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# **Multimodal Data Fusion for Brain-Computer Interfaces A literature review**

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#### Context

Several factors have made medical progress in neurosciences possible, including optimization of the patient care:

- New data acquisition technologies combined with the multiplication of health data;
- A lot of different data to describe a patient's physiological and physical state;
- New algorithmic methods able to integrate

## **Problematic and objectives**

The purpose of this work is to complement current research on hybrid BCI [4].

How to integrate different modalities at the scale of the algorithms in BCIs?

#### The objectives are the followings:

#### Methods

This study is part of a comprehensive literature review, conducted according to PRISMA recommendations, on deep learning data fusion mechanisms. The review is currently being written.

The comprehensive search depicted here was based on several databases. A total of 339 articles were screened.

## these different modalities.

**Brain-Computer Interfaces** (BCI) usually take electroencephalograms (EEG) signals as single inputs. However, studies show that hybrid systems such as **Body-Computer Interfaces**, combining the advantages of different types of input signals, offer competitive results compared to conventional interfaces [3,5].

1.Conduct a literature review focusing on multimodal data fusion methods that could be integrated in hybrid systems.

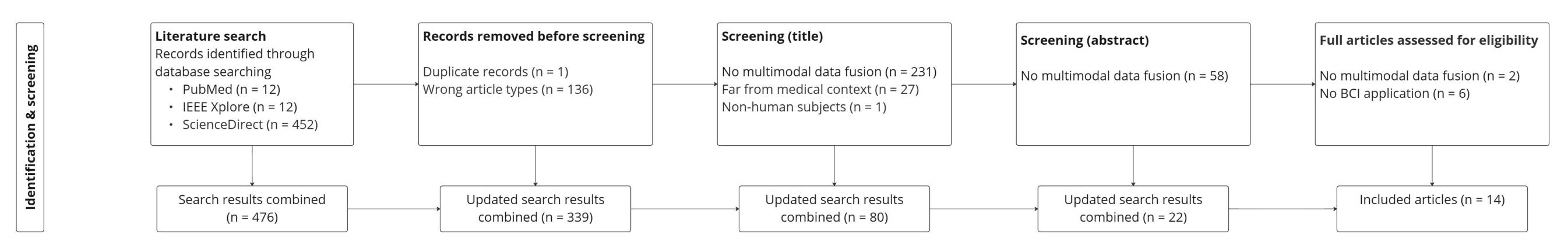
2. Identify relevant **combinations** of physiological signals for improving traditional BCI systems.

3.Compare above-mentioned methods.

The diagram below represents the contributions of this research, applied for BCI, adding 14 more articles.

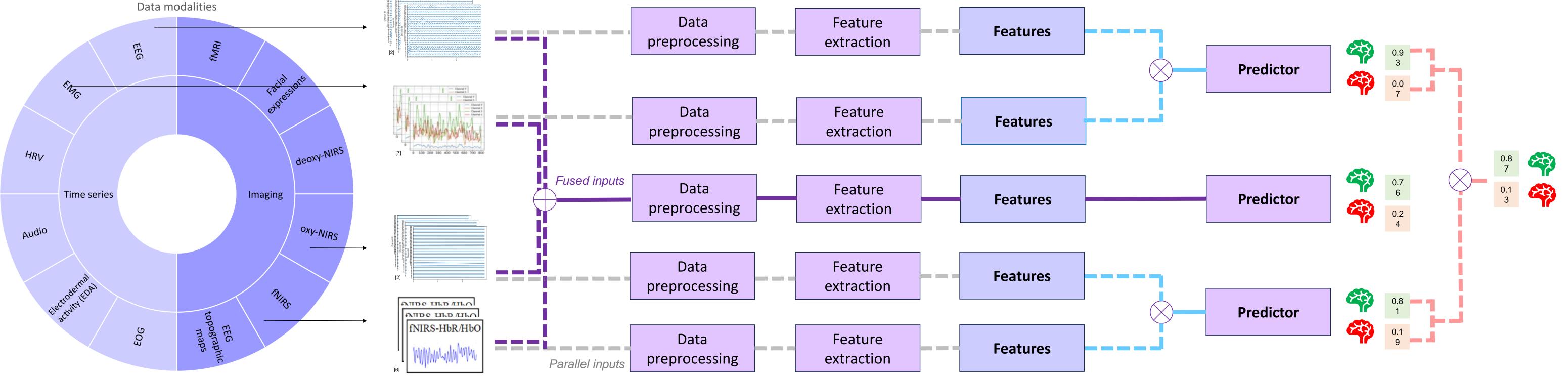
**Decision-level fusion** 

## **PRISMA** diagram



## **Different levels of fusion mechanisms**





Multi-dimensional matrices, concatenation (linear fusion), ... Linear fusion, pth-order polynomial fusion, tensor fusion, Ensemble learning, ... cross-modal and self-attention transformers, multimodal factorized bilinear pooling (MFB), ...

**Feature-level fusion** 

#### **Methods and limitations**

• Entry-level fusion : a shared representation is learnt from a multimodal single input formed by the fusion of all data at the entry level of the network. Non-linearity of correlations between data limits learning [8].

#### Conclusion

Different modalities can be interesting but complicated to integrate without complicating nor degrading the algorithms. Rationale behind fusion strategy highly depends on relationship between data. Relationship is given by the consistency of specific patterns concomitant with the occurrence of the target event of the BCI: thus, multimodal inputs must represent the same recording time at the same scale. Ideally, models should combine independent and correlated analysis of each normalized modality to accurately learn multi-modal patterns. Thus, adapted feature-level fusion seems the most appropriate. Such method showed promising results in motor imagery classification with a reported accuracy of 82.11% [6].

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• Feature-level fusion : multimodal features are learnt independently then concatenated at a deeper level to better learn correlations later. Difficulties lie in the weight given to each feature, regardless of its dimension, as well as the size of the feature vector [1].

Decision-level fusion : same independent • decision-making process for all data whose results are combined at the end-level. **However**, final result is based on independent input processing without learning modalities correlations [8].

