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DIAGNOSIS AND EARLY DETECTION OF POST-TRAUMATIC STRESS DISORDER USING COMPUTATIONAL PSYCHIATRY

ДІАГНОСТИКА ТА РАННЄ ВИЯВЛЕННЯ ПОСТТРАВМАТИЧНОГО СТРЕСОВОГО РОЗЛАДУ ЗА ДОПОМОГОЮ ОБЧИСЛЮВАЛЬНОЇ ПСИХІАТРІЇ

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Computational psychiatry (CP) is an interdisciplinary field of study that uses mathematical modelling and computational methods to describe the relationships between brain neurobiology, the environment, and the symptoms of mental disorders [1]. CP aims beyond descriptive classification and create a mechanistic, quantitative understanding of mental disorders. This allows for the formulation of computational phenotypes that can form the basis for precise, personalised psychiatry, where diagnosis and treatment are based on the individual biological and cognitive characteristics of the patient.

Computational psychiatry distinguishes between two main approaches:

- Data-Driven: uses machine learning algorithms to analyse large, multidimensional data sets to identify complex patterns. Its main tasks are classification, prediction, and clustering of mental disorders. This approach is agnostic mainly about underlying mechanisms, focusing on predictive accuracy [2].
- Theory-Driven: uses formal, mathematically defined models of cognitive processes (e.g., learning, decision-making, etc.) to generate and test specific hypotheses about why symptoms of mental disorders arise. These models allow us to link the symptoms of mental disorders to the dysfunction of specific computational parameters that reflect neural processes [2].

These two approaches are complementary and create a powerful tool for in-depth and comprehensive study of mental disorders, which significantly exceeds the capabilities of traditional clinical diagnostics.

The application of machine learning to neuroimaging data opens up opportunities for early prediction of post-traumatic stress disorder (PTSD).

A study by Yale University showed that a model trained on data obtained from fMRI one month after trauma accurately predicts symptom severity 14 months later, indicating early stable neurobiological markers of vulnerability [3].

The model also found that different brain networks and symptom clusters are predictive at different stages of the disorder's development. One month after the trauma, the most predictive patterns of activity were those associated with avoidance symptoms and negative mood changes. In contrast, after 14 months, the model better predicted intrusion symptoms (flashbacks, intrusive memories) and hyperarousal. Interestingly, the visual and sensorimotor networks were among the most important for long-term prognosis, which probably reflects the neural substrate of flashbacks (involuntary reliving of trauma as a real event) [3]. These functional data are supplemented by studies of structural changes in the brain. Patients with PTSD consistently show a reduction in the volume of the hippocampus, amygdala, and anterior cingulate cortex (key areas responsible for memory, emotion processing, and stress regulation) [4].

Structural data complete the picture: a stable reduction in the volume of the hippocampus, amygdala, and anterior cingulate cortex; aberrant connectivity in the ventral attention network, associated with impaired verbal memory and poorer response to psychotherapy. In addition, EEG biomarkers (P300, MMN) detect attention and memory impairments and are more accessible for screening. The highest accuracy is provided by a multimodal approach (fMRI+EEG; structural+diffusion MRI), which combines high spatial and temporal resolution and improves classification and prognosis accuracy.

Natural language processing (NLP) is a robust, inexpensive, and easily scalable approach to PTSD screening. Human language directly reflects a person's inner state, thoughts, and emotions, making it a rich source of diagnostic information. Text analysis consistently reveals linguistic markers characteristic of people with PTSD: frequent words about death, negative emotions (especially anger) and descriptions of bodily sensations [6]. The length of the narrative is also predictive. The convergence of neuroimaging and NLP results points to a single "computational phenotype" of PTSD, where hypervigilance and threat bias are reflected in language patterns. In other words, both modalities record manifestations of a single system "stuck" in a mode of predicting high threat. Therefore, NLP can be considered a quantitative explication of the same neurocomputational processes recorded by fMRI. Their integration into a standard model forms a reliable multi-level biomarker for PTSD. In turn, theory-driven models of PTSD formalise the disorder as a disruption of basic cognitive processes.

One approach views PTSD as a pathological outcome of reinforcement learning (RL). In this framework, PTSD is the result of extremely strong associative learning of fear, where a traumatic event creates powerful associations between previously neutral stimuli (triggers) and an internal state of threat. A key role is played by prediction error – the difference between the expected and actual outcome. This means that any unexpected situation is interpreted as a potential threat, which only reinforces the model of a dangerous world. The severity of PTSD correlates directly with how strongly an individual weighs these errors, which may be a compensatory mechanism for reduced neural tracking of associativity in the striatum and hippocampus. [5, p. 334].

Another approach used in the theory-driven model of PTSD is Predictive Coding. This approach views the brain as a prediction machine that constantly generates a model of the world and tries to minimise prediction errors by reconciling the model with sensory data [1]. From this perspective, PTSD can be modelled as a state in which previous beliefs about threat are extremely strong and inaccurate. The brain gives excessive weight to these beliefs and loses the ability to adequately update them based on new, safe evidence from the environment. This explains the persistence of avoidance symptoms (actions aimed at avoiding situations that could disprove beliefs about safety) and hypervigilance (constant search for evidence confirming danger).

The theoretical models above all agree on one central mechanism: impaired belief updating. The fundamental problem with PTSD is the brain's inability to flexibly update its model of the world from "dangerous" to "safe" after the traumatic event has ended. A healthy brain constantly updates its beliefs based on new evidence. Trauma creates a very strong belief about danger. In most people, further evidence of safety gradually weakens this belief. In PTSD, this updating process is impaired. This computational rigidity is at the core of the pathology and points to direct therapeutic targets: interventions should aim to increase the flexibility of belief updating, for example, by enhancing the processing of safety signals.

Computational psychiatry thus offers a revolutionary shift towards an objective, predictive and personalised diagnostic paradigm. Data-driven methods, including machine learning on neuroimaging data and natural language processing, have already demonstrated significant potential in the early detection of individuals at high risk of developing chronic PTSD and the identification of objective biomarkers. At the same time, theory-driven models deepen our fundamental understanding of PTSD as a disorder of computational learning mechanisms, pointing to belief updating dysfunction as a central pathology.

For Ukraine's mental health system, these technologies are of enormous strategic importance in the long term, offering scalable and effective solutions for screening and monitoring PTSD. However, their implementation requires a balanced and responsible approach that involves carefully addressing complex ethical issues related to data confidentiality, algorithmic bias, and transparency.

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