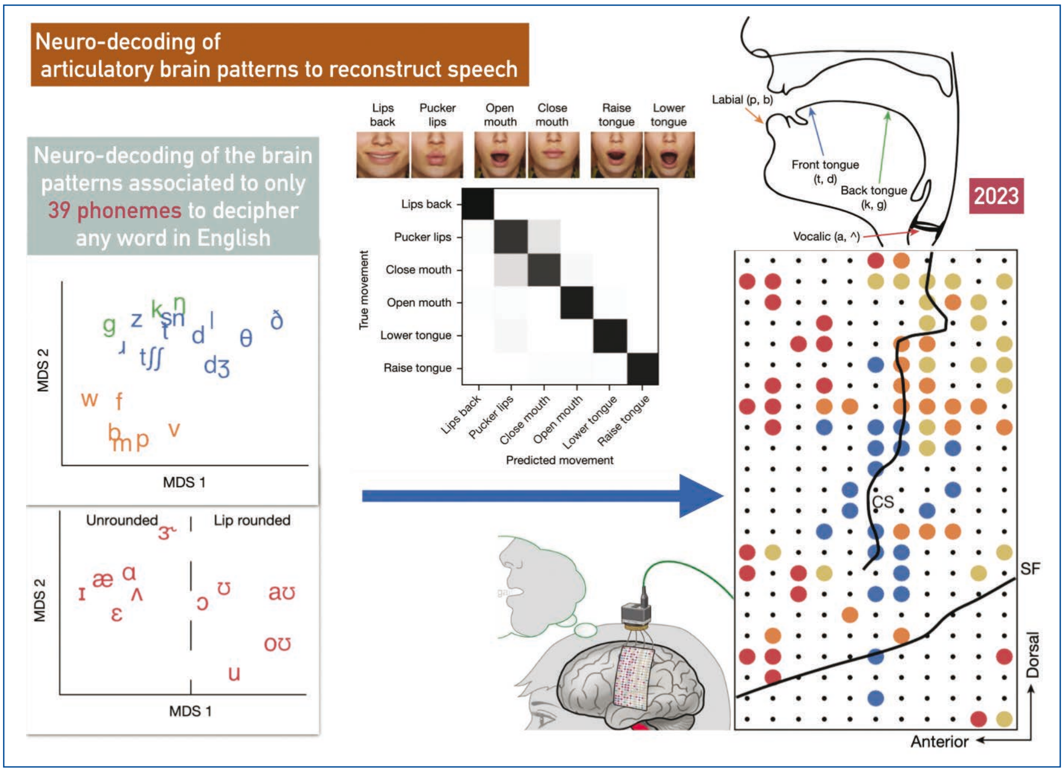
2023 was a prosperous year for Machine Learning and Generative AI applied to brain data decoding (henceforth neuro-decoding) as several scientific achievements further brought brain mapping and monitoring techniques to an unprecedented level of real-time efficiency by powering neuro-prosthetics.

Neuro-Decoding of movements: the neuro-prosthetics of walk

2023's breakthrough in Switzerland showed a young man with a spinal cord injury walk again thanks to a digital bridge transferring neural signals recorded by an implant in his motor cortex transferred to his. This experiment shows the fundamental contribution of Deep Learning in leveraging real-time data recorded from cortical implants on the left and on the right of the motor cortex[15]. These data are analyzed to decode different muscles, hips or knee movements involved in the complex movement coordination task that is walking. The system is tracking the probability of neural patterns to represent a left move or a right move of the legs and then transforming them into electrical impulse to activate the limbs accordingly. It is a continuous brain pattern decoding taking place in a wearable processing unit that is making this happen, while a digital bridge is transferring what is decoded to the part of the spine that is below the injury, in order to activate the muscles for walking through an implanted pulse generator. This achievement is showing to what extent AI is instrumental for the functional understanding of brain patters in real time, while more and more precise cortical recoding and muscle pulse stimulation is achieved through engineering and miniaturization of electrodes, or advancement in material science (see Taxonomy and compounding effects, Section B).

Figure 10.

Multimodal speech decoding in a participant with vocal-tract paralysis. Signal processing and Machine Learning allow extracting activation patterns from the raw signal recoded by the electrodes grid implanted on the cortical surface. Pattern recognition articulatory feature helps further separate the 39 phonemes to decipher English words and reconstruct speech intention of the patient. *Source: Metzger et al. (2023)*.



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15 Lorach, H., Galvez, A., Spagnolo, V. et al. Walking naturally after spinal cord injury using a brain–spine interface. Nature 618, 126–133 (2023). https://doi.org/10.1038/s41586-023-06094-5.

Neuro-Decoding of speech intention: the neuro-prosthetics of speech

2023 as a major year for the field of neuro-decoding offers a second example based on speech recognition and speech recovery, demonstrating once again to what extent AI is a multifaceted enabler for online brain decoding. If AI is fundamental to achieve a functional understanding of brain patters and to decode Neuro-markers and monitor them through neuro-analytics, in this experimental setting for speech decoding in a participant with vocal-tract paralysis, what is being decoded is not what people think or want to say, but what the aphasic patient is imagining pronouncing. The technological breakthrough of reconstructing speech is based on a three-layer algorithm that is decoding brain patterns through electrodes implanted in the brain of the patient on the part of the motor cortex responsible for the vocal tract (Figure 10, bottom-right).

As shown in Figure 10, different movement features of how to pronounce a given phoneme in English, like aperture of the mouth, the position of the tongue, the position of the back part of the tongue are being decoded and reconstructed to reproduce artificially the speech intention of the patient. It means that what the algorithm initially needs to decode is only the 39 patterns of activation in the electrode grid that are unique to each of the 39 phonemes of English, and then decipher them in real time across the activation patterns that are recorded inside the brain of the person that lost her ability to speak.

AI is present a second time in the decoding process to constrain calculations through an additional layer where a neural network is evaluating the probability of each phoneme in English words, one after the other, to reconstruct the likely words, thus calculating the next more likely phoneme, according to the rules of English[16].

Such a brain computer interfaces (BCI) is in conclusion a multi layered decoding machines that is (1) transforming the phonemes internally articulated by the patient, (2) considering the phone probabilities of English to reconstruct words from the signal in the brain, and (3) compounding this information with the sound speech feature and the sub-articulatory brain signal together[17]. The whole is orchestrated and brought together in real time to enable a new form of assisted communication of the patient with the external world.

Generative AI and Neuro-decoding

More recent research has replicated these results in a more complex setting by successfully decoding bilingual, Spanish and English speech intentions. Thus, showing Machine Learning role as a multifaceted enabler for online brain decoding, not forgetting that Computational

[16] Metzger, S.L., Littlejohn, K.T., Silva, A.B. et al. A high-performance neuroprosthesis for speech decoding and avatar control. Nature 620, 1037–1046 (2023). https://doi.org/10.1038/s41586-023-06443-4 . https://www.nature.com/articles/s41586-023-06377-x.

[17] See also a study on high-performance speech neuroprosthesis leveraging the neural representation of orofacial movement and attempted speech with the help of language model by Willett et al. (2023). Willett, F.R., Kunz, E.M., Fan, C. et al. A high-performance speech neuroprosthesis. Nature 620, 1031–1036 (2023). https://doi.org/10.1038/s41586-023-06377-x.

research on neural networks and Large Language Models (LLM) has shown that these AI architectures are computationally more and more efficient to find patterns in noise[18] to translate a person's brain activity into continuous text. If there is an increasing body of evidence showing that language models fit brain data, several studies since 2023 have attempted to link LLMs with the decoding language from brain signals in language brain-computer interfaces, recent studies confirm initial promising results when leveraging brain representations as inputs to large language models after a brain adapter has extracted features from brain recordings and has transformed them into hidden vectors that match the shape of text embeddings in a standard LLM. Brain data can be thus directly inputted inside an LLM (Llama-2) to decode their linguistic meaning and reconstruct the narratives heard during the brain recording through a hybrid prompt integrating "brain modality" and text modality (so-called brain LLM)[19].

B. Situating Neurotechnology in the Taxonomy of Foundational Technologies

Section B presents an analysis and a mapping of the intersections between all the enabling innovations allowing the current rise of the neurotechnology industry and its products to precisely situate Neurotech innovation strands. As represented in Figure 11, selected emerging technologies and innovations like Material science and Pharmacology, Hardware miniaturization, Connectivity and Sensors, Cloud and Privacy technologies, Neuro-data collection and Advanced Biometrics all converge around AI and Machine Learning as the main orchestrator and enabler.

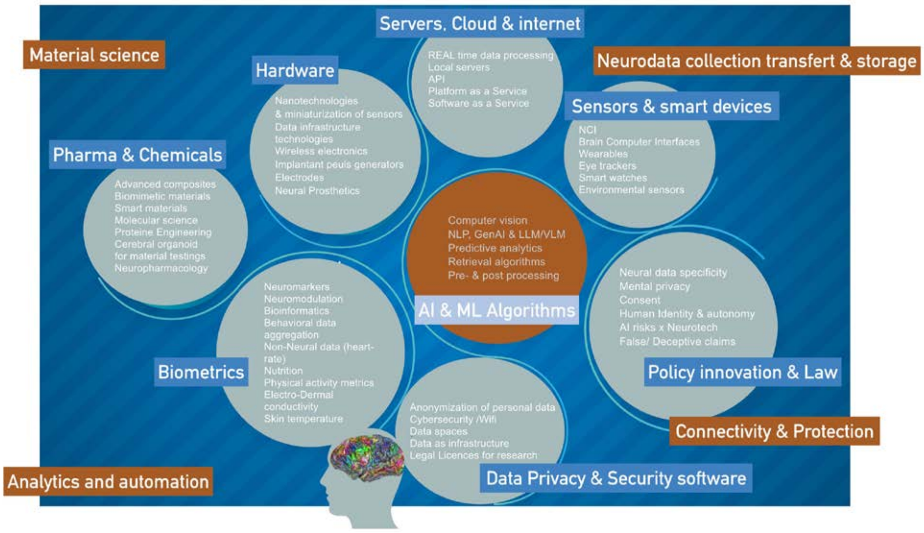
Exactly as one can understand in the graphic analyzing the benefits and risks of neuro-technologies across different fields (see Figure 6), neurotechnology is not a monolithic industry, it emerges from agglomeration of an organic network of enabling technologies and innovation clusters that are converging around AI and Machine Learning.

[18] 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.

[19] Ye, Z., Ai, Q., Liu, Y. et al. Generative language reconstruction from brain recordings. Commun Biol 8, 346 (2025). https://doi.org/10.1038/s42003-025-07731-7 Ye, Z., Ai, Q., Liu, Y. et al. Generative language reconstruction from brain recordings. Commun Biol 8, 346 (2025). https://doi.org/10.1038/s42003-025-07731-7.

Figure 11.

The major convergence and compounding effects enabling neurotechnology current development and raise of wearables. A graphic of the mapping of the intersections between all the enabling innovations allowing the current rise of neurotechnology.



For the purposes of this action research, the following taxonomy of foundational technologies is divided in infrastructure and application, with a strong interpretative focus put on algorithms, understood as infrastructure enabling emerging technologies.

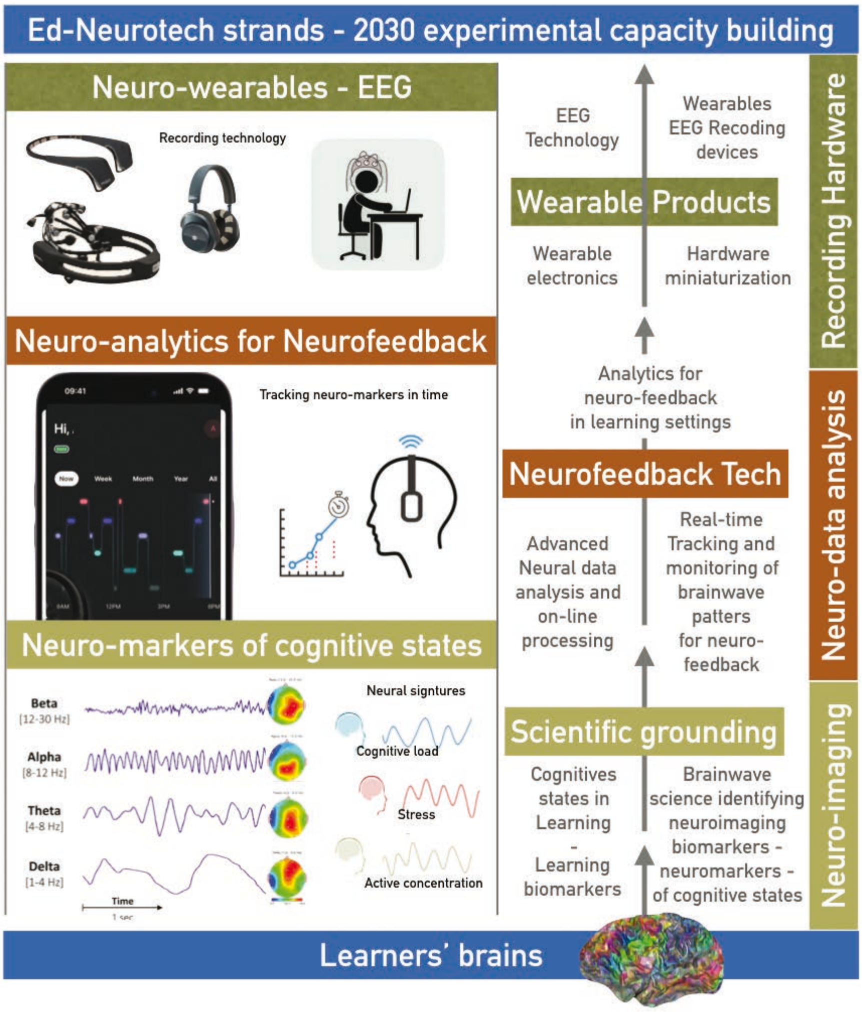
<table>
<tr><th colspan="2">Emerging technologies in infrastructure domains</th></tr>
<tr><td>Energy
• Metrics: energy produced per unit cost, distribution distance per unit cost, energy sustainability measures etc.
• Technology drivers: Renewable Energy (Solar, Wind, hydro, incl. space-based solar), energy storage (batteries, supercapacitors), smart grids, hydrogen fuel cells, fusion, carbon capture, circular economy, green algorithms, etc.</td><td>Compute
• Metrics: FLOPs-equivalent per unit cost, data storage per unit cost, data retrieval speeds etc.
• Technology drivers: digital algorithm progress, transistor miniaturization (e.g., via nanotechnologies), retrieval algorithms, superconductors, data infrastructure technologies, neuromorphic computers, DNA data storage, quantum computing hardware etc.</td></tr>
<tr><td>Materials
• Metrics: number of unique materials/physical functions we can construct, cost for bespoke construction, ability to intervene in existing physical systems etc.
• Technology drivers: atomic/molecular science, protein engineering, smart materials, nanotechnology (e.g., carbon nanotubes), 3D & 4D printing/additive manufacturing, advanced composites, metamaterials, biomimetic materials (e.g., polymeric biomaterials), elastocalorics, quantum materials, etc.</td><td>Connectivity
• Metrics: reliable GB/second per unit cost/energy, population connectivity coverage ratios, number of items connected to the Internet, latency, etc.
• Technology drivers: 6G and successor technologies, optic fiber cables, infrastructure build-out, protocols and standards, high altitude platform stations, LEO satellite constellations, quantum networking, Neural/silicon hybrid chips with the potential of expanding the rate and the quality of information exchange between a computer and human, etc.</td></tr>
<tr><td colspan="2">Algorithms (AI & ML)
• Metrics: computational efficiency and complexity of the task/process simulated or modeled.
• Technology drivers: mathematical, modelling and computational architecture components that are the main driver, can be correlated with compute efficiency.
- Deep neural networks
- Computer Vision
- Natural Language Processing
- Predictive Analytics
- Robotic Process Automation and Simulation
- AI Agentic workflows
- Generative AI / LLMs/ Diffusion models
- AI Observability / AI alignment and security management
- Explainable AI / mechanistic interpretability
- Quantum AI/ML algorithms</td></tr>
</table>

Emerging technologies in application domains		
Biotechnology • Bioinformatics • Gene editing, incl. CRISPR • Synthetic biology / bioprinting • Adult stem cells • mRNA therapeutics • Fluxomic • Personalized omics medicine • Cellular programming • Quantum biotechnology	**AR & VR** • Mixed Reality • Extended Reality • Remote Assistance & Collaboration • Training and Simulation • Haptic interfaces • Holography for communication	**Cybersecurity** • Threat Intelligence • Zero Trust Security / ZKPs • Cyber Resilience • Identity and Access Management • Cybersecurity mesh architecture • Disinformation security • Homomorphic encryption • Quantum cryptography
Distributed Ledgers • Blockchain • Cryptocurrencies • Smart Contracts • Decentralized Finance • Supply Chain Management	**Sensors & Internet of Things** • Industrial IoT • Smart Homes • **Wearables & sensors miniaturization** • Connected Vehicles • Environmental/machine sensors • VLEO satellites • Spatial computing • Quantum metrology	**Simulation** • Digital twins • Predictive Maintenance • Product Lifecycle Management • Smart Cities and Infrastructure • Virtual prototyping • Quantum simulation
Cloud & Edge Computing • Infrastructure as a Service • Platform as a Service • Software as a Service • Serverless Computing • Fog Computing • Edge AI / AI as a service • Real-Time Data Processing • IoT Edge • GitOps / Infrastructure as computing	**Advanced Robotics& Automation** • Collaborative Robots • Autonomous Mobile Robots/ Vehicles • Drone Technology/Swarm robotics • Robotics Process Automation • Soft robotics • Self-organizing, self-healing robotics • Space manufacturing • Reconfigurable/intelligent surfaces	**Space & Transport** • Nuclear space propulsion • Hypersonic • Ion propulsion • On-orbit maintenance • Next-gen satellites • Reusable rockets
Neurotechnology • **Neuroimaging and Neuroscience Brain Mapping – Neuro-markers of mental states** • Brain-Computer Interfaces (BCI) - **Neuro-wearables recoding brainwaves with EEG technology** • **Neuro-analytics for Neurofeedback** • Neurostimulation/Neuromodulation • Neural Prosthetics • Neuro-pharmacology/-modulators • Neuro-organoids		

In the following Part II, the most promising neurotechnology strands will be elected to further develop capacity building in the educational domain. To achieve the goal of this action research investigating the impact of neurotech in life-long learning by 2030, the three different technologies selected can strategically compound into one neurotech product, thus enabling immediate experimentation by adapting it and pilot it in ITC-ILO learning settings. While a step-by-step introduction to neuro-wearables, neuro-analytics and neuro-markers can be found inn Annex II, the following will present the reasons to select these strands for further consideration.

- **Neuro-Wearables**
  - **Definition** Brain recording wearable hardware strand.
  - **Why** Specifically, consume-grade wearable EEG-headsets are selected for their market. readiness and adaptability to the class and smart classroom setting.
  - **Strand Product embedding** The increasing maturity of non-invasive EEG-recording, the adaptability and flexibility of the materials have led and increasing number of companies to develop consumer-grade neuro-wearables products on the market. Today, Neuro-wearable products vary form sleep tracking to comfortable EEG-headphones monitoring EEG signal and offering Neurofeedback on engagement, stress, focus, etc. that can be visualized through smartphone apps to help routines changes or mindfulness training.
- **Neuro-analytics for Neurofeedback**
  - **Definition** Advanced software for brainwaves data analysis allowing to monitor complex brain waves patterns in real-time thanks to AI-powered Neuro-Data Analysis methods.
  - **Why** This strand is selected to tackle the questions of which Neuro-analytics are suitable for adult educational settings. These brainwaves patterns processed in real-time are structurally only proxies of cognitive states. Real-time Neurofeedback effectiveness for learning deserves experimentation.
  - **Strand Product embedding** Market-ready Neuro-wearables and their neuro-feedback apps monitoring different neuro-analytics that are not specific to learning enhancement should be tested to understand which learning market ready neuro-analytics are efficient. This is even more urgent in a market configuration where neuro-analytics are starting to be commercialized together with more and more easy to adopt neuro-wearables.
- **Neuro-markers identified by Neuroimaging and Neuroscience Brain Mapping**
  - **Definition** Neuro-markers are neuroimaging and biological indicators of the presence or progression of cognitive condition or mental state. These biomarkers are identified as being neural signatures of mental states in scientific research thanks to fine-grained neuroimaging techniques.
  - **Why** The developing field of Neuro-markers is selected as the foundational scientific grounding for decoding brain patterns thanks to the last two decades of more and more mature neuroscience results in neuro-imaging and the incremental discovery specific neural signatures of cognitive processes and learning predictors.
  - **Strand Product embedding** If real-time tracking of the right brainwaves to give neurofeedback through neuro-analytics is instrumental for better educational outcomes, targeting the right underlying neuro-markers is even more fundamental to leverage the cognitive states that do enhance learning.

Figure 12.
Three selected stands in neuro-technology. The different technologies selected for this action research investigating the impact of neurotech in education can be compounded in one single neurotech product to enable experimentation.



PART II.
THE FIELD OF CONSUMER NEUROTECHNOLOGY: THE RAISE OF NEURO-WEARABLES PRODUCTS

In Part II, the major neurotechnological strands presented in Part I are demarcated, and three selected strands are prioritized for further analysis of their impact on learning and social justice. Hence, after presenting the success of neuro-implants presented in Part I, the focus of this action research is to leverage the strategic moment of product deployment of neuro-wearables devices to timely harvest the benefits for life-long learning and address ahead of time the challenges and impact that these new devices monitoring people's brains will have on the future of learning and society at large.

By focusing on three of the major strands presented in Part I: (1) the Neuro-wearable Brain-Computer Interfaces strand, (2) Neurofeedback strand through real-time monitoring of Neuro-analytics, and (3) the emergence of learning neuro-markers in the brain imaging strand, we will first address in Section A to what extent the fast-developing AI-powered techniques of Neural Data Analysis and Computational Neuroscience to model and process neural data in real-time are among the main enablers of the three selected strands. AI will be thus introduced as a game-changer to rapidly analyze vast amounts of noisy brain data in real-time. Section B will be dedicated to the rise of EEG Neuro-wearables products and their adoption, data, and privacy challenges.

Three neurotech strands for education

The search for neuroimaging biomarkers—neuromarkers—of learning is a highly promising avenue toward improved learning methods leveraging Neurofeedback in tracking these neuro-markers through neuroanalytics recoded by neuro-wearables that can be directly be used in classrooms or in distal learning settings.

Thanks to EEG technology helping recording brain waves in a non-invasive manner, more fine-grained neural signatures of mental states are identified through research and can be tracked through wearables in traditional educational settings through applied research on the effects neurofeedback through of neuro-analytics and reach science and technology transfer out of the Lab settings.

What makes Neuro-wearables products unique is how they are currently bringing so many neuro technological strands together into a single market-ready product, where Hardware engineering, EEG-technology to monitor brain waves activity are associated with real-time data processing techniques enable consumer-grade EEG-headsets to analyze in real time what's going on with people's brain activity, and to try to identify cognitive states at a certain time, like focus or relaxation.

A. AI enabled non-invasive recording products: neuro-wearables record neuro-analytics for neurofeedback based on neuro-markers of cognitive states

Neuro-wearables: the hardware challenges to enable neural-data quality recordings

The first challenge to bring neurotech out the lab setting is making Brain Computer Interfaced an everyday device that is reliable irrespective of the neuro-data recoding conditions. In this as presented above in Part I the progress in signal processing and AI to make Electro Encephalography (EEG) be used to explore with high temporal resolution when cognitive changes happen in consumer-level products has been instrumental since 2011.

A second challenge is linked to the recoding hardware, EEG brain monitoring equipment is more and more efficient, small, and comfortable[20]. As shown in Figure 12 several hardware technologies are instrumental to making neuro-wearable hardware record reliable data in everyday settings. Notably, the flexibility of the materials to adhere to the scalp like elastomeric hair electrodes or flexible dry hair and skin-like 5mm electrodes, the reduced size of amplifiers needed to record micro-volts (μV) at the level of the scalp, the production of wireless electronics to avoid cables[21].

AI as a fundamental enabler for real-time Neurofeedback: Neuro-analytics can be obtained with less data and less sensors

To obtain reliable neuroimaging data while recording brain activity in an everyday learning setting one requires a sufficient Signal-to-Noise ratio to trust the tracking of Neuro-analytics for learning neurofeedback. Perceptual or motor confounds may distort data of interest, e.g., a student scratching his head. While signal-to-noise ratio is making the recoding of brain activity often useless in consumer grade systems, applied research by recent neuro-wearable startups indicates that signal processing AI systems help reconstruct around 90% of the original signal in noise (2021, Neurable).

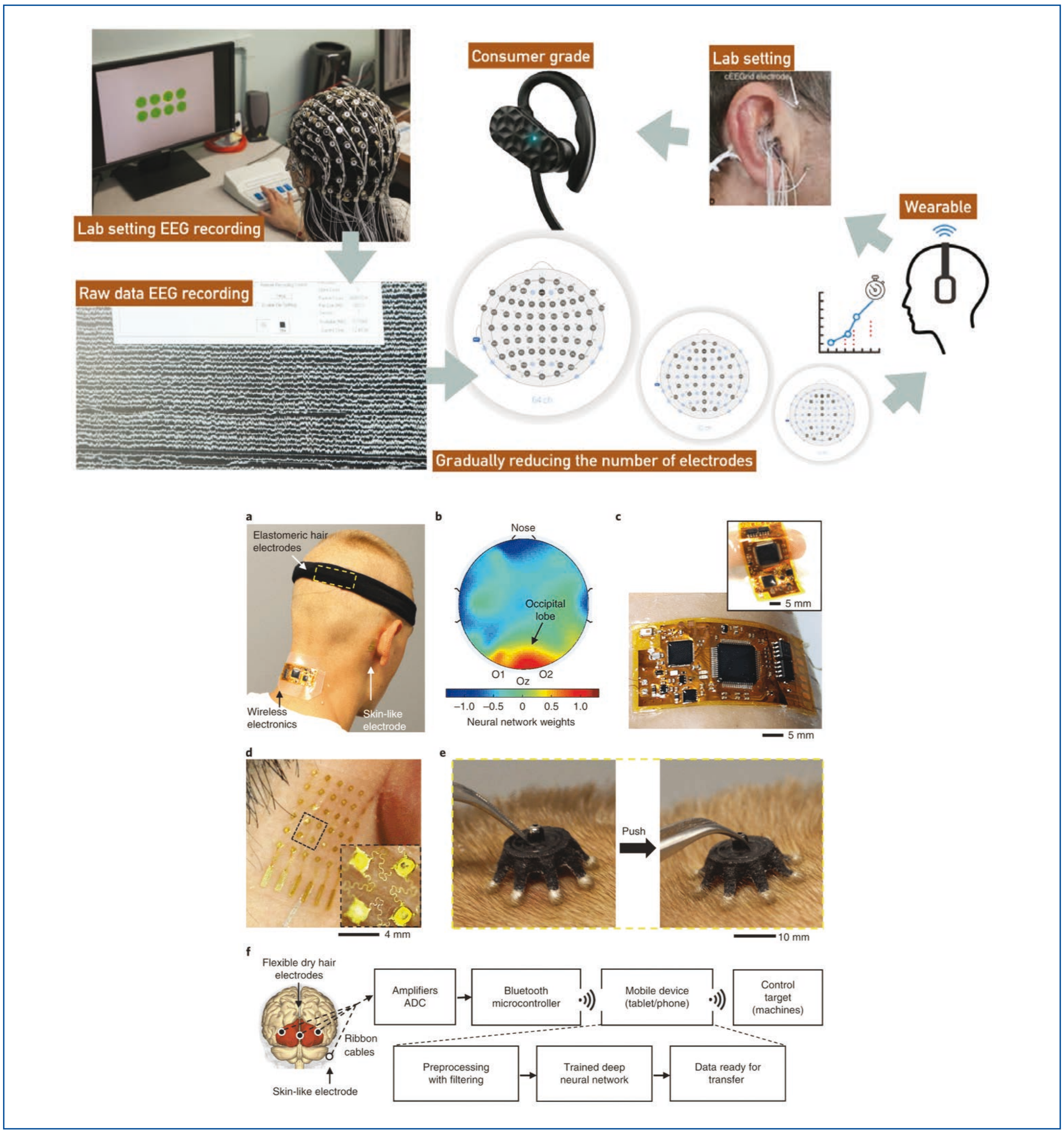
AI is helping decode, but AI is also helping you having less sensor, which is fundamental to move to the wearable space. In research settings EEG caps of more than 100 electrodes were used at the level of the scalp and were needing saline water gel in order to be fixed and assure the contact with the scalp.

[20] For a horizon scanning of EEG wearables see: Nuraini Jamil, Abdelkader Nasreddine Belkacem, Sofia Ouhbi and Abderrahmane Lakas (2021). 'Noninvasive Electroencephalography Equipment for Assistive, Adaptive, and Rehabilitative Brain–Computer Interfaces: A Systematic Literature Review'.

[21] Mahmood, M., Mzurikwao, D., Kim, YS. et al. Fully portable and wireless universal brain–machine interfaces enabled by flexible scalp electronics and deep learning algorithm. Nat Mach Intell 1, 412–422 (2019). https://doi.org/10.1038/s42256-019-0091-7.

Figure 13.

Sensors obtain information from wearable devices. The recent path of reducing the number of electrodes and still being able to capture brainwaves of participants to Lab experiments. Now, with wearables, one can decode the brain waves of somebody wearing simple consumer grade air pods (top middle). Right Flexible and miniaturize scalp electronics to record EEG signal with dry electrodes sensors, and wireless electrotonics.



Thanks to AI, the number of sensors, to obtain the same prediction and diagnosis with more affordable and accessible medical devices like, medical grade neuro-headband and connected server data platform in the cloud is lower (e.g., *Bitbrain* wearables for example diagnose in sleep, and offer personalized treatment in dementia).

A concrete example is the possibility to track focus and attention without frontal electrodes.

AI is thus enabling bringing Laboratory grades quality data to the consumer space, allowing real-time feedback on neuro-analytics from brain sensor to be accessed for insights one's own smart phone. Real world examples include suggestions to when to take break, etc.

AI enabling Science and Technology transfer out of the Lab settings: the rise of neuro-markers

Leveraging the science and technologies developed since the 50s in laboratory settings is nowadays possible thanks to several enabling factors and the compounding effect of miniaturization of sensors with computational developments yielded by AI.

Bring neuro-technology to society outside the labs is simpler through neuro-wearables, this shift is critical to democratize for example research on mindfulness[22], or on PTSD and help achieving 36% reduction in PTSD symptoms severity, for example with products developed for traumatic brain injuries in soldiers that brought to consumer use[23]. This shift outside the lab also brings research protocols with full scale medical grade EEG systems, as their signal quality is so close to lab EEG systems.

Crucially, by combining AI with neurotechnology researchers are discovering **new biomarkers and brain patterns** for better diagnosis and prediction and promising new treatments, but also new neural signatures that can be correlated to cognitive activity and can therefore gradually become reliable Neuro-markers of complex and high-level cognitive functions like focus, attention, concentration, cognitive load, working memory.

B. Consumers' adoption of neuro-analytics: implications for data, form factors and privacy

I. Neuro-feedback from neuro-wearables is data-vorous: real-world neuro-data are needed to track and process neuro-analytics in real-time

AI is enabling neuro-wearables with less channels to be using real-world data to give neurofeedback to users with neuro-analytics. Real-world data are nonetheless essential to train algorithms to track and decode neuro-analytics from consumer-grade neuro-wearables. As it is the case in the field of AI, where data are increasingly considered as an infrastructure, current efforts are made at the product level in neuro-wearables to bridge the data gap, and be able to train algorithms to find brainwaves' patterns in noise, and to find consistent brainwave signatures across larger and larger populations. To build successful neuro-feedback products based on neuro-analytics it is not only important to deliver at the level of neuro-wearable technology, but it is necessary to acquire sufficient representative data in order to be able to

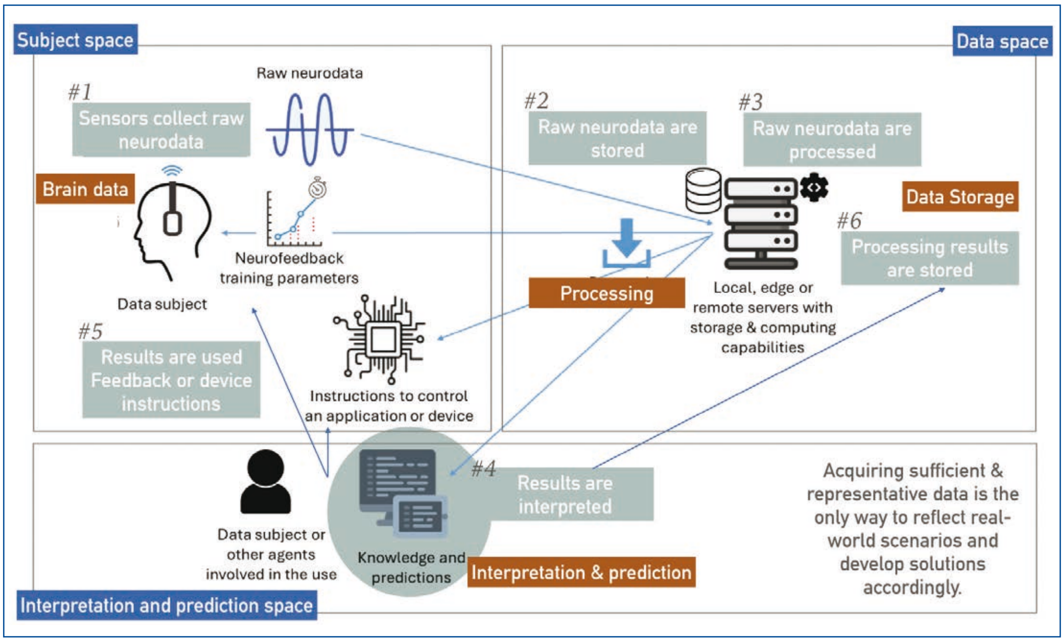
[22] Shaw Saurabh Bhaskar , Levy Yarden , Mizzi Allison , Herman Gabrielle , McKinnon Margaret C. , Heisz Jennifer J. , Becker Suzanna, Combined Aerobic Exercise and Neurofeedback Lead to Improved Task-Relevant Intrinsic Network Synchrony, Frontiers in Human Neuroscience, Volume 16 – 2022, 10.3389/fnhum.2022.838614.

[23] Saurabh Bhaskar Shaw, Andrew A. Nicholson, Tomas Ros, Sherain Harricharan, Braeden Terpou, Maria Densmore, Jean Theberge, Paul Frewen, Ruth A. Lanius, Increased top-down control of emotions during symptom provocation working memory tasks following a RCT of alpha-down neurofeedback in PTSD, NeuroImage: Clinical, Volume 37, 2023, 103313, ISSN 2213-1582, https://doi.org/10.1016/j.nicl.2023.103313.

reflect real-world situations in a certain domain like wellness or learning. These real-world neuro-data achirid through consumer EEG-headsets are then necessary to train **neural-data analysis algorithms** to decode brainwaves and offer quality neuro-analytics during users' learning daily routines.

As in AI the tradeoff between data privacy and product development is complex, the schematic representation of the data lifecycle in Figure 14 shows how important the privacy and data-consent awareness of the end-consumers is. The only way to address the fundamental privacy challenges of the pipeline and ecosystem of the neuro-data that is involved in wearables is to adopt a privacy by design approach, and to address the human rights risks that emerge[24], without forgetting that educational settings have their own privacy challenges[25].

Figure 14.
The data lifecycle in a neuro-wearable device identifying three fundamental spaces with different risks: (1) the subject space, (2) the data space and (3) the space where AI and signal processing is interpreting raw signals. Adapted from Neuro-data processing EDPB Dispatch[26].



[24] Australian Human Rights Commission (2024). Protecting Cognition: Background Paper on Human Rights and Neurotechnology. https://humanrights.gov.au/our-work/technology-and-human-rights/publications/protecting-cognition-background-paper.

[25] The use of wearable technology in education raises important questions about data privacy and security. Wearable devices can collect sensitive information about students, including health metrics and behavioral data. Ensuring that this data is stored securely and used ethically is a major concern for educators and policymakers. According to a 2021 report by the Center for Democracy and Technology, 38% of parents express concerns about how their children's data are used by educational institutions, Students' number one worry: a data breach that would give outsiders access to their personal records. Seventy-two percent of students surveyed said they were either "very concerned" or "somewhat concerned" about that happening. highlighting the need for robust data protection measures. Data Privacy Concerns in Educational Wearables. 2021. Center for Democracy and Technology. https://cdt.org/insights/emerging-safety-technologies-in-schools-addressing-privacy-and-equity-concerns-to-ensure-a-safe-in-person-school/.

[26] EDPB TechDispatch #1/2024 – Neurodata https://www.edps.europa.eu/data-protection/our-work/publications/techdispatch/2024-06-03-techdispatch-12024-neurodata_en.

II. Form factors considerations driving consumers adoption of wireless neuro-wearables

In the Neurotech product development space there is always a tension between the form factor and the placement and density of the EEG recording channels that can be embedded in one EEG-headset. It is essential to find a balance between factors that enable consumer adoption like comfort and appearance, and how to maximize the quality of the neuro-data brainwaves recorded from a limited number of electrodes at certain places.

Taking Research out of the lab in Translational neuroscience

Reducing the number of channels is instrumental to move from research settings to the level of the consumer products, but also enhancing the ergonomics of these devices has been possible thanks to research in materials and engineering targeting the miniaturization of electrodes. Additionally, innovation in dry electrodes made it possible to insert them in hair bands, while wireless electronics enabled to communicate what is being recorded at the level of the scalp without cables.

If all these elements are fundamental, form factors are one of the current main enablers of consumer neurotech products as design is fundamental for adoption from a variety of perspectives, people, and hairstyle preferences, like dreadlocks hair style[27]. Having a variety of form factors is a vector to neuro-wearables democratization that is enabled by the hardware focus on miniaturization of electrodes, or by the AI-driven neuro-signal processing.

III. End-users monitoring habits and the adoption of Neuro-analytics: the priority of developing privacy-aware wearables

A digital data ecosystem is now in place as consumers became used or acquainted to the tracking of their health data through smart watches, but the ethics and privacy of neuro-data need more development. An **advocacy actionable** would thus be to bring ethics in the core development of a neurotech company and find ways to make the incentive for the companies.

Pairing neuro-analytics with smartphones: inferring mental states from non-neural data

It is fundamental to understand that people's mental state can be inferred not only based on neuro data[28]. For instance, smartphones are rich hubs for several non-neural data that can help decode, predict, or track mental states of the owner, as represented in Figure 15.

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[27] Etienne A., Laroia T., Weigle H., Afelin A., Kelly S. K., Krishnan A., Grover P. (2020). Novel electrodes for reliable EEG recordings on coarse and curly hair. In 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (pp. 6151–6154). https://doi.org/10.1109/EMBC44109.2020.9176067.

[28] Magee, Patrick et al. Beyond neural data: Cognitive biometrics and mental privacy, Neuron, Volume 112, Issue 18, 3017 – 3028 https://www.cell.com/neuron/pdf/S0896-6273(24)00652-4.pdf.

Some basic elements that can help reconstruct a detailed picture of the individual through essentially simple sensors like GPS or a gyroscope tracking what is the orientation of your telephone to deduce physical activity and location. Hence, social rhythm can be detected through GPS, while Wi-Fi can help you can help identify if people go to the gym, to the bar or to the doctor. Proximity sensors are also a cue that can help measure social relationships by detecting smartphones of other individuals through Bluetooth. Less intuitively, a camera can track eye movement which are a source of understanding of the emotional state through face expressions.[29] Additionally, eye movements are also a proxy allowing to check for example medication effects on pupillometry (dilatation of the pupil)[30]. The touchscreen is also a source of information allowing to understand some elements of cognition, like response-time in tasks, or to infer elements of cognition, etc.

Other sensors embedded in smartphones can offer indirect cues about learning. For example, a basic light sensor can already be a proxy to understand the sleep status, which is highly correlated also with successful educational outcomes and knowledge retention. Heart sensors are indirectly helping track the nervous system, anxiety, arousal that can help understand the stress status of a student, while voice recording, can be a source of detection of emotion, but also of social environment.

Importantly, all these behavioral sources of information can be coupled to neurophysiological data like EEG brainwaves, or to the electrodermal responses to emotional stimuli a smart watch can record, privacy becomes the priority to prevent any possible profiling, or manipulation accessing to a rather complete picture of individuals personal life and identity. A recent partnership (May 2025) between Apple and the brain implant company Synchron[31] demonstrate that what could have been only a promising venue for therapeutic and assistive technologies helping individuals with paralysis or ALS[32], is now being concretely investigated by important actors in this echo-system. As stated by the press release "Apple is helping to pioneer a new interface paradigm, where brain signals are formally recognized alongside touch, voice and typing."

[29] See https://spectrum.ieee.org/media-library/diagnosis-by-smartphone-graphic.jpg?id=25583331&width=1600&quality=85.

[30] Torous J, Kiang MV, Lorme J, Onnela JP New Tools for New Research in Psychiatry: A Scalable and Customizable Platform to Empower Data Driven Smartphone Research JMIR Ment Health 2016;3(2):e16 doi: 10.2196/mental.5165, https://spectrum.ieee.org/a-software-shrink-apps-and-wearables-could-usher-in-an-era-of-digital-psychiatry.

[31] See press release 'Apple's new BCI Human Interface Device protocol marks the creation of a new input category powered by thought, enabling hands-free, voice-free digital control through Synchron's BCI system https://www.fastcompany.com/91333747/apple-partners-with-a-brain-computer-startup-to-turn-thoughts-into-device-control, https://www.wsj.com/tech/apple-brain-computer-interface-9ec69919?mod=hp_lead_pos8, https://www.businesswire.com/news/home/20250513927084/en/Synchron-To-Achieve-First-Native-Brain-Computer-Interface-Integration-with-iPhone-iPad-and-Apple-Vision-Pro.

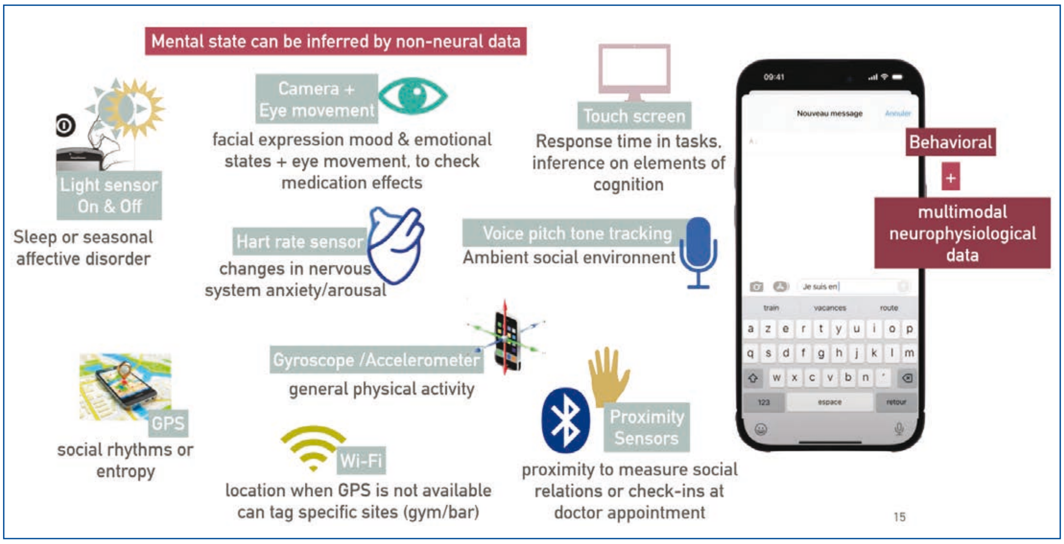
[32] See the BrainGate2 clinical trial at Stanford University where a 69-year-old man with C4 AIS C spinal cord injury successfully piloted a virtual quadcopter using only his thoughts.https://www.rdworldonline.com/paralyzed-man-flies-virtual-drone-with-thought-controlled-finger-movements/.

Beyond medical uses, non-invasive brain decoders could act as hands-free keyboard for notetaking or device control purely decoding online brain patters and neuromarkers, achieving more precise communication rates, sometimes reaching up to 62 words per minute[33].

In conclusion, neural data are not isolated as long as one possess a smartphone and such a configuration should be tackled by an adequate data protection regulatory landscape, knowing that the more consumer-level Neuro-wearable are adopted the easier it will be to just take a snippet of an EEG recording to be able to identify by to whom these neural-data belong.

Figure 15.

Mapping of the Interplay of data sources to be merged with brain data to get a 360 profile of the user, and inferring mental states from non-neural data.



[33] See also a study on high-performance speech neuroprosthesis leveraging the neural representation of orofacial movement and attempted speech with the help of language model by Willett et al. (2023). Willett, F.R., Kunz, E.M., Fan, C. et al. A high-performance speech neuroprosthesis. Nature 620, 1031–1036 (2023). https://doi.org/10.1038/s41586-023-06377-x.

PART III.
NEUROTECH WEARABLES PRODUCTS AND THE POSSIBLE RECONFIGURATIONS OF EDUCATION BY 2030

In Part III, the impact on the future of learning of all-in-one neuro-wearable products offering neurofeedback through neuro-analytics based on cognitive neuro-markers is further assessed with the help of the purpose-built evaluation grid introduced in Section A.

To assess in further detail the impact of selected neuro-technology products' building blocks (neuro-markers, neuro-analytics and neuro-wearables) on the future of adult learning, it is essential to divide into three main domains the evaluation parameters considered here. Hence, the following analysis will concentrate on (a) educational strands, (b) cognitive and behavioral strands, and finally (c) socio-technical strands. For the latter, the advocated approach is strongly rooted in the Report of the Human Rights Council Advisory Committee (Aug 8th, 2024) by the UN General Assembly, "Impact, opportunities and challenges of neurotechnology with regard to the promotion and protection of all human rights". Namely, the human rights impact assessment perspective is a fundamental methodological tool for the recommended experimentation paths presented in Section C. It allows not only to understand the impact of Neurotechnology's latest developments on the future of learning, but it also guarantees to follow and delineate a concrete capacity building strategy that harness Social Justice for ILO constituents and other ILO development partners.

In Section B supporting educational evidence from several innovations in the neurotechnology field will be given through concrete examples taken by the latest developments in neural data decoding in the field of education. Research papers in cognitive neuroscience and neuroimaging of cognitive functions will be presented to discuss possible experimental venues for adult learning, remote learning (smart classroom) and for learners with disability like attentional disorders (ADHD), to capture the short-/mid- term potential of neuro-wearables products by 2030.

A. Assessing the impact of neurotechnology on the future of learning: an educational, cognitive and socio technical evaluation grid

The parameters considered by the action research analysis grid for capacity building recommendations are organized across three main domains:

1. Educational
2. Cognitive and behavioral
3. Sociotechnical

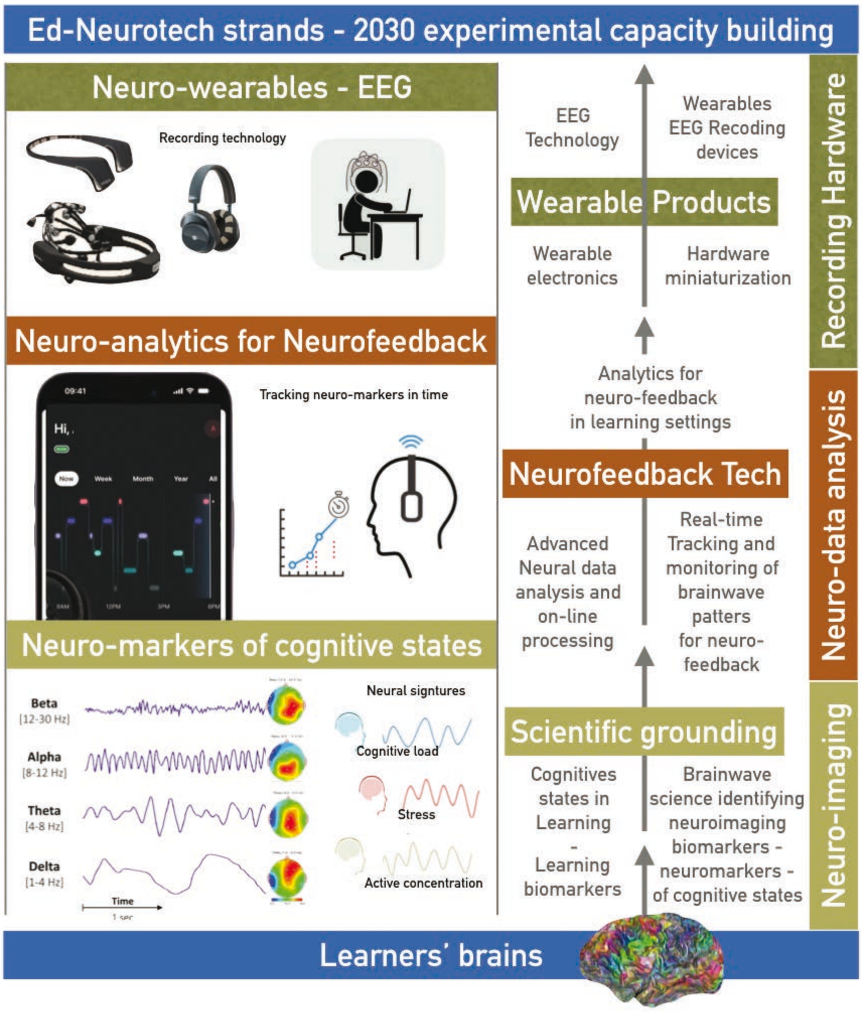
The first two major domains can be identified as the main educational domain of application for adult learning and to address disabled learners' educational needs, while the crucial aspects under the sociotechnical domain should be understood as transversal enablers to foster responsible implementation strategies.

The three selected stands have the strategic advantage to able to be compounded together into one market-ready neurotech product, as represented in Figure 16, that can be adapted, piloted, and experimented with by 2030. The compoundable nature of the three stands facilitates the focus of action research on the following fundamental questions for the future of learning:

1. Now that **neuro-wearables** allow tracking neural activity in a classroom setting or for individual learning outcomes, what is the psychological impact of monitoring learners mental states? How is this going to change the student-teacher relationship?
2. Are the right **neuro-analytics** to enhance life-long learning being monitored? And does neurofeedback from neuro-analytics really enhance learning experience at individual- and group level?
3. Are the neuro-analytics deployed in market-ready apps rooted in reliable **neuro-markers** grounded in a scientific approach to the brain, to cognition and education?

Figure 16.

Selected strands for further analysis. Consumer-level EEG-wearable device recoding individual brainwaves. Continuous tracking of brain waves through neuro-analytics visualized for Neurofeedback to the consumer in a smartphone app that monitors daily of neuro-analytics related to brain activity patterns like stress, fatigue, focus, etc. Scientifically grounded brain signatures evoked by cognitive tasks and mental states across different band widths (beta, alfa, theta, gamma delta) in the EEG signal. See also Annex II for a step-by-step introduction to neuro-wearables, neuro-analytics, and neuro-markers.



By identifying some key evaluation criteria and points of caution, practical insights are here offered to integrate these technologies effectively in educational settings. These criteria serve as navigational tools through the multifaceted landscape of neurotechnological adoption by 2030, while a concrete action plan encompassing six capacity building steps is delineated in Section C and further detailed capacity building recommendations are presented in Part IV.

To systematically distil complex considerations into actionable guidance for the selected three strands, the eleven parameters are further qualified at the three different level of capacity building intervention of ITC-ILO service portfolio, i.e., individual, organization, an ecosystem-level.

I. A Neurotechnology evaluation grid for learning: educational, scientific and technology readiness and ethics' criteria

The evaluation grid presented in Figure 17 provides a comprehensive assessment of three neurotechnology categories selected in Part II and further developed in Part III.B (i.e., neuro-wearables, neuro-analytics, and neuro-markers) across different educational, cognitive-behavioral, and socio-technical dimensions.

The grid uses a color-coded system to indicate different readiness levels based on the literature reviewed in Section B. Hence, educational, scientific, technological Readiness and ethical considerations for experimentation are assessed at four different level:

1. **Ready for testing/adoption (dark green)**

   Existing EEG neuro-wearable products on the market can facilitate the testing of the inbuilt neurofeedback apps including a series of general neuro-analytics like stress, engagement, interest, focus, excitement, or relaxation in an educational setting. However, these consumer-grade neuro-wearables can be designed to answer the needs of student populations that typically underperform on traditional learning assessments, or for students with disabilities, and students from low socioeconomic backgrounds. Addressing the educational needs of these population should also require testing of consumer-grade neuro-wearable products and their inbuilt neuro-analytics. Neurofeedback is currently given on a fixed set of neuro-analytics and it is harder to track other or more advanced neuro-markers without building a collaboration with academia and/or the private sector.

2. **Educational experimentations needed (light green)**

   Most experimentation using EEG headsets and neurotech tools is performed in tightly controlled lab experiments using either simple lab stimuli or non-interactive experimental designs over short periods of time. It is thus essential to assess the educational validity of market-ready neuro-wearables and the neurofeedback apps to measure the real impact of monitoring through neuro-analytics certain neural cognitive signatures (neuro-markers) in real-world learning contexts. The specific challenges and potential of market-ready neuro-analytic captured at the level of EEG-wearable and research-level neuro-markers associated to a mental state in scientific research settings should be considered to run experimentations and address the effectiveness of deployment within adult learning settings[34]. Even scientifically well-grounded neuro-markers may not survive the test of reality in a real-world educational setting as recoded by the neuro-wearable devices currently available on the market.

3. **Only initial scientific grounding (light yellow)**

   As science advances by collecting insights about the brain mechanisms involved in understanding and learning, additional applied research work is required to further objectivize that neuro-marker and neuro-analytics measures are useful for learning and in real world learning contexts. Applied experimentation and piloting is necessary Before evaluating and optimizing education methodologies according to students' brain responses, otherwise the identified neuro-markers neural and cognitive process may remain unstable and not generalizable to larger learning populations.

4. **Careful scrutiny (light purple)**

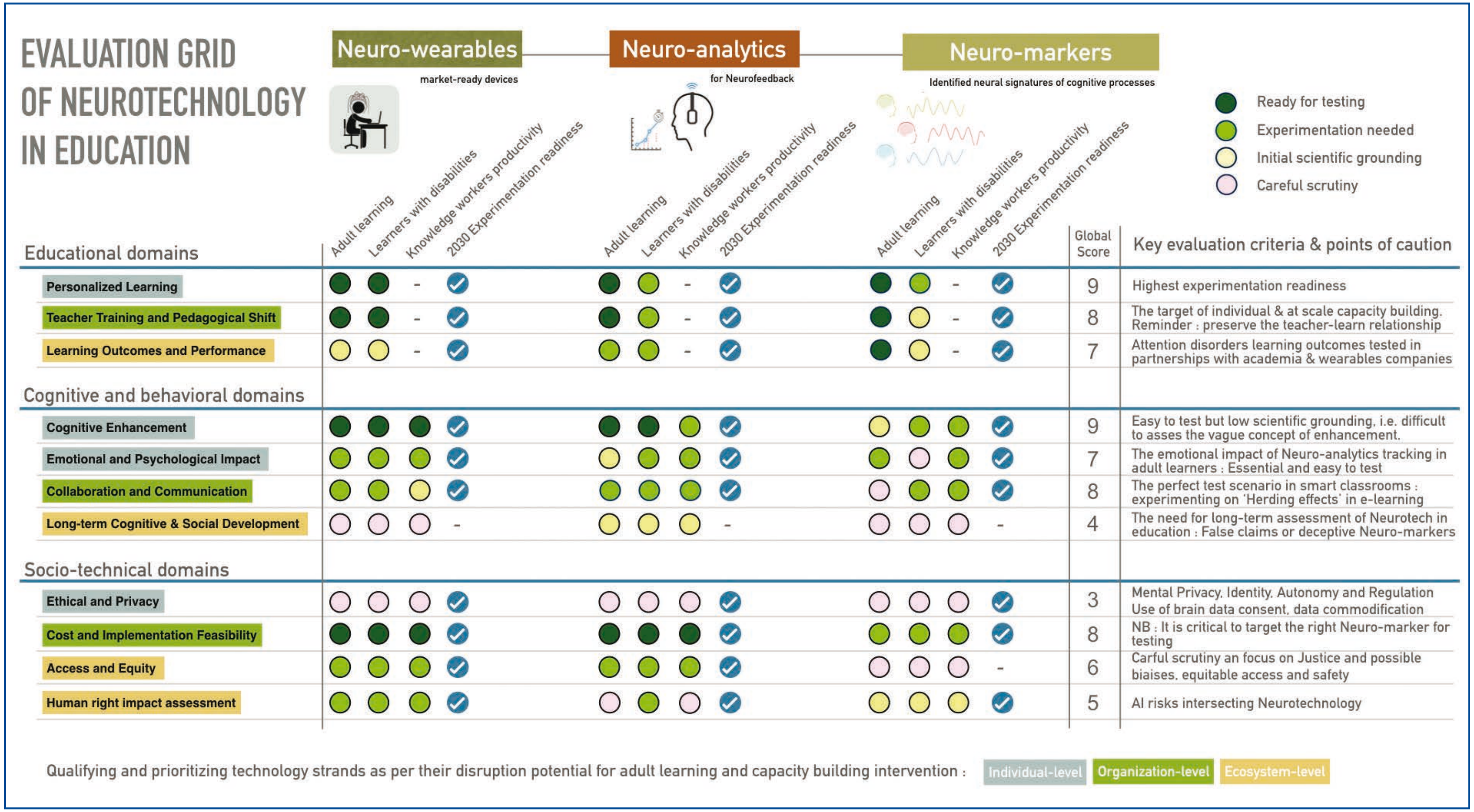
   Given the importance of ethical and privacy concerns regarding student privacy and the potential misuse of students' brain data (i.e., use of brain data consent, data commodification), this score is associated to several risks and concerns presented in Figure 6 like the existence of deceptive Neuro-markers not having sufficient scientific grounding, mental privacy, identity, autonomy, and human rights.

Each technology is evaluated across different learning contexts (adult learning, learners with disabilities, knowledge workers) with a temporal focus on experimentation readiness by 2030.

[34] For a review of experimentations, see Hernández-Mustieles, M. A., Lima-Carmona, Y. E., Pacheco-Ramírez, M. A., Mendoza-Armenta, A. A., Romero-Gómez, J. E., Cruz-Gómez, C. F., Rodríguez-Alvarado, D. C., Arceo, A., Cruz-Garza, J. G., Ramírez-Moreno, M. A., & Lozoya-Santos, J. d. J. (2024). Wearable Biosensor Technology in Education: A Systematic Review. *Sensors*, *24*(8), 2437. https://doi.org/10.3390/s24082437.

Figure 17.

Evaluation grid of neurotechnology in education including capacity building recommendations, presented in a nutshell under "Key evaluation criteria and points of caution (right part) of the analysis grid. Qualifying and prioritizing technology strands as per their disruption potential for adult learning and capacity building intervention: individual, organization and ecosystem-level. See also Annex II for a step-by-step introduction to neuro-wearables, neuro-analytics, and neuro-markers.



II. Key Observations on readiness

The analysis grid represents the synthesis of this action research findings, combining scientific, theoretical understanding with practical market and product readiness and ethical application concerns, and highlighting both opportunities and potential pitfalls. The carefully calibrated recommendations for future experimentation (in Part IV) acknowledge the diverse educational and lifelong learning contexts in which capacity building occurs, providing a framework that is adaptable rather than prescriptive, and ensuring that implementation efforts remain aligned with core values of inclusion, accessibility, and human dignity, through the sociotechnical domains identified. In the following some key observations by domain are addressed in the details.

Key observations for the educational domain:

- **Personalized learning** shows high readiness across all technologies, particularly for Neuro-wearables.
- **Teacher training** is well-positioned for implementation, especially for neuro-markers and neuro-analytics.
- **Learning outcomes** shows mixed readiness, with neuro-analytics requiring more experimentation to assess the effectiveness of deployment in the learning setting.

Key observations for cognitive and behavioral domain:

- **Cognitive enhancement** is most advanced in neuro-wearables technology leveraging neurofeedback apps.
- **Emotional impact** of mental state monitoring through neuro-analytics requires careful consideration across all neuro-technologies and biosensors.
- **Collaboration and communication** shows promising potential, especially in neuro-analytics, but deserve experimentation, specifically at the level of the teacher/student interaction and relationship, to be sure the teacher is not overwhelmed by information from students neuro-analytic and it can correctly interpret it to improve learning path and outcomes, and to ensure that human connection—the heart of learning—does not get replaced by algorithms analyzing brain data.
- **Long-term cognitive development** requires the most caution (predominantly purple circles) because there is not enough experimentation to assess the cognitive effect of relying on neuro-markers, neuro analytics recorded from neuro-wearables for educational purposes in lifelong learning.

Key observations for socio-technical domain:

- **Ethical and privacy** concerns are significant across all technologies, with an impact on identity, autonomy, and privacy requiring careful scrutiny.
- **Cost and implementation** appears relatively feasible across technologies.

- **Access and equity** shows better readiness in neuro-analytics and neuro-wearables than in neuro-markers, even if there are several ethical factors generally ignored by researchers or government, especially in the case of disabilities [35].
- **Human rights impact assessment** requires full-spectrum analysis and experimentation across all technologies in collaboration with Human Rights experts and educators[36].

III. Key evaluation criteria highlights and transversal critical considerations

While the grid is designed to guide decision-making about which neuro-technologies to prioritize for adult learning and capacity building interventions, consideration for implementation at individual, organizational, and ecosystem levels shouldn't be forgetful of the following critical considerations.

- The importance of targeting "sweet spots" for capacity building at different levels (individual, organizational, and ecosystem levels).
- The importance of targeting enhanced learning opportunities for those with disabilities.
- Prioritizing concerns about scientific grounding and vague concepts often embedded in the marketing of **deceptive neuro-analytics**.
- The emotional impact for individuals and learners of tracking neuro-markers and brain states.
- **Warnings about deceptive neuro-markers and false claims in associating certain neuro-markers with certain mental states**[37].
- Critical emphasis on mental privacy, data consent, and equity.

Cross cutting concerns: digital and gender divide

The potential for neurotechnology educational and life-long learning applications to exacerbate existing digital divides represents a significant challenge that spans multiple dimensions of our analysis. These technologies, while promising unprecedented advancement in learning capabilities, risk for example deepening inequalities between women and men due to persistent gender imbalances in STEM fields, between developed and developing regions with varying technological infrastructure, and between workers with different skill levels. As educational systems worldwide may adopt these technologies at uneven rates, the gap between technology-rich and technology-poor environments threatens to create new forms of educational

[35] Hetzel, Patrick (2022). Neurotechnology: Scientific and Ethical Challenges, Science and Technology Briefings – Briefing 32, Parliamentary Office for Scientific and Technological Assessment.

[36] In October 2021, Chile addressed these problems by passing a law protecting citizens' "brain rights", which covers the protection of neurorights, including the rights to personal identity, free will and mental privacy.

[37] As noted by a recent UNICEF Working paper on Some of these devices, aimed at children and youth, claim to improve concentration or learning. Such devices and not all of them receive the necessary oversight to ensure children are safe. Pauwels, Eleonore, Neurotechnology and Children, UNICEF Innocenti – Global Office of Research and Foresight, Florence, June 2024.

disadvantage. This concern necessitates deliberate and calibrated policy interventions and capacity-building initiatives that prioritize equitable access and skills development across demographic and geographical boundaries, especially for teachers.

The globally observed gender divide in generative AI tool adoption[38]—with platforms like ChatGPT showing disproportionate usage patterns in favor of men use that currently left without an explanation in research—raises pressing questions about potential similar patterns in neurotechnology adoption. This unexplained phenomenon in AI tools suggests that neurotechnology may follow comparable trajectories unless intentionally countered. The root causes likely extend beyond simple access issues to encompass complex sociocultural factors, confidence gaps, and structural barriers that influence how different genders engage with emerging technologies. As neurotechnology products and their possible applications for learning grow, monitoring adoption patterns through a gender lens becomes essential, as does researching the underlying causes of any observed disparities. Early awareness of these potential divides creates opportunities for preemptive measures—including gender-responsive design, targeted teachers outreach programs, and inclusive testing protocols—that could prevent neurotechnology from reinforcing existing.

B. Impact of neurotechnology wearable products on life-long learning and on the learner-teacher relationship

I. Neurotechnology landing in the student-teacher space: the new neuro-assisted classroom

Generative AI pedagogical shifts

Just as medicine has witnessed a profound transformation over the past quarter-century—with technologies from medical imaging to large-scale clinical statistics and AI-driven analyses reshaping the doctor-patient relationship—we now stand at the threshold of a similar evolution in education. The emergence of generative AI has already begun reconfiguring the educational landscape through the availability of automatic text and image generation, augment search and AI agents altering pedagogical approaches in both traditional classrooms and remote learning environments while raising fundamental questions about learning effectiveness across individual experiences, scalable implementations, and long-term outcomes.

Neurotechnology in the student-teacher relationship

When neurotechnology enters the educational space, the traditional student-teacher relationship undergoes a fundamental transformation. The role of the teacher evolves from a

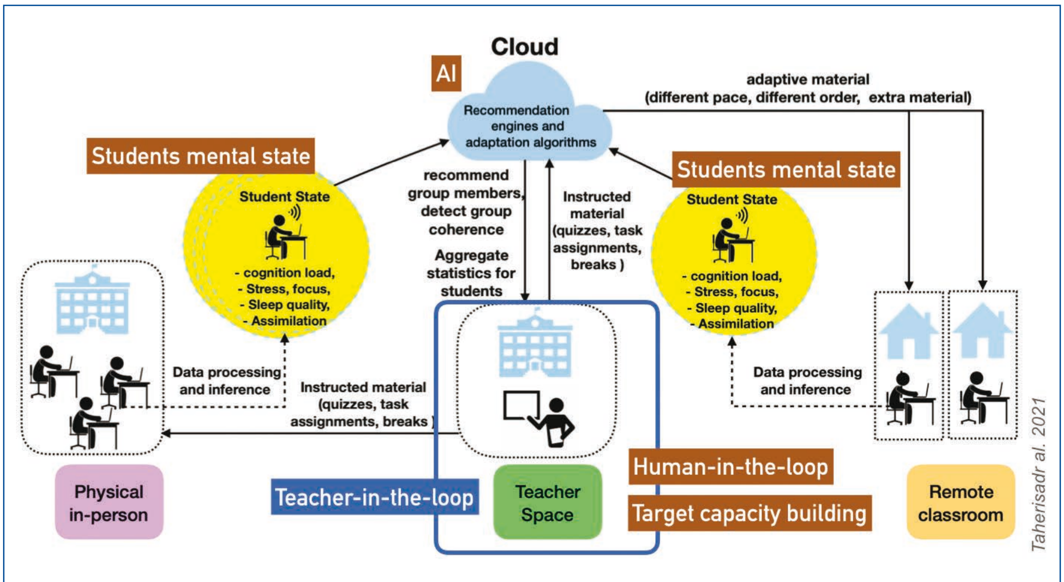
[38] Otis, Nicholas G., Solène Delecourt, Katelynn Cranney, and Rembrand Koning. “Global Evidence on Gender Gaps and Generative AI.” Harvard Business School Working Paper, No. 25-023, October 2024. Humlum & Vestergaard, 2024.

human knowledge provider and mentor to additionally becoming a technological orchestrator of neurologically optimized learning experiences. To leverage insights from neuro-analytics teacher need to be helped in better understand physiological and cognitive functions relevant for learning (attention, memory, sleep, the impact of nutrition, ...) and to the design of novel classroom interventions and new teaching strategies, leveraging Neurofeedback and Neuro-analytics for teachers' use.

Through neuro-analytics adoption the potential to precisely identify each student's cognitive patterns, attention thresholds, and emotional responses to learning stimuli, can be pedagogically leveraged only after teachers' advanced training. Specifically, a thorough understanding of the scientific and psychological validity of neuro-markers tracked through neuro-analytics to skillfully interpret learners' neuro-data in context and thus meaningfully personalize educational approaches while maintaining crucial human connections that technology cannot replicate.

Figure 18.

Analysis and mapping of the new neuro-assisted classroom configuration inspired from Taherisadr al. 2021. Future smart classroom disrupted by wearable neurotech products. Student's mental state inferred from wearable sensors is used to provide feedback and recommendation to the student and to the teacher for both physical and remote classes.



In the new classroom paradigm above[39] the teachers should possess both technological fluency and heightened emotional intelligence, enabling them to make informed decisions about when to leverage neurotechnology data and when to rely on conventional human interaction to understand the student's learning and human path. Previous studies on applied classroom

[39] Taherisadr, M., Demirel, B.U., Faruque, M.A., & Elmalaki, S. (2021). Future of Smart Classroom in the Era of Wearable Neurotechnology. *ArXiv, abs/2110.11475*.

instruction[40], have been investigating how teacher leverage other biosensors analytics, they show to what extent it can be complex for teachers to navigate the intricacies of including stress analytics dashboards or other multimodal learning analytics to their teaching and pedagogy[41].

Educational institutions leveraging neurotechnology may also navigate complex ethical considerations regarding student data privacy and cognitive autonomy, while simultaneously using neurotechnology to create more inclusive environments that accommodate diverse learning needs. As neurotechnology potentially becomes increasingly integrated into educational settings, the teacher space will be increasing crowded with data and algorithmic feedback, it is thus essential to target teachers for capacity building as they will stand as the core human in the loop that both guides and preserves human contact and mentoring—maximizing technological benefits while ensuring learning remains a fundamentally human experience.

Targeting the teacher space: the neuro-enhanced classroom pedagogical shift

By focusing on the transformation of learning and pedagogy through the introduction of neuro-analytics in the classroom. It is in first line important to understand that neuro technology is making the teacher space be an overcrowded space. As shown in the neuro-augmented classroom schema, the teacher has not only the feedback of quizzes, task assignments, but has also a lot of information about the students' physiological and mental states, be it in the classroom or remote classroom configuration. Therefore, it is essential to develop thoughtful educational capacity building to target this very central space which is mainly interfacing with AI and recommendation engines that target and analyze the data of neuro technology wearables from students.

As neurotechnology enters in the teacher-student space the following critical element should be tracked:

1. **Digital divide** can be widened by unequal access to quality learning.
2. **Transparency** for the learner and for the teacher on the learning process.
3. **Risk of social and gender biases**, as observed in the latest developments of generative AI.
4. **Diluting the human interaction**: the trust dimension and its emotional and society building effect.
5. **Risks of automation biases**: loosing competences and responsibility shifts to the learner or the tech tools.
6. **Privacy and autonomy**: technological consequences on the right to privacy for the learner, and autonomy for example through neuro-data portability.

[40] Dahlstrom-Hakki I., Asbell-Clarke J., Rowe E. (2019). Showing is knowing: The potential and challenges of using neurocognitive measures of implicit learning in the classroom. *Mind, Brain, and Education*, 13(1), 30–40. https://doi.org/10.1111/mbe.12177.

[41] Alfredo, R. D., Nie, L., Kennedy, P., Power, T., Hayes, C., Chen, H., et al. (2023). "That Student Should be a Lion Tamer!" StressViz: Designing a Stress Analytics Dashboard for Teachers. LAK23: 13th International Learning Analytics and Knowledge Conference, 57–67.

II. Neuro-markers to track individual learning outcomes

If the young discipline of educational neuroscience has been exploring the cognitive processes that underlie learning[42], practical insights from teachers and trainers should now be integrated into Ed-Neurotech product developments. Specifically, at a scientific research level, four directions of work are generally identified:

1. Investigation of general abilities and functions subserving the learning process (such as attention, emotion regulation, engagement).
2. The impact of some basic physiological requirements for better learning (impact of sleep, nutrition).
3. The focus on elementary education to be built upon for advanced education (reading, writing, calculus).
4. Finally the research direction targeting specific needs in population with small to major disabilities or with specific educational needs like attentional disorders.

Analysis and typology of neuro-markers in learning environments

When it comes to education, it is crucial to understand what scientifically lies behind the neuro-markers that target intervention in capacity building. These cognitive biomarkers identified in cognitive neuroscience are sometimes complex neural signatures identified through neuroimaging as proxy measures of cognitive and metal states and processes. Only careful task and study design in cognitive neuroscience of education, coupled with precise interpretation of neurophysiological data within learning performance contexts, will enhance the validity of EEG-monitoring educational experiments. This methodological precision directly improves data reliability and strengthens the generalizability of research findings across educational settings and populations.

Figure 19 illustrates three categories of neuro-markers that can be monitored and utilized in educational settings.

Individual-level markers focus on cognitive metrics for a single learner and encompass proxy measures of

1. **Cognitive load**: Measuring the mental effort being used in working memory.
2. **Focus**: Tracking attention levels and concentration during learning tasks.
3. **Memory enhancement**: Monitoring how effectively information is being encoded and stored.

[42] Antonenko, P.D. (2019). Educational Neuroscience: Exploring Cognitive Processes that Underlie Learning. In: Parsons, T.D., Lin, L., Cockerham, D. (eds) Mind, Brain and Technology. Educational Communications and Technology: Issues and Innovations. Springer, Cham. https://doi.org/10.1007/978-3-030-02631-8_3.

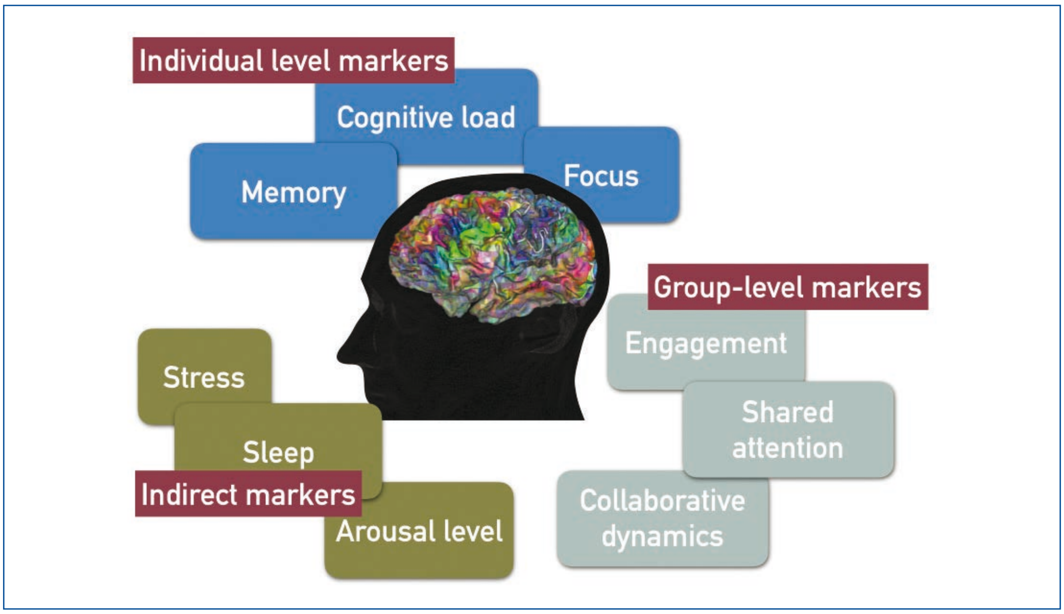
These markers could help personalize learning experiences by identifying when a student is overwhelmed, optimally challenged, or under-stimulated, allowing for real-time adjustments to instructional difficulty.

Group-level markers track and capture collective learning dynamics encompassing proxy measures of

1. **Engagement:** Measuring overall interest and participation across learners[43].
2. **Group level attention:** Monitoring collective focus and attentional patterns through proxy measures like brainwaves synchrony (see Figure 20).
3. **Collaborative dynamics:** Tracking interaction patterns and knowledge sharing.
4. **Arousal level:** Measuring collective emotional and physiological response.

These group-level metrics could radically change smart classroom dynamics by providing insights into group dynamics, helping educators identify when collaboration is effective or when the collective attention is waning.

Figure 19.
Mapping of educational, cognitive, and behavioral neuro-markers illustrates three categories of neuro-markers that can be monitored and utilized in educational settings, with a focus on identifying neuro-markers for attention, engagement, and collaborative dynamics.



[43] Cohen S. S., Madsen J., Touchan G., Robles D., Lima S. F., Henin S., Parra L. C. (2018). Neural engagement with online educational videos predicts learning performance for individual students. *Neurobiology of Learning and Memory*, 155, 60–64. https://doi.org/10.1016/j.nlm.2018.06.011. Engagement can be captured at individual level also with other biomarkers, see Bustos-López et al. 2022 for a review. Bustos-López, M., Cruz-Ramírez, N., Guerra-Hernández, A., Sánchez-Morales, L. N., Cruz-Ramos, N. A., and Alor-Hernández, G. (2022). Wearables for engagement detection in learning environments: a review. *Biosensors* 12:509. doi: 10.3390/ bios12070509.

Indirect markers monitor physiological factors affecting learning like:

1. **Stress**: Tracking stress indicators that may impede learning.
2. **Sleep**: Monitoring sleep patterns that influence cognitive performance.

These indirect measures acknowledge that learning doesn't occur in isolation from physical wellbeing, providing a more holistic view of factors influencing educational outcomes, along this view emotion-related measure of arousal or nutritional factors (e.g., simple nutrition or light neuro-pharmaceutical) could also be classified as indirect.

This three-tiered typology effectively shows how a neurotechnology product can operate at multiple levels simultaneously, from individual cognitive processes to group dynamics to integrating physiological states, potentially creating more responsive and effective learning environments. However, this comprehensive monitoring also raises important ethical questions about privacy, consent, and the potential "medicalization" of education.

Neuro-markers for e-learning: individual and group-level questions

E-learning configuration is transforming learning in an experience where learners are no more in the shared space of the classroom. In this distal learning setting, being able to track group-level markers can be viewed as a proxy to grasp collaborative dynamics and try and enhance them. Alternatively, it can help to sense at individual level engagement, arousal level, attention, and interest of learners at distance. Preliminary studies have been experimenting this distal learning configuration to assess attention in online courses[44].

Learning with neuro-analytics tracking: open questions

When the mental state of a learner is tracked (e.g. stress, engagement, interest, focus, excitement, relaxation) many questions worth consideration and research are raised.

Namely, what is emotionally happening in the student? Additionally, one may question what is the relationship one has with his own scoring? What could be considered normal, not normal? And what will the teacher say about my neuro-analytics? And finally, how can mental privacy be understood in this context? And especially, when neuro-analytics are tracked in apps using "thumbs up" or gamified through time constraints, or even through winning points, what is the personal experience a learner has of such product design? Are addictive patterns developed through gamification?

[44] Aggarwal, S., Lamba, M., Verma, K., Khuttan, S., & Gautam, H. (2021). A preliminary investigation for assessing attention levels for Massive Online Open Courses learning environment using EEG signals: An experimental study. Human Behavior and Emerging Technologies, 3(5), 933-941. https://doi.org/10.1002/hbe2.274.

All these questions merit to be closely scrutinized, especially after the documented examples of addictive design harms of social platforms and apps. Answering experimentally to these challenges and open question is important to craft significant and healthy pedagogical innovation in the neurotechnology space.

The last decade has been the testing ground for several pilot studies on individual learning outcomes[45] and in higher education[46], either by targeting the issue of cognitive performance in the classroom or by assessing the reality check that certain EEG neuro-markers where effective markers of cognitive abilities to be deployed in training and learning environments[47] and specifically in classrooms[48] (see Annexes, Table of 26 studies).

III. Group-level neuro-markers tracking class dynamics in learning

Scientific grounding of group-level neuro-markers to empower teachers: focus and engagement

Exploration of the pedagogical interest of group-level neuro-markers to then use them as pedagogical neuro-analytics is the third direction to take for capacity building for distal learning settings and in the domain of collaboration and communication tasks. Prioritizing the scientific meaningfulness of group-Level neuro-markers to empower teachers implies a focus on how to track engagement through the synchrony of the temporal recording of brainwaves.

Group-level neuro-markers, particularly brain-to-brain synchrony measurements, represent a transformative opportunity for adult education by providing instructors with insight into collective engagement. Research has repeatedly demonstrated that when students exhibit high neural synchrony during instruction as depicted in Figure 20, they are sharing attentional focus and engagement—a phenomenon replicated across several studies and that it can serve as a predictor of learning outcomes[49].

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[45] Apicella, A., Arpaia, P., Frosolone, M. et al. EEG-based measurement system for monitoring student engagement in learning 4.0. Sci Rep 12, 5857 (2022). https://doi.org/10.1038/s41598-022-09578-y.

[46] Ramírez-Moreno, M. A., Díaz-Padilla, M., Valenzuela-Gómez, K. D., Vargas-Martínez, A., Tudón-Martínez, J. C., Morales-Menendez, R., et al. (2021a). EEG-based tool for prediction of university students' cognitive performance in the classroom. Brain Sci. 11:698. doi: 10.3390/brainsci11060698 Ramírez-Moreno, M. A., Carrillo-Tijerina, P., Candela-Leal, M. O., Alanis-Espinosa, M., Tudón-Martínez, J. C., Roman-Flores, A., et al. (2021b). Evaluation of a fast test based on biometric signals to assess mental fatigue at the workplace—a pilot study. Int. J. Environ. Res. Public Health.

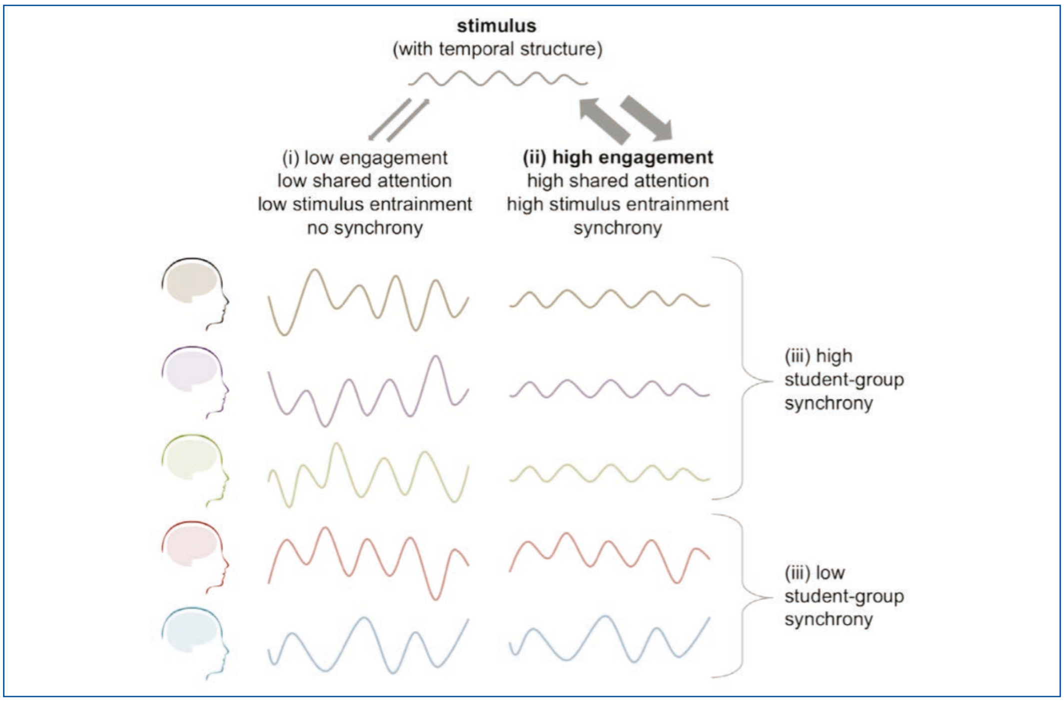
[47] Davidesco, I., Matuk, C., Bevilacqua, D., Poeppel, D., & Dikker, S. (2021). Neuroscience Research in the Classroom: Portable Brain Technologies in Education Research. *Educational Researcher*, *50*(9), 649-656. https://doi.org/10.3102/0013189X211031563.

[48] Babiker, A., Faye, I., Mumtaz, W. et al. EEG in classroom: EMD features to detect situational interest of students during learning. Multimed Tools Appl 78, 16261–16281 (2019). https://doi.org/10.1007/s11042-018-7016-z.

[49] Davidesco I., Laurent E., Valk H., West T., Dikker S., Milne C., Poeppel D. (2019). Brain-to-brain synchrony between students and teachers predicts learning outcomes. *bioRxiv*, 644047. https://doi.org/10.1101/644047.

Figure 20.

Neuro-markers of a student group indicating level of attention inside the classroom.



For a teacher, it is fundamental to understand what individual and group-level neuro-markers mean for learning outcomes to adapt communication and pedagogy accordingly. Thus, selecting neuro-markers, like brainwaves synchrony, that are adapted to the pedagogical context and that have a stable and real scientific grounding is the priority for an informed and responsible adoption of neurotechnology in the classroom and beyond[50]. By prioritizing the development and implementation of these synchrony metrics in both traditional and smart classroom environments, educators gain access to objective feedback on instructional paths that transcends traditional assessment limitations, allowing for dynamic pedagogical adjustments that respond to the collective cognitive state rather than relying solely on visible behavioral cues. A final careful note is nonetheless necessary in order to stress the fundamental risks of (1) over relying on such metrics and possibly losing the focus on teachers' experience -based understanding of classroom dynamics, or (2) the issues underlying the possible use of these metrics to algorithmically and blindly evaluate teachers.

Shared attention as a possible account of the observed brain to brain synchrony.

As shown in Figure 20, brain-to-brain synchrony can be used as a possible account of shared attention across students participating to the same class[51]. By calculating the synchrony

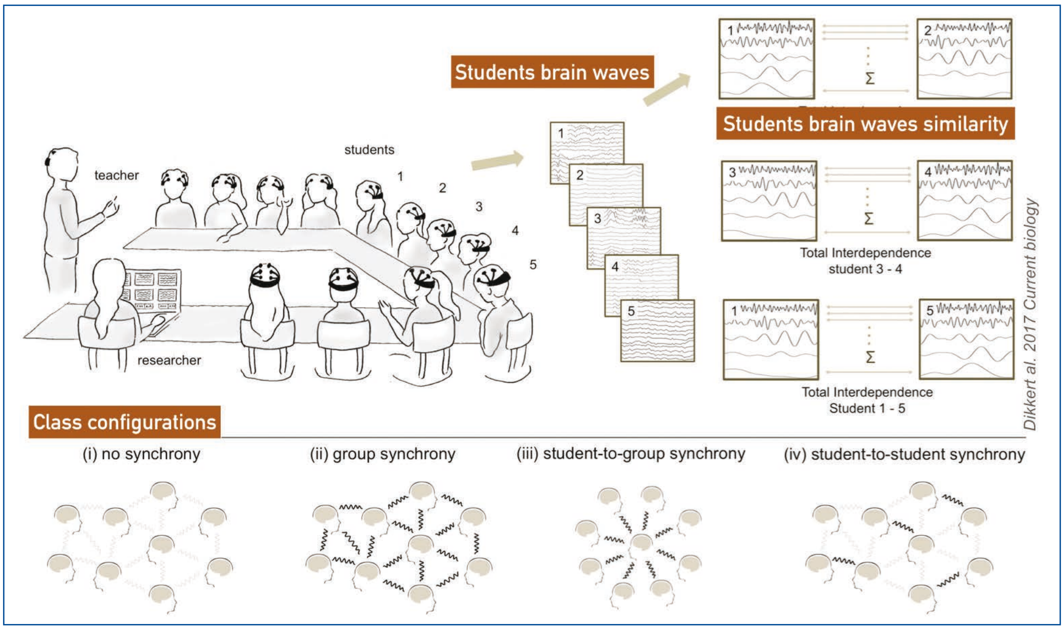
[50] Antonenko P. D. (2019). Educational neuroscience: Exploring cognitive processes that underlie learning. In Parsons T., Lin L., Cockerham D. (Eds.), *Mind, brain and technology. Educational communications and technology: Issues and innovations* (pp. 27–46). Springer https://doi.org/10.1007/978-3-030-02631-8_3.

[51] Bevilacqua D., Davidesco I., Wan L., Chaloner K., Rowland J., Ding M., Poeppel D., Dikker S. (2019). Brain-to-brain synchrony and learning outcomes vary by student–teacher dynamics: Evidence from a real-world classroom electroencephalography study. *Journal of Cognitive Neuroscience*, 31(3), 401–411.https://doi.org/10.1162/jocn_a_01274.

between what is being heard and what the brain waves of an individual look like, one can find that one group has a high synchrony, while the other group has a low synchrony. If this hypothesis that has been repeatedly replicated in the research literature[52], having the possibility to experiment on these group neuro-markers, is the only way to be sure that they are meaningful for education both in class and in a smart classroom. Figure 21 is representing the setting with students wearing their neuro-wearable EEG-headsets to record brainwaves and then calculate brainwaves' similarity, both at the level of the group, or between two students. If the listeners' brain dynamics are more similar, they cluster together with the speaker and with the students engaging in shared attention[53]. Interestingly, seminal research work has been given some initial scientific grounding to using EEG to explore team neuro-dynamics during distal collaborative problem solving[54].

Figure 21.

Illustration reproduced from Dikker et al. (2017) of the general classroom recording setup for each session. Bottom: Different synchrony configurations in the class can be observed, between student-to-teacher, but also student-to-group (iii) can be explored in relation to performance and social factors. Dikker et al 2021 findings confirmed that EEG-based brain-to-brain synchrony is a sensitive measure that can predict dynamic classroom interactions, and this relationship may be driven by shared attention within the group.



[52] Dikker S., Michalareas G., Oostrik M., Serafimaki A., Kahraman H. M., Struiksma M. E., Poeppel D. (2021). Crowdsourcing neuroscience: Inter-brain coupling during face-to-face interactions outside the laboratory. *NeuroImage*, 227, 117436. https://doi.org/10.1016/j.neuroimage.2020.117436 Dikker S., Wan L., Davidesco I., Kaggen L., Oostrik M., McClintock J., Rowland J., Michalareas G., Van Bavel J. J., Ding M., Poeppel D. (2017). Brain-to-brain synchrony tracks real-world dynamic group interactions in the classroom. *Current Biology*, 27(9), 1375–1380. https://doi.org/10.1016/j.cub.2017.04.002.

[53] Neurosynchrony in teamwork is a long studied topic. A semial work analyzed neurosynchrony between team members during submarine piloting simulations, by focusing on EEG-derived measures of cognitive engagement. Stevens, R. H., Galloway, T. L., Wang, P., & Berka, C. (2012). Cognitive neurophysiologic synchronies: What can they contribute to the study of teamwork? Human Factors, 54(4), 489–502.

[54] Antonenko, P. (2016). On the same wavelength: Exploring team neurosynchrony during technol- ogy-enhanced collaborative learning. In Proceedings of the 2016 Conference of the National Association for Research in Science Teaching (p. 154), Baltimore, MD. Retrieved from: http://narst.org/annualconference/NARST_2016_Abstracts.pdf.

The herding hypothesis: a new neuro-marker for group-level engagement dynamics

The “herding hypothesis” further strengthens the case for investigating the educational impact of group-level neuro-markers. Recent neuroimaging studies reveal that listeners who better follow a speaker show increased neural clustering—both with each other and with the instructor. The fundamental idea being that *the better the listener followed the speaker, the closer the listener clustered together*. This progressive increase in neural pattern similarity across a group listening to a narrative can serve as a powerful proxy for listening engagement during an educational course[55].

For distance adult learning environments, identifying which teaching approaches, content presentations, and interactive methods generate the highest levels of group synchrony, could give substantial evidence to changes in instructional design, by helping instructors to empirically refine their practices to maximize collective engagement. Some recent piloting in real educational scenarios have shown promising results[56].

Evidence-based approach to measuring group cognitive states without identifying each individual learners represents perhaps the most immediately implementable and ethically straightforward application of neurotechnology in the classroom, offering concrete benefits while minimizing the privacy concerns associated with individual-level cognitive monitoring.

C. Action plan

As we conclude Part III, it is clear that neuro-technologies present transformative potential for learning and capacity development in and out of classrooms settings. However, given the possibly wide effects on individuals’ capacities and classroom dynamics, and being conscious of the ethics and privacy challenges together with the inclusion and collaborative enhancement potentials, a six steps action plan for exploratory adaptation to educational needs, classroom piloting and full-fledged sandbox experimentation is synthetically delineated in the following action plan (summarized in Figure 21) and further detailed in the Part IV.

[55] Claire H C Chang, Samuel A Nastase, Asieh Zadbood, Uri Hasson, How a speaker herds the audience: multibrain neural convergence over time during naturalistic storytelling, Social Cognitive and Affective Neuroscience, Volume 19, Issue 1, 2024, nsae059, https://doi.org/10.1093/scan/nsae059.

[56] Mendoza-Armenta, A. A., Blanco-Téllez, P., García-Alcántar, A. G., Ceballos-González, I., Hernández-Mustieles, M. A., Ramírez-Mendoza, R. A., Lozoya-Santos, J. d. J., & Ramírez-Moreno, M. A. (2024). Implementation of a Real-Time Brain-to-Brain Synchrony Estimation Algorithm for Neuroeducation Applications. *Sensors*, *24*(6), 1776. https://doi.org/10.3390/s24061776.

Effects on individuals' capacities

Need for testing the educational and psychological effect of market-ready Neurowearables and neuro-analytics apps

If these technologies have a proven and quantified effect on enhancing individuals' capacities to learn and communicate, they will open new pathways for knowledge acquisition and skill development, and for ever-evolving pedagogical responses to today's learning challenges.

- **Question:** What are the effects of monitoring learners mental state?
- **Testing agenda:** Test the psychological and learning impact of focus, engagement and stress monitoring with on the shelf EEG Neuro-wearables.
- **Method:** In a pilot study, establish regular questionnaires to track the experience of learners being monitored through EEG Neuro-wearables and neuro-analytics apps. Questionnaires centered around questions related to student engagement, cognitive load, and self-regulation.
- **Priority:** Ensure a healthy and privacy preserving deployment of neuro analytics tracking.

Effects on classroom dynamics

Explore the Future of neuro-assisted Smart Classroom

Leveraging on EEG-Wearable Neurotechnology alongside with ongoing progress in neuroscience and machine mearning neuro-data processing, exploratory adaptation testing on how teachers and learners perceive neurotechnology leading in the classroom can be easily achieved through classroom piloting of market ready neurotech products

- **Question:** What are the new learning dimensions and challenges when neurotechnology lands in the student-teacher relationship?
- **Testing agenda:** Gather feedback after piloting in the neuro-enhanced class & smart classroom:
  - Investigate the new learning dimensions and challenges when Neurotechnology lands in the student-teacher relationship.
  - Understand the Neuro-enhanced classroom pedagogical shifts seen from the teacher point of view.
- **Method:** Establish regular questionnaires to track the experience of teachers in the neuro-augmented class and smart classroom, focusing on (1) student-teacher relationship and (3) pedagogical shifts.
- **Expected outcome:** Preserve the teacher-space as the human-in-the-loop in the neuro-assisted classroom.

Empower the teachers to become the Teacher-in-the-loop

In today's rapidly evolving technological landscape, teachers and educators are at turning point where they can play the role of critical bridge between AI-powered technologies, neuroscientific innovation, and practical classroom experience. Integrating neuroscience content into teacher preparation and professional development has therefore become imperative, without forgetting that empowered educators can contribute valuable practical insights to technology refinement, and meaningful human experience. This knowledge empowers educators to critically assess neurotechnology applications, interpret neuro-analytics data within appropriate educational contexts, and make informed decisions about their implementation in diverse learning environments and for different learners' profiles. Without this targeted neuroscience literacy, the educational potential of these technologies may remain unrealized or, worse, be misapplied through misunderstanding of the underlying cognitive processes.

- **Question:** How to empower teachers and prevent that human connection—the heart of learning—gets replaced by Neurotech devices and AI algorithms? How to ensure educators can play the role of critical bridge between neuroscientific innovation and practical classroom?
- **Curricula agenda:** Teach the science behind neural signatures and cognitive neuro-markers. As educational neurotechnology advances from research laboratories into classrooms, teachers must develop foundational knowledge of brain function, cognitive processes, and neurological development to effectively implement and evaluate these tools.
- **Method:** Build a three layers approach teaching the basics about the brain and education, then teaching about neurotechnology and finally teaching about neurotechnology for education.
- **Expected Outcome:** Ensure proper understanding of neuroscience behind the technology and improving teachers' critical analysis of neuro-analytics embedded in consumer-grade neuro-technologies on the market, for successful adoption of these tools in classrooms.

Conscious about the challenges

Advocacy: Neurotech manifesto in education

Beside the impressive technological success of neurotechnology one must remain vigilantly conscious of the challenges that persist in implementing these technologies responsibly. A truly human-centered approach to neurotechnology in training and capacity development requires ongoing ethical reflection and action, privacy protections, and autonomy and equitable access considerations. Only by addressing these challenges proactively it is possible to ensure that technological advancement serves human dignity and social justice rather than undermining them. The path forward demands critical awareness while piloting and experimenting about the possibilities that Neuro-technological responses entail for training and capacity development.

- **Question:** How can we integrate ethical positions to research design and methods in educational neuroscience? What policy considerations can be deducted from the above Pilots questionnaires in 1 and 2?

- **Policy agenda:** Advocacy for (1) equity in access to neuro-technology, (2) privacy together with (3) Human Rights impact assessment by design.
- **Method:** Address first testing individuals' capacities (#1) and on classroom dynamics (#2) to nurture a cognizant approach of the challenges and root the Manifesto in initial ground testing.
- **Expected Outcome:** preserving learner autonomy and dignity of learner and empowering the teacher space.

Inclusion component

Need for experimenting for learning reality-check on individual neuro-markers

Importantly, if neuro-technologies can offer unprecedented opportunities for inclusion, enabling access to better education for populations marginalized by frequent or under-detected syndromes like ADHD, or excluded from traditional learning environments, it is essential to appropriately address the challenges of adapted neuro-assisted learning path with specific tools, to test for example ADHD learning outcomes with neuro-feedback form appropriate neuro-analytics at the interface with academics working on these types of learning impairments.

- **Question:** How can we leverage neuro-technologies for more inclusive, just and tailored learning paths?
- **Experimental agenda:** Design sandbox experiments to address the challenges of neuro-enhanced learning to support ADHD learning path.
- **Method:** Partner with companies at the nexus between academia and neurotech that already developed solutions to address ADHD to propose adult testing ground and longitudinal (e.g., Propel).
- **Expected Outcome:** Establish links between the rapidly expanding field of neuroscience and the practice of education for learning disabilities.

Learning beyond individual performance in a Lab setting

Need for piloting distal learning group-level neuro-markers

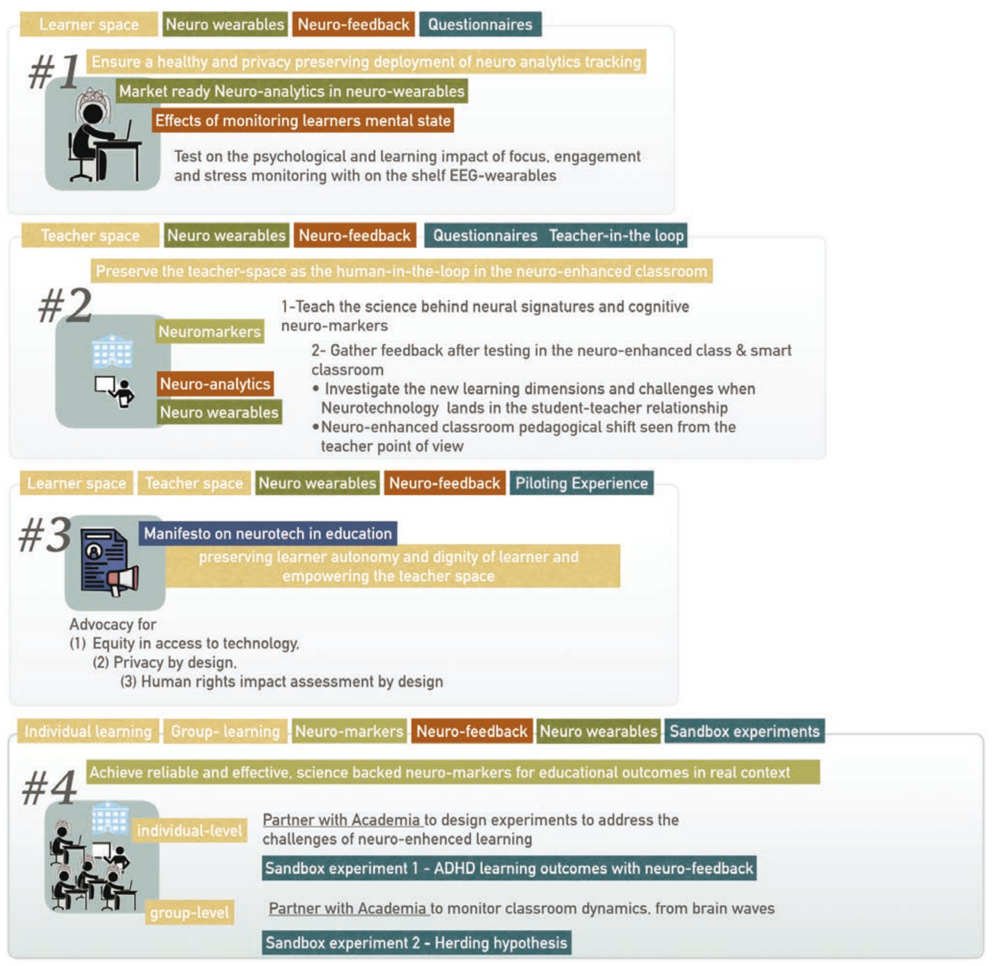
If educational systems increasingly incorporate neurofeedback, attention-monitoring, and cognitive load assessment neuro-analytics, collective learning dynamics risk to be undermined. Therefore, investing in understanding pedagogical shifts becomes not merely advantageous but essential for responsible and effective integration of these tools in collaborative adult learning settings.

Not only Neurotech-induced pedagogical shifts require a new vision for working together of scientists, educators, together with the new profile of the educational neuroscientist but, as cognitive neuroscience research is typically conducted in controlled laboratory environments, educators' contribution to understanding of learning in real-world environments is critical.

EEG Neuro-wearable classroom-based experiments can shed light on how Neuroscience findings can generalize to smart classroom contexts.

- **Question:** How can we leverage neuro-technologies for more inclusive, just, and tailored learning paths in distal learning?
- **Experimental agenda:** Design sandbox experiments to monitor of classroom dynamics through brain waves synchrony to address the challenges of distal learning.
- **Method:** Partner with academia to propose adult learning testing ground at ITC-ILO to investigate the viability of group-level neuro-markers for attention-monitoring, cognitive load, and collective learning dynamics in a classroom-based EEG-wearable experiments and smart classroom contexts
- **Expected outcome:** Achieve reliable and effective, science backed neuro-markers for educational outcomes in real context and distal learning.

Figure 22.
The recommended 6 steps action plan for integrated capacity building at ITC-ILO.



PART IV. NEUROTECHNOLOGY AND CAPACITY DEVELOPMENT INTERVENTION IN EDUCATION

From research to action.
The experimental spectrum for follow-up capacity development support

After having shown the compounding impact AI and neurotechnology can have on learning outcomes in Part II and III, we must now address the necessary capacity development interventions required across multiple levels of the educational ecosystem. Part IV presents strategic recommendations for interlinked interventions at three critical levels: enhancing the skills and abilities of individuals; strengthening organizational capacities to fulfill educational mandates; and facilitating improvements in policies, legislation, regulations, labor market institutions, and broader societal systems.

These recommendations and experimental planning are designed within a framework that acknowledges the dynamic and iterative nature of capacity development, requiring continuous feedback loops and participatory analysis to refine approaches as implementation progresses.

Our primary aim is to prepare educational stakeholders for inevitable technological change and to facilitate just digital transitions as we move toward the future of education in 2030. This preparation must be grounded in evidence-based approaches that leverage strategic foresight techniques to design forward-looking policies and programs.

By integrating insights from neuroscience and behavioral science into decision-making processes, more effective interventions can be developed, that consider fundamental human factors in technology adoption like the psychological impact of neuro-analytics tracking in the learning context. The experimental stepped approach we propose encompasses, individual-level neuro-analytics, the teacher space (including training and curricula development), and class/group neuro-markers that can potentially herald shifts in cognitive engagement and learning outcomes.

In pursuing this agenda, **three core priorities** should guide evidence-based implementation efforts:

1. **Achieve reliable and effective, science backed neuro-markers for educational outcomes in real context** First, we must achieve reliable and effective science-backed neuro-markers for educational outcomes in real-world contexts, ensuring that the data collected genuinely reflects meaningful learning progress.

2. **Preserve the teacher-space as the human in the loop classroom design** Second, we must preserve the teacher space as the critical human-in-the-loop element in classroom design, recognizing that technology should enhance rather than replace the essential role of educators in guiding learning experiences.
3. **Ensure a healthy and privacy preserving deployment of neuro analytics tracking** Third, we must ensure healthy and privacy-preserving deployment of neuro-analytics tracking, establishing robust safeguards that protect learner data while still enabling beneficial applications of these technologies.

The coordinated interventions proposed in this chapter operate as a dynamic cycle, recognizing that capacity development is not a linear process but occurs through iterative loops at different level of educational ecosystem (e.g., student autoregulation, teacher space, classroom dynamics or long-term curricula) and its technological stack and infrastructure (e.g., data, cloud, wearables) that demand ongoing assessment and adjustment. By fostering simultaneous development across individual capabilities, organizational structures, and system-level frameworks, a resilient educational ecosystem can be enhanced by harnessing neurotechnology's benefits while mitigating identified risks. This approach acknowledges the complex interplay between technological innovation and human factors, positioning evidence-based experimentation and strategic foresight as essential tools for navigating the rapidly evolving landscape of educational neurotechnology and fostering for forward looking polices.

A. Capacity building strategy through experimentation and recommendations for neurotech lifelong learning

I. Individual level experimental recommendations

Invest in experimenting at the level of the individual impacts on learning experiences through neurofeedback in learners with disabilities.

Investing in neurofeedback experimentation represents a critical frontier for understanding how neurotechnology can enhance personal learning experiences. This investment should focus on controlled studies that measure specific cognitive outcomes when learners receive real-time feedback about their brain activity during or close to educational tasks. Such experiments would establish baseline measurements of attention spans, cognitive load, and information retention, allowing for the development of personalized learning interventions based on individual neurological responses in both adult learners and learners with disabilities. The current state of translation neuroscience research has stated to deploy neurofeedback therapy apps that can address the treatment of disabilities related to ADHD or PTSD. While ADHD impacts the work and career of around 11 million of US adults, migrant populations show an increasing prevalence of PTSD.

Nowadays there are systems that are built to assist people with ADHD that experience issues in being productive and working in everyday life despite the therapies and drugs[57]. While the main whole idea behind these interventions is simply to help learners and workers to identify priorities, measure focus, optimize schedules based on patterns that were learned from individual focus patterns, these tools start to prove their effectiveness in helping ADHD workers to perform better and increase their task completion rate. Based on neurotechnology and AI, these types of applications use computer vision and AI tracking to predicts a lot of the focus metrics. By taking subjective measurement of the focus, a focus score is measured and tracked to yield monthly trends that can be coupled with learning outcomes.

Direct investigation of whether individual-level neuro-analytics improve educational outcomes is essential

Direct investigation into educational outcome improvements through neurotechnology requires rigorous assessment protocols that combine traditional academic measurements with neurological data in real world learning settings. These investigations can be meeting point of academia and private sector together with the public good and social justice focus of ITC-ILO unite forces to address evidence based forward looking experimentation, through mid- to longitudinal studies tracking students who use neuro-analytics apps against control groups to determine whether meaningful learning performance differences emerge over time, and whether continuous tracking of brain waves and the associated mental state by the learner himself of by teachers has a negative or positive psychological effect, for example over self-esteem. The research must account for variables such as subject matter, learning environment, and pre-existing cognitive abilities to isolate the specific impact of neurotechnology interventions and their impact on students' mental health.

Targeting the Learner Individual-level: assessment of the psychological impact of learners' brain tracking

When addressing what it means to learn with neuro-analytics, there remain a set of open questions on the impact on learners of mental states tracking, that should be further addressed in empirical approaches to capacity building. The assessment of the psychological impact of learners' brain and mental state tracking should encompass the following questions:

1. Relation to my scoring?
2. What counts as 'not normal', 'normal' or enhanced?
3. What does mental privacy mean in this configuration?
4. What will the teacher say about my neuro-analytics?
5. What is the effect on learning and on the learner mental health of the visualization features found in consumer devices (e.g., thumb up/thumb down or gamification of neuro-analytics through point gathering for personized insights).

[57] See as an example of sandbox experiment a Neurotech tool developed by Academics at Northwestern University (Canada) to help ADHD to manage everyday focus: https://www.propelfocus.com.

Implementation in students' learning path of neuro-analytics tools, tracking focus engagement interest, stress, excitement or relaxation at the individual level necessitates careful attention to accessibility, usability, and ethical considerations. Educational institutions adopting these technologies should establish clear protocols for data collection, storage, and interpretation that protect student privacy while maximizing learning benefits. Training programs for students in self-regulation techniques based on neurofeedback can enhance their metacognition, potentially creating lasting improvements in their capacity to direct their own learning processes effectively.

II. Organization level recommendations

Target the teacher space in neuro-enhanced learning or in e-learning to understand how to leverage students' neuro-markers for forward looking pedagogical developments

Targeting the teacher space represents a strategic approach to integrating neuro-enhanced learning into educational frameworks. Organizations should develop comprehensive professional development programs that train educators to interpret neuro-markers and adjust teaching methodologies accordingly. This requires creating interfaces that translate complex neurological data into actionable pedagogical insights, enabling teachers to recognize patterns in student engagement and cognitive processing in real-time, thereby facilitating immediate instructional adjustments and more fundamental pedagogical developments in the long run to fit the learners needs.

The teacher space is the most fundamental because it is the space where the human in the loop priority can take place in such a new neuro-assisted classroom configuration and it is thus the first and most urgent target for a capacity building approach that is rooted in the perspective of understanding human rights impact developed in the Report of the Human Rights Council Advisory Committee (Aug 8, 2024) by the UN General Assembly, 'Impact, opportunities and challenges of neurotechnology with regard to the promotion and protection of all human rights', to be able to harness Social Justice and to delineate a concrete capacity building strategy for ILO constituents and other ILO development partners.

Teach the science behind cognitive neuro-markers to teachers

Crucially, if teachers do not master the implications of neuro markers and cognitive patterns observables through neurotechnology the benefits of neuro-enhanced pedagogical paths fall short and even the ripest neurotechnological educational tool won't be leveraged. Hence, teaching the science behind neuro-markers should be incorporated into teachers' preparation programs and ongoing professional development.

These educational initiatives must cover the neurobiological foundations of learning, the technical aspects of neurotechnology data collection, and appropriate interpretive frameworks for classroom application. Organizations should establish communities of practice where educators can share experiences, discuss challenges, and collaborate on developing best practices for neuro-enhanced teaching methodologies.

Organizational infrastructure should evolve to support neuro-enhanced educational environments. This includes infrastructure and technical systems for data collection and analysis, revised administrative procedures that incorporate neurological insights into educational planning, and modified physical learning spaces that minimize neurological distractions while maximizing engagement. At his organizational level, educational institutions should develop feedback loops between neurological data analysis teams and instructional designers to ensure continuous refinement of teaching approaches based on empirical neurological evidence.

Targeting the class-level: Experiment on group-level neuro-markers in smart classrooms

Group level neuro-markers can help bridge the gap between the teacher and the classroom in distal learning, Notably, group brain waves synchrony as a proxy of better shared attention deserve a special focus to understand how these measures can be adapted outside the classroom. As brain-to-brain synchrony can be used as a possible account of shared attention across students participating to the same class, one may evaluate engagement and attention following the rational that the better the listener follow the speaker the closer the listeners cluster together. By calculating the synchrony between what is being heard and what is the brain waves of an individual look like, one can find that this group has a high synchrony, while this group has a low synchrony. Relevant open questions on the impact on class dynamics recorded at the level of neuro-wearables can be addressed by experimentation in collaboration with academics that developed these neuro-makers and the herding hypothesis (see Part III B 3) and companies developing neuro-wearables.

III. Eco-system level actions

Coordinated action to experiment on the validity and operability of neuro-markers for the future of learning

Ecosystem-wide experimentation on neuro-marker educational validity and interoperability requires coordinated efforts across multiple educational institutions, research facilities, and technology developers. These collaborations should establish standardized protocols for neuro-data collection that enable cross-institutional comparisons while accommodating diverse learning environments. Such large-scale coordination in experimentation would accelerate the identification of reliable and pedagogically effective neuro-markers that correlate with successful learning outcomes across different demographic groups and educational contexts.

Build data commons or data spaces of neuro-data collected in classrooms to leverage in a privacy preserving setting the dynamics that can be observed

Building privacy-preserving neuro-data commons represent an essential infrastructure development for advancing neurotechnology in education. These data hubs would aggregate anonymized classroom neuro-data, creating comprehensive datasets that reveal patterns of cognitive engagement, learning progression, and knowledge retention across diverse populations. Governance frameworks for these commons must balance open research access with stringent privacy protections, employing advanced encryption technologies and transparent consent processes that maintain ethical standards while facilitating scientific progress.

Target ecosystem intervention by developing evaluation frameworks in a dynamic data- and evaluation-driven cycle of interventions

Targeting ecosystem interventions through dynamic, data-driven cycles requires **establishing evaluation frameworks** that track interventions from implementation through impact assessment and refinement. This approach necessitates developing standardized metrics for measuring neurotechnology effectiveness while maintaining flexibility to address context-specific factors. Additionally, creating regulatory frameworks that support responsible innovation while protecting learner interests will ensure that neurotechnology developments align with broader educational goals rather than merely pursuing technological advancement for its own sake.

B. Strategic Alignment with ITC-ILO Capacity Development Framework: Training, Learning and Neurotech

The International Labour Organization's capacity development strategy from 2019 provides a valuable framework for structuring this action research approach to neurotechnology integration in educational contexts. This framework identifies three interconnected levels of capacity development that mirror our proposed intervention structure: the individual level focused on enhancing personal skills and abilities; the organizational level aimed at strengthening institutional capacity to fulfill mandates; and the system level addressing improvements in policies, legislation, regulations, labor market institutions, and broader societal systems. By aligning the proposed neurotechnology experimentation initiatives detailed in Section A with this established framework, we can ensure a comprehensive approach that addresses both immediate educational applications and longer-term workforce development considerations relevant to educational outcomes.

Particularly significant is the ILO framework's distinction between technical and functional capacities across all three levels. In the context of neurotechnology and education, technical capacities encompass specific competencies in neuroscience application, data interpretation, and technology implementation. Functional capacities, meanwhile, include leadership in educational innovation, management of neurotechnology resources, budgetary considerations for technology acquisition, and relationship building between academic and educational institutions, technology developers, and regulatory bodies.

This dual focus ensures that the current capacity development recommendations address not only the technical aspects of neurotechnology implementation but also the organizational and leadership capabilities necessary for sustainable integration into educational systems, thereby creating a comprehensive framework for navigating the complex intersection of neuroscience, technology, and education.

Individual-Level Capacity

Individual level development encompasses the immediate objective of enhancing of cognitive performance of all learners including those with disabilities. This initiative focuses on leveraging neurotechnology to directly improve cognitive functions that support learning in order to test and assess if neuro-analytics do what they promise in learning. The primary means of action is to experiment on neuro-analytics for learning, and asses the psychological impact of neuro feedback and tracing in both adult learners and learners with disabilities such as ADHD in learners or PTSD in migrant populations.

The primary goal is to assess the reported psychological impact of neurotechnology-based interventions to optimize brain function during educational activities, potentially addressing areas such as attention, memory consolidation, and information processing. This represents a fundamental shift from traditional educational approaches by targeting the neurological underpinnings of learning rather than solely focusing on educational outcomes, thanks to wearables and selected neuro-analytics.

Institutional-Level Capacity

At the institutional level, the strategy identifies Responsible adoption of Neurotech in learning as one of the main and immediate objectives of an action research focusing on the teacher-level capacity building efforts. This institutional commitment emphasizes the ethical implementation of neurotechnology within educational organizations. It acknowledges that while neurotechnology offers significant potential benefits, its adoption must be governed by robust ethical frameworks that protect learner privacy, ensure informed consent, and prevent potential misuse of neurological data. The focus on responsibility suggests institutions must develop governance structures and policies specifically designed for neurotech integration that balance innovation with protection of individual rights. This includes means of actions based on:

1. Informing and teaching the fundamentals of neuro-markers to teachers.

2. Preserving a responsible human in the loop approach in the Neuro-augmented classroom by empowering teachers.
3. Developing through experimentation the processes and tools to leverage on neuro-analytics for inclusive and efficient pedagogical paths.

System-Level Capacity

The system-level addresses as an immediate objective to foster anticipatory improvements in policies, legislation, regulations, labor market institutions, and societal systems to yield positive change in education through neurotechnology. This represents the broadest scope of intervention, focusing on creating an enabling regulatory and social environment for neurotechnology in education. The anticipatory nature indicates a proactive rather than reactive approach to governance, suggesting the need to develop meaningful experimentation to inform frameworks before widespread adoption creates potential problems. This includes means of actions based on:

1. Advocacy through experimental reporting and a neurotech manifesto for future of learning, in order to catalyze dialogue and eco-system building around human rights-centric neurotech products, that would enable as a unique feature to embed social justice and human rights in the design and development of neurotech products.
2. Consideration of labor market implications as neurotechnology potentially changes skill requirements and educational outcomes, along with broader societal adjustments needed to accommodate neurotechnology's integration into learning systems.

Integration Across Levels

All together, these strategies illustrate a comprehensive approach that connects individual learners' cognitive enhancement with institutional responsibility, teacher awareness, and system-level governance. This multilevel action strategy acknowledges that successful integration of neurotechnology in learning requires coordinated development at all three levels to create sustainable, ethical, and effective implementation.

The central recommendation for an interlinked capacity development intervention to improve the preparedness of the Centre, of ILO constituents and ILO development partners to harness neurotechnology for better learning, and ultimately accelerate positive change along just digital transition pathways, is to target the bulk of the neuro-learning configuration that is the teacher space.

Figure 23.

Training + Neurotech & Learning: The ITCILO capacity-development service portfolio illustrated by neurotech and learning actionable and goals. The orange squares in this table represent specific actionable initiatives and strategic goals across three levels of capacity development in the context of neurotechnology applications for learning. Selected means of action are listed in the table above with neurotech/learning capacity development interventions at the different levels.

Individual-level

Organization-level

Ecosystem-level

	Immediate objective	Some means of action	Intended outcome	Unique feature
Individual capacity	To strengthen the delivery capacity of individuals	Teaching Training	Increased functional and technical skills, resulting in improved individual	Portability (skills move with the individual)
Individual capacity neurotech	Enhancement of cognitive performance of individuals	Experiment individual learning outcomes with Neurofeedback from Neuro-anlaytics	Testing if neuro-analytics do what they promise in learning	EEG Werables & neuro-analytics on smartphone
Institutional capacity	To strengthen the delivery capacity of organizations (representing individuals)	Consultancies Product development support	Improved institutional capacity to operate in a sustainable manner	Anchored at organizational level through processes and tools
Institutional capacity in neurotech	Responsible adoption of Neurotech in learning	Teach the fundamentals of the underlying cognitive/ learning neuro-markers to teachers	Preserve a responsible human-in-the-loop in the Neuro-augmented classroom	Develop through experimentation the processes and tools to leverage on neuro-analytics for inclusive and efficient pedagogical paths
System-level capacity	To strengthen the holding capacity of the system (within which organizations and individuals interact)	Research Policy advise Knowledge disseminatien (e.g. conferences Advocacy	A more enabling environment for interaction between individuals and institutions, and where applicable between social systems	Focus on the rules of the bigger game* (incl. values and perceptions)
System-level in neurotech	Anticipatory improvements in policies, legislation, regulations, labour market institutions, and societal systems	Neurotech manifesto and experimental reporting	Prevent Human connection—the heart of learning—gets replaced by neuro-analytics and AI powered recommendations	Embedding social justice and human rights in Neurotech development by design through collaboration with the stakeholders

ANNEXES

Abbreviations & Acronyms

FUS	Focus ultrasound
ADHD	Attention-deficit/hyperactivity disorder
PTSD	post-traumatic syndrome disorder
EcoG	Electro-corticography
FMRI	functional Magnetic Resonance Imaging
EEG	Electro-encephalography
MEG	Magneto-encephalography
PET	Positron Emission Tomography
DTI	Diffusion Tensor Imaging
fNIRS	functional Near-Infrared Spectroscopy
TMS	Transcranial Magnetic Stimulation
tDCS	Transcranial direct current stimulation
FES	Functional electrical stimulation
VNS	Vagus Nerve Stimulation
DBS	Deep Brain Stimulation

Physiological signals detectable through an EEG headband are features such as:

PSD	Power Spectral Density
SP	Signal Power
CSP	Common Spatial Pattern

Typically recorded measures in Biosensors:

HRV	Heart Rate Variability
HR	Heart Rate
EDA	Electrodermal Activity
GSR	Galvanic skin response
ST	Skin temperature
BVP	Blood pressure volume
ACC	Accelerometer data
IBI	Interbeat interval
SpO2	Oxygen saturation
BP	Blood pressure

ANNEX I – Tables review of experiments with EEG-wearables in education

Horizon scanning on EEG-wearables experimentations in education from 2018 to 2024. Tables hereunder summarize the Neuroeducation projects details of each study.

Source : Orovas, C., Sapounidis, T., Volioti, C., & Keramopoulos, E. (2025). EEG in Education: A Scoping Review of Hardware, Software, and Methodological Aspects. *Sensors*, *25*(1), 182. https://doi.org/10.3390/s25010182

* BP: Brain Products GmbH (also as Brain Vision LLC in the U.S).

Up-to-date consumer-level Neuro-wearables products (EEG-headphones/headbands-segment) by price: Eno ($399), MUSE ($495), Neurable ($699), Vital Neuro ($795), Neurosity ($1,200), Sense/ai ($1,500).

Id	Project	Subject	Sample	EEG Metrics	H/W Used	S/W Used	Wireless	Issues Addressed
1	Anderson et al. (2018)	Efficacy of Just in Time teaching in anatomy education	24 students (11 m. + 23 f.), m., age = 20.74	N250 and RewP ERPs	BP * ActiCAP Xpress + 16 ch V-Amp	Psychophysics Matlab Toolbox, Brain Vision Recorder	No	Detailed examination of learning and retention with pre-class exercises. ERPs in accordance with expected behavior.
2	Anderson et al. (2023)	Diagnostic accuracy factors examination	26 students (23 f. + 3 m.), m. age = 19.8, and 9 experts (6 f. + 3 m.), m. age = 44.1	RewP and N170 ERPs	BP 32 ch ActiCAP slim + LiveAmp	Psychophysics Matlab Toolbox, Brain Vision Recorder	Yes	Was diagnostic accuracy due to image recognition or acquisition of diagnostic expertise? ERPs in accordance with expected behavior.
3	Doukakis et al. (2019–2020)	Students' performance in programming tasks	8 first-year students (3 f. + 5 m.)	EEG negative means value and time	BIOPAC MP150, 2 ch used (C4-P4)	AckKnowledge 4.3	No	Differentiated teaching is required in programming. Limitation of small sample size.
4	Fard et al. (2020)	Transfer learning during computer programming tasks	8 male students (18–21 y.o.)	EEG alpha and theta band power spectrums and models of neuronal connectivity	Emotiv EPOC-X, 14 ch	OpenSesame, EEGLAB, NeuCube with Spike Neural Networks (SNNs) models.	Yes	How to facilitate activation of prior knowledge. Cognitive load and prior knowledge. Use of neuronal activity patterns to interpret brain activity.
5	Poulsen et al. (2017)	Brain synchronization and engagement while watching videos	42 f. (m. age = 22.4)	Intersubject correlation (ISC)	Emotiv EPOC+, 14 ch	Corrmap Matlab Toolbox	Yes	Measure inter-subject correlation with portable low-cost equipment.
6	Schroer et al. (2020)	Spatial reasoning in children	21 children (11 m. + 10 f.), 6–12 y.o.	N2 and P3 ERPs, joint time frequencies of alpha band	NetAmps300 (EGI), 64 ch	Nestation 4.5 (EGI)	No	Can a simple educational video game be used to get children to learn the law of reflection? Suppressed alpha band after learning is confirmed. Limitation of exact localization of brain waves (inherent in EEGs)
7	Zhao et al. (2023)	Effectiveness of AR app to assist learning	28 persons (7 m. + 21 f.) m. age = 20	Emotional state indexes from brain waves	Emotiv EPOC+, 14 ch	EmotivPro	Yes	Emotional state indexes for engagement, relaxation, interest, and focus are used for checking the effectiveness of using an AR app to learn photography. Limitations due to sample size and structure. Familiarization with experiments and tools is desired.
8	García-Monge et al. (2023)	Exploration of potentialities and issues using portable EEG in classrooms	17 primary sch. children, (10 f. + 7 m.), 8–9 y.o.	2′ EEG recording with eyes closed and 2′ with eyes open. Frequency domain analyses.	Brainlink Pro (2 ch), Emotiv Epoc (14 ch), Epoc Flex (32 ch), Muse (4 ch)	EEGLAB, Lucid Scribe, Emotiv TestBench, EmotivPro, Mind monitor	Yes	Examine the methodological aspects for EEG analysis in the classroom.
9	Bouhdana et al. (2023)	Effects of context and gender in physics problems	60 participants, (32 f. + 28 m.), m. age = 23.7	Cognitive engagement indexes $\beta/(\alpha + \theta)$	BP ActiCAP + 32 ch BrainAmp	BrainVision Analyzer (v2.0), Matlab	No	Multisensor data. EEG is employed for measuring cognitive engagement while solving problems in physics. Is context related to engagement?
10	Bos et al. (2020)	Effects of low frequency binaural waves on attention levels	2 students with ages from 20 to 28 y.o.	Frequencies analysis performed by the proprietary software	Neurosky Mindwave, 2 ch	Effective Learner app. (Neurosky)	Yes	Attention levels are measured while subjecting the brain to low frequency (10 Hz) binaural waves. Limitation: very small sample size.
11	Oniev (2021)	Brain response differences and similarities while reading digital or paper textbooks	3 pupils (1 m. + 2 f.), 12 y.o.	Emotional state indexes from brain waves and FAA	Emotiv EPOC-X, 14 ch	Emotiv software	Yes	Multisensor data. EEG employed in commitment, interest, attention, stress, and relaxation estimation. Limitation: very small sample size.
12	Byczynski and Angiulli (2024)	Congruence judgement in relation to school days and starting times	24 female students, m. age = 16.9	Frontal P300 ERP asymmetry	Neurosoft EEG quick caps (9 ch) and SynAmps2 (Compumedics Neuroscan) for amplification and digitization	SCAN 4.3 (Compumedics Neuroscan) and Stim2 for stimuli presentation	No	The frontal P300 ERP asymmetry from locations F3 and F4 is used as biomarker of cognitive control abilities. Variations in congruence judgement were observed, with lower levels in the mornings.
13	Fu et al. (2020)	Inhibitory control performing fraction comparisons	28 students, m. age = 20.8	N1, N2, and P3 ERPs	BP ActiCAP, 64 ch	BrainVision Analyzer (v2.0)	No	Examines the negative priming effect (impaired reaction to stimulus that has been previously ignored). Adults still need to inhibit initial reactions in fraction comparisons.
14	Skelling-Desmeules et al. (2021)	Persistence of misconceptions in biological studies	28 students, (13 f. + 15 m.), m. age= 23.7	N2 and LPP ERPs	BP ActiCAP, 64 ch	BrainVision Analyzer (v2.0), E-prime	No	Inhibitory control to initial decisions when seeing images of moving (or not) and alive (or not) things. Suppression of "moving thing is alive" heuristic. Suppression of counter intuitive (alive but not moving) information results in longer reaction times and differences in N2 and LPP ERPs.

Id	Project	Subject	Sample	EEG Metrics	H/W Used	S/W Used	Wireless	Issues Addressed
15	Williams et al. (2019)	Intuitive and analytical thinking	30 undergrad students (22 f. + 8 m.), (m. age = 22.8)	Alpha and theta activity in parietal and frontal areas	BP ActiCAP, 64 ch + ActiCHamp	BrainVision (v.1.10), EEGLAB and R language	No	Neural signatures for intuitive (System 1) and analytical (System 2) thinking are explored. System 1 is characterized by an increase in parietal alpha power. System 2 is characterized by an increase in frontal theta power.
16	Juarez-Varon et al. (2023)	Analysis of stress, attention, interest, and engagement in onsite and online learning	20 pg students (22–25 y.o., 10 m. + 10 f.)	Alpha, beta, and theta activity	Emotiv EPOC+, 14 ch	EmotivPRO (v2.0) and R language	Yes	Brain wave power was used for estimating the levels of stress, attention, interest, and engagement. Commitment was also reflected in the variation in the brain waves' power. Onsite learning related to higher levels of these indexes.
17	Garcia-Monge et al. (2020)	Brain activity differences in various types of throwing games	8 children (m. age = 7.2)	Brain band (mostly beta) activity	Emotiv EPOC-X, 14 ch	Emotiv Brain Activity Map and Emotiv TestBench, EEGLAB	Yes	Higher β wave EEG power levels due to higher demand for motor control and competition situations in games using a goal. Three types of games, two with a goal and the third just throwing a ball are examined.
18	Khramova et al. (2021)	Differences in cortical activities of adults and children	12 children (3 f. + 9 m.) 7–8 y.o. and 10 adults (3 f. + 7 m.) (18–20 y.o.)	Brain band (mostly alpha and beta) activity	BP ActiCAP, 32 ch + ActiCHamp	EEGLAB and FieldTrip	No	Use of different problem-solving strategies (e.g., procedural vs. fact-retrieval) was demonstrated among adults and children. Visual search, working memory, and mental arithmetic were employed for the tasks.
19	Williams et al. (2018)	Reflection of reinforcement learning in RewP ERP	30 students (23 f.+ 7 m.), m. age = 20	RewP ERP	BP ActiCAP, 64 ch ActiCHamp	BrainVision Analyzer	No	Reward positivity (RewP) ERP studied with prediction of disease types. RewP amplitude diminishes with learning.
20	Williams et al. (2020)	Reward prediction errors as indications of learning processes	30 students (19 f. + 11 m.), m. age = 20	RewP ERP	BP ActiCAP, 64 ch ActiCHamp	Brain Vision Analyzer and Psychophysics Toolbox for stimuli presentation	No	Reward positivity studied in learning words of a novel language. RewP amplitude diminishes with learning.
21	Hassal et al. (2019)	The role of control over actions in reward *processing*	26 students (13 m. + 13 f.), m. age = 21.54)	RewP ERP	BP ActiCAP, 64 ch ActiCHamp	BrainVision (v.2.1.2) and EEGLAB, Psychophysics Toolbox Extension for stimuli presentation	No	Is action required to elicit reward positivity? Agency (sense of control) affects the generation of neural prediction error signals.
22	Barrella et al. (2019)	Measurement of cognitive load in concept-handling tasks	23 students (13 m. + 10 f.), m. age = 19.25)	Alpha over theta waves ratio	B-Alert X10 EEG (ABM), 9 ch	ABM's B-Alert Live software	Yes	More effort when creating concept maps than listing tasks. Self-reported cognitive load for concept mapping appears higher than the EEG estimated.
23	Hernandez-Mustieles et al. (2024)	Public dataset of parallel EEG recordings during collaboration and competition tasks	16 subject pairs of 1 m. and 1 f. (aged 18–24)	n/a	Enophones, 4 ch	EEGLAB	Yes	Publicly available synchronized EEG dataset. Recordings of 2 × 1 min + 2 × 10 min involving face to face and online collaboration (puzzle solving) and competition (domino) tasks.
24	Romo-De Leon et al. (2024)	Public dataset of EEG and other physiological signals recordings during two teaching scenarios for humanities studies	24 students (10 m. and 14 f., aged 18–25, mean = 21.33, s.d. = 1.4)	n/a	OpenBCI Ultracortex Mark IV, 8 ch	OpenBCI GUI and EEGLAB	Yes	Publicly available EEG dataset. Recordings of 2 × 1 min + 4 × 3 min involving traditional learning and partially immersive learning experiences.
25	Jamil et al. (2024)	Brain to brain synchronization during remote learning	10 students aged 18–28 and one instructor	Time series and frequency domain correlations	Unicorn Hybrid systems (8 ch, 250 Hz)		Yes	Cross-correlation of 10 *student–instructor* pairs' EEG signals to produce synchronization percentages. Detections of patterns of similarity. Limitations: vulnerability to artifacts.
26	Grubov et al. (2024)	Cognitive abilities assessment and feedback in the form of recommendations	60 pupils in two age groups, 9–10 and 11–12 years old, 36 boys and 24 girls	Alpha band power variance	BP LiveAmp (64 ch, 500 Hz)	EEGLAB	Yes	Neuroadaptation in the educational process. Assessment of cognitive ability types such as visual search, working memory, mental arithmetic, and combinations of them.

ANNEX II – Neuro-wearables, neuro-markers, and Neuro-analytics

In the context of education and lifelong learning, neuro-wearables, neuro-markers, and neuro-analytics form a connected sequence that works like a chain — each step depending on the previous one to function meaningfully.

It all begins with neuro-wearables. These are the physical devices, like EEG headbands or smart earbuds, that students or learners wear. Their job is to capture real-time brain waves. Just like a microphone picks up sound, neuro-wearables pick up brain signals. Alone, these raw signals don't tell us much, they're noisy and hard to understand.

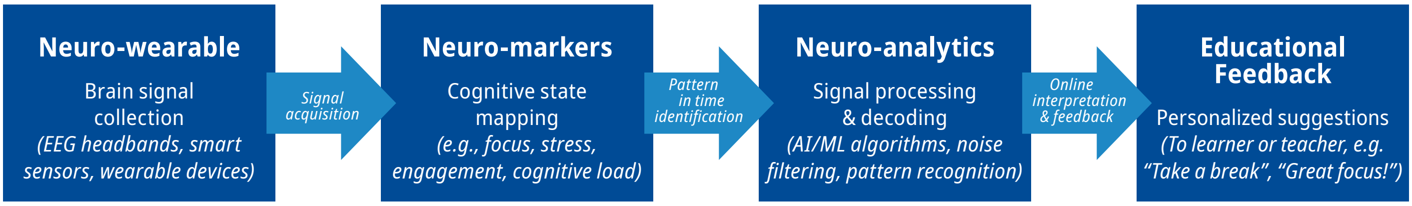
To make sense of these patterns, it is necessary to process and clean up the raw signals collected by the wearable to identify the neural signatures or neuro-markers that have been associated with certain cognitive states. In other words, Neuro-markers are like a scientific dictionary that tells us which brain patterns are linked to which mental states. For example, if a certain type of brainwave is known by fundamental neuroscience research to appear when someone is deeply focused, that becomes a "neuro-marker of focus." This step is essential to interpret what the brain data really mean and avoid deceptive interpretations from signals captured in wearables.

That's where neuro-analytics come in, once a neuro-marker is identified in the raw brain signal from the wearable the tracking of this neural signature through Neuro-analytics help monitor the modification in time of the neuro-marker of focus or stress. This real-time data processing often powered by artificial intelligence allows to offer a window on the cognitive state of individuals across time. For example, they might detect a drop in attention or a peak in stress, thus offering a window on brain activity and cognitive states.

Finally, once a neuro-analytics have been tracked by the system, the neurofeedback app can display them and deliver feedback— either to the learner or the teacher. It is up to the student or to the teacher to meaningfully interpret them in context however automated feedback embedded inn apps might suggest taking a break, repeating a difficult topic, or switching to a more engaging activity. This last step turns invisible brain activity into something that can be leverage improve learning in real time.

Sequential steps can be summarized in the following: analyze the raw brain data collected by neuro-wearables, look for patterns that are known to correlate with a particular cognitive state (neuro-markers), and try to recognize what's happening in the brain through time (neuro-analytics), and finally offer neuro-feedback based on real-time brain waves monitoring (see Table and graphic hereunder).

Component	Role in System	Intersects With...
Neuro-wearables	Capture neuro-data non invasively	Need accurate and precise capture of the right neuro-marker (cognitive brain signature) to be useful for education
Neuro-markers	Provide validated interpretation	Are the scientific reference for analytics
Neuro-analytics	Track and monitor in time educational neuro-markers	Depend on neuro-markers to assign meaning
Neuro-Feedback loop	Applied through UX/UI, apps, or dashboards	Requires all three to function meaningfully to inform individual learning and give feedback for teachers to inform pedagogical action



Neuro-wearables collect brain data where neuro-markers associated with cognitive states are identified and tracked through neuro-analytics that interpret in time. Together, they allow to understand the mental state of a learner and respond in ways that make education more adaptive, inclusive or personalized.

ANNEX III – Additional emerging neurotech fields to be monitored beyond 2030

1. Focus ultrasound: neurotech beyond electricity wearable device for non-invasive optical brain imaging

Non-invasive approaches to modifying brain activity and state are currently being developed through focus ultrasound, targeting more and more precise areas that were usually only the target of pharmaceutical or deep brain surgery. Companies in different regions of the world are developing approaches to treat illness without surgery with a focused beam of low energy to modulated nervous tissues like neurons, ranging from ablation, to opening the Brain Blood Barrier (BBB), to performing neuromodulation.

Focus ultrasound wearable devices, providing non-invasive brain interfacing, will see earlier and perhaps wider adoption. Technological advancements are gradually removing the inability to penetrate deeper into the brain only accessing top-level neural signals. Mindfulness and depression studies are showing that focus ultrasound neuromodulation devices can expand their depth of insight and neuromodulation capabilities.

Possible path of evolution of Focused Ultrasound neuromodulation technology (FUS) neuromodulation technology can be divided into three main evolutionary stages, starting with MRI-guided FUS characterized by Treatments delivered inside an MRI machine, in One-time ablation procedures, primarily targeting essential tremor and Parkinson's disease, evolving towards a second stage of Neuronavigated FUS with Treatments delivery in physician's offices, through Weekly sonication protocols that can expand to applications for depression, addiction, and epilepsy. A final stage would represent a possible future evolution to "Wearable" FUS technology, possibly enabling at-home care possibilities, with daily sonication treatments and self-dosed applications, targeting sleep disorders, anxiety, and eating disorders.

Such evolutionary pathway illustrates how FUS neuromodulation could progress from hospital-based, high-powered, single-session treatments toward more accessible, frequent, and eventually self-administered interventions. The technology appears to be expanding from treating primarily movement disorders to addressing a wider range of neuropsychiatric and behavioral conditions, with increasing convenience and accessibility for patients and should be kept under the radar.

2. Optical brain imaging: non-invasive neurotech device beyond electricity

Among the brain imaging techniques that facilitate accurate, high-resolution observations of the brain and its functions, functional near-infrared spectroscopy (fNIRS) is a widely used noninvasive imaging technique that employs near-infrared light (wavelength >700 nm) to determine the relative concentration of hemoglobin in the brain, via differences in the light absorption patterns of hemoglobin.

To overcome some of the limitations of this technique, recent evolution of this technique is time-domain (TD)-fNIRS, which uses picosecond pulses of light and fast detectors to estimate photon scattering and absorption in tissues. If such systems are expensive and complex and have a large form factor, limiting their widespread adoption, a neurotechnology company called Kernel, developed a wearable headset based on TD-fNIRS technology that overcomes these challenges. This device, called "Kernel Flow," weighs 2.05 kg and contains 52 modules arranged in four plates that fit on either side of the head[58].

[58] Ban, H. Y., Barrett, G. M., Borisevich, A., Chaturvedi, A., Dahle, J. L., Dehghani, H., ... & Zhu, Z. (2022). Kernel Flow: a high channel count scalable time-domain functional near-infrared spectroscopy system. *Journal of biomedical optics*, *27*(7), 074710.

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