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Decoding cognition in neurodevelopmental, psychiatric and neurological conditions with multivariate pattern analysis of EEG data

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ABSTRACT

Multivariate pattern analysis (MVPA) of electroencephalographic (EEG) data represents a revolutionary approach to investigate how the brain encodes information. By considering complex interactions among spatio-temporal features at the individual level, MVPA overcomes the limitations of univariate techniques, which often fail to account for the significant inter- and intra-individual neural variability. This is particularly relevant when studying clinical populations, and therefore MVPA of EEG data has recently started to be employed as a tool to study cognition in brain disorders. Here, we review the insights offered by this methodology in the study of anomalous patterns of neural activity in conditions such as autism, ADHD, schizophrenia, dyslexia, neurological and neurodegenerative disorders, within different cognitive domains (perception, attention, memory, consciousness). Despite potential drawbacks that should be attentively addressed, these studies reveal a peculiar sensitivity of MVPA in unveiling dysfunctional and compensatory neurocognitive dynamics of information processing, which often remain blind to traditional univariate approaches. Such higher sensitivity in characterizing individual neurocognitive profiles can provide unique opportunities to optimise assessment and promote personalised interventions.

1. Decoding cognition using time-resolved MVPA of EEG data

1.1. The multidimensional nature of neural representations in the EEG signal

Understanding how the human brain encodes sensory information, forming neural representation of the external environment, and ultimately orchestrating human behaviour has been a paramount pursuit in cognitive neuroscience for research generations. In this framework, neuroimaging techniques have emerged as powerful operative tools capable of addressing these questions, allowing to identify patterns of neural activity reflecting specific mental states, characterizing their origin in space and informing how they unfold over time. In this regard, electroencephalography (EEG) provides an optimal temporal resolution to visualize fine-grained, time-sensitive brain signal information, sampling at the millisecond level spontaneous or event-related brain electrical activity on the scalp generated by the underlying neuronal populations (Davidson et al., 2000; Biasiucci et al., 2019). Although the EEG technique represents one of the most suitable neuroimaging methods to identify how the neural representations of information are encoded by our brain, it also presents a critical challenge: how can we accurately identify patterns of neural activity associated with specific cognitive processes from the complex and multidimensional dataset they generate?

The nature of the neuroelectrical EEG activity is intrinsically multidimensional, characterized by a complex signal structured in different - but related – spatio-temporal features (Peters et al., 1998; Mitra and Pesaran, 1999; Davidson et al., 2000; Biasiucci et al., 2019). Traditionally, the analysis of EEG activity has relied on univariate techniques, which implies a hypothesis-driven approach. This approach focuses on examining the average activity of a-priori-defined specific temporal windows (*when?*) and specific electrodes placed on the scalp (*where?*), and applies constraints to the analysis of the differences between groups or experimental conditions identified in specific components with a

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well-known meaning (e.g., event-related potentials; ERPs; Luck, 2023). While this approach aims to reduce the number of comparisons, thus increasing the power of statistical analysis (e.g., Hebart and Baker, 2018), it also induces investigators to index distinct neural components from individual electrodes and timepoints, ultimately seeking interactions between condition/group, electrodes and timepoints, a strategy that generally reduce statistical power (Luck et al., 2014; Hebart and Baker, 2018). Furthermore, constraining the analysis of EEG data to specific spatio-temporal features can lead to the possibility of ignoring relevant neural information excluded a priori from the statistical analysis (Poldrack, 2006; Luck et al., 2014; Hebart and Baker, 2018; Grootswagers et al., 2017; Bae et al., 2020; Li et al., 2023; Li et al., 2022; 2023; Peelen and Downing; 2023; Marsicano et al., 2024). For example, univariate approaches ground on the assumption that all individuals exhibit a similar scalp distribution for a given spatio-temporal ERP component, although there is substantial interindividual variability in how neural activity is unfold, with the risk of obfuscating peculiar neural dynamics at the individual level (Borrell, 2018; Kroenke and Bayly, 2018; Fahrenfort et al., 2018; Farran et al., 2020; Bae et al., 2020; Li et al., 2022; 2023; Marsicano et al., 2024).

As our understanding of the complexity of neural processes has deepened, it has become increasingly evident that we require analysis methods capable of unveiling how information is coded in complex, multidimensional EEG signals (Haynes and Rees, 2006; Pratte and Tong, 2017; Kaiser et al., 2016; Fahrenfort et al., 2017; Marti and Dehaene, 2017; Hebart and Baker, 2018; Grootswagers et al., 2017; Fahrenfort et al., 2018; López-García et al., 2022; Ashton et al., 2022; Peelen and Downing, 2023; Borst and Anderson, 2024).

1.2. MVPA: decoding from EEG data neural representations of information content

In this context, exploiting machine learning techniques coupled to multivariate statistics, Multivariate Pattern Analysis (MVPA; or "decoding") of EEG data has emerged as a revolutionary approach in this field, providing a *data-driven* method capable of considering neural activation patterns associated to specific neural representations of information content emerging from multiple electrodes at each individual timepoint (Cauchoix et al., 2014; Haxby et al., 2014; Grootswagers et al., 2017; Holdgraf et al., 2017; Fahrenfort et al., 2017; Bayet et al., 2018; Fahrenfort et al., 2018; López-García et al., 2022; Ashton et al., 2022; Peelen and Downing, 2023; Borst and Anderson, 2024). The MVPA decoding approach, going beyond the constraints presented by traditional univariate techniques, offers a way to consider the relationship among multiple spatio-temporal variables of EEG data, leading to an increased analysis sensitivity for decoding neural representations of information content which do not occur in a spatio-temporal focal manner (e.g., Norman et al., 2006, Haxby et al., 2014; Grootswagers et al., 2017; Hebart and Baker, 2018; Takacs et al., 2020; Petit et al., 2023; Marsicano et al., 2024). Differently from univariate analysis, which oversimplifies the multivariate structure of EEG signal by taking the average of the neural activity emerging from specific time points/-windows in a defined pool of electrodes, MVPA preserves the complexity of information present in EEG data (Grootswagers et al., 2017; Hebart and Baker, 2018; Fahrenfort et al., 2018; López-García et al., 2022; Ashton et al., 2022; Peelen and Downing, 2023; Borst and Anderson, 2024). As such, MVPA offers a more comprehensive understanding of the neural dynamics underlying information processing, enabling the detection of complex neural patterns and discriminative spatio-temporal features that may elude the operative confines of univariate methodologies (see Fig. 1 for a graphical summary; for a more detailed description of the differences between univariate and MVPA approaches, see: Hebart and Baker, 2018).

At an operational level, MVPA of EEG data provides a way to quantify an individual's information content in the neural signal and to probe whether the neural activation patterns of information processing evoked by different experimental conditions are represented differently at the neural level. In detail, for each individual, a machine learning classifier (e.g., Linear Discriminant Analysis, LDA; Carlson et al., 2003; Fahrenfort et al., 2017; Melinda et al., 2023; Trammel et al., 2023; Support Vector Machine, SVM; López-García et al., 2022; Trammel et al., 2023; Zhang et al., 2024) is trained to discriminate the neural activity associated with each of the different experimental conditions in a subset of the data, subsequently testing in an independent subset of the data whether and to what extent (i.e., level of decoding accuracy) the trained classifier is successfully able to discriminate the different conditions based on patterns of neural activity, ultimately allowing to compare decoding accuracy across each timepoint to test the time course of neural information processing. While univariate analyses are typically performed on the mean voltage in order to assess the consistency of the effect across individuals rather than uniformity across trials (Luck et al., 2014; Hebart and Baker, 2018; Luck, 2023), MVPA is computed independently for each individual, using averages of neural activity derived from distinct subsets of trials for training and testing (Luck et al., 2014; Grootswagers et al., 2017; Hebart and Baker, 2018; Fahrenfort et al., 2018; Bae et al., 2020; Li et al., 2023; Borst and Anderson, 2024; Marsicano et al., 2024). An above-chance classification accuracy of MVPA decoding performance indicates that the information associated with different experimental conditions is decoded by the algorithm and represented by different patterns of neural activity, thus enabling the identification of unique neural dynamics linked to individual profiles of information processing (e.g., Cauchoix et al., 2014; Grootswagers et al., 2017; Fahrenfort et al., 2018; López-García et al., 2022; Ashton et al., 2022; Peelen and Downing, 2023).

1.3. Differences between classical univariate analysis and MVPA

A crucial difference between MVPA and classical univariate approaches is that in the latter, the analysis is constrained to neural responses that typically exhibits uniform direction with similar activations (e.g., ERPs with positive or negative amplitude; Hebart and Baker, 2018; Grootswagers et al., 2017; Peelen and Downing, 2023). However, when neural responses with different signs are present, there is a risk of obscuring potential patterns of information processing, due to the averaging of neural activity that exhibits a mixture of sign directions. Conversely, MVPA demonstrates greater sensitivity in identifying patterns of information processing, even in the presence of non-uniform neural response signs (Hebart and Baker, 2018; Grootswagers et al., 2017), as both positive and negative responses are equally meaningful, contributing evenly to identifying patterns of neural activity associated with different information content (Hebart and Baker, 2018). At the same time, in MVPA the direction of the effect is typically hidden, due to the intrinsic inability of multivariate approaches to identify the direction (e.g., positive or negative) of the neural response decoded. This crucial difference makes it difficult to evaluate whether one experimental condition is associated with greater or lesser neural activation compared to another (e.g., signal components with higher/lower amplitude). In most cases such an objective lies outside the scope of the decoding approach, for which the primary goal is to discern the discriminability between patterns of neural activity associated with different experimental conditions (Cauchoix et al., 2014; Grootswagers et al., 2017; Fahrenfort et al., 2018; López-García et al., 2022; Ashton et al., 2022; Peelen and Downing, 2023; Borst and Anderson, 2024). However, in cases where information on the direction of the effect is informative and directly relevant to the investigator's interests, it is possible to evaluate the direction of the decoded neural differences by employing various strategies. For example, it is possible to characterize the underlying neural activity by transforming the classifier weights (i.e., electrodes) into forward weights (for more details, see: Haufe et al., 2014; Fahrenfort et al., 2018), projecting the classifier weights back onto the topographical map of the electrodes, and thus providing insights into the source of decodable information. This operation

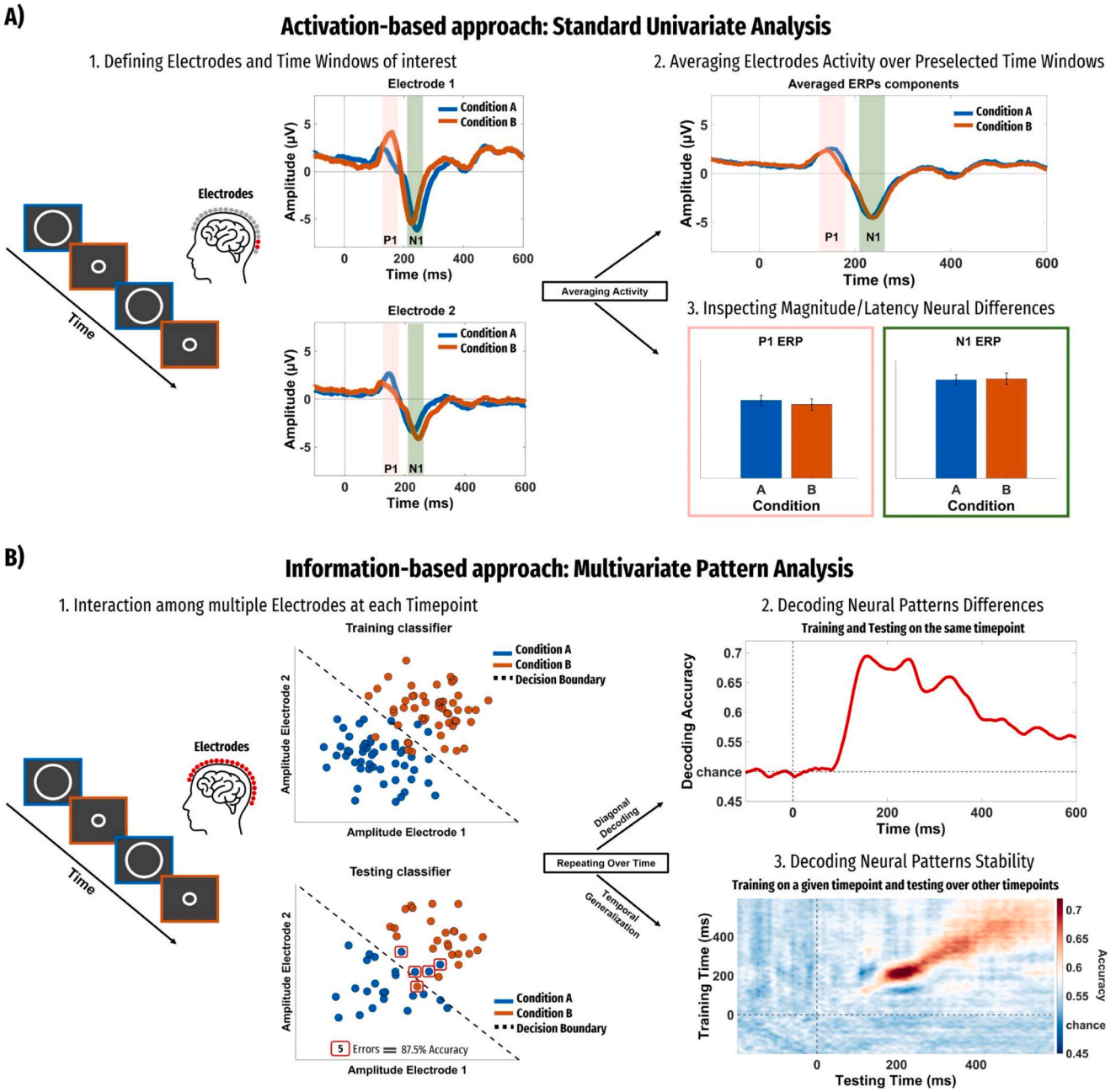

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Fig. 1. Schematic illustration depicting the methodological and conceptual contrast between univariate and multivariate analyses of EEG data. **A)** Univariate Analysis. Using a hypothetical experimental scenario, this example schematizes the typical univariate analysis framework applied to EEG data obtained from an experimental paradigm featuring two distinct conditions (A = large circle condition depicted in blue squares; B = small circle condition depicted in orange squares). Investigators identify specific scalp electrodes of interest (*where?*), averaging neural activity across predetermined temporal windows (*when?*) with established meaning (e.g., event-related potentials; ERPs). EEG activity elicited by Condition A and Condition B at two distinct posterior electrodes is examined, inspecting potential differences over predetermined temporal windows corresponding to P1 and N1 ERPs components. While qualitative differences are observable at the level of individual electrodes at different timing, averaging neural activity evaluating magnitude and latency differences over specific spatio-temporal features can reveal comparable neural activation patterns across conditions. Although this approach frequently proves effective in determining magnitude and latency differences between experimental conditions, constraining EEG data analysis to predetermined spatio-temporal features may significantly increase the risk of overlooking relevant neural information showing different latencies and localizations. **B)** Multivariate Pattern Analysis (MVPA). Using the same example, this panel illustrates the sequential steps involved in MVPA of EEG data. Employing a data-driven decoding approach, investigators examine patterns of neural activity associated with specific neural representations of information content emerging from multiple electrodes at each individual timepoint. This allows to probe whether the neural patterns of information processing elicited by different experimental conditions are represented differently at the neural level, investigating potential effects which may not occur in a spatio-temporal focal manner, with variable neural latencies and magnitudes. A machine learning classifier is trained and tested to discriminate between the neural activity associated with condition A and condition B, inspecting whether and to what extent (i.e., level of decoding accuracy) it accurately discriminates the different conditions, by defining a decision boundary. Here, for simplicity, the interaction of the neural activity at one individual timepoint in two different electrodes is represented in a two-dimensional plot. When the classifier undergoes training and testing at each time point (i.e., diagonal decoding), the decoder's accuracy provides information regarding potential differences on how and when the related information content is encoded at the neural level. In this example, considering the complex interplay of neural activity emerging from multiple electrodes at each timepoint, the decoding accuracy is above-chance level starting from ~150 ms. Here, differently from the univariate approach, this decoding analysis reveals information processing even at extended temporal latencies. When evaluating off-diagonal decoding performance, wherein the classifier is trained on specific timepoints and tested over other timepoints, it is possible to probe whether specific patterns of neural activity recur and generalized over time (i.e., temporal generalization), allowing to evaluate the stability of the neural representation associated with the processed information. Here, a transient neural response pattern is observable starting from ~200 ms after stimuli onset, followed by the emergence of a stable neural pattern of information processing identifiable starting from ~400 ms.

generates activation patterns at each individual timepoint and electrode that reflect the univariate differences between conditions. These patterns are directly interpretable as neural sources (i.e. raw amplitude), allowing for the evaluation of the direction of the effects resulting from the comparison between different experimental conditions (Haufe et al., 2014; Fahrenfort et al., 2017; Fahrenfort et al., 2018). Furthermore, by integrating both univariate and multivariate approaches, when uniform neural response differences are detected, MVPA can proves to be more sensitive than univariate analyses because it allows for the optimal integration of data across multiple electrodes and timepoints (Haynes and Rees, 2006; Norman et al., 2006; Hebart and Baker, 2018; López-García et al., 2022; Ashton et al., 2022; Peelen and Downing, 2023).

Importantly, such a decoding technique can probe how neural representation of information differs between different experimental conditions even in the presence of a moderate level of decoding accuracy (Christophel et al., 2015; Grootswagers et al., 2017; Hebart and Baker, 2018). Indeed, when the decoding performance reliably exceeds chance levels, it indicates that the information related to the conditions of interest is encoded by the brain, suggesting that the information content associated with different experimental conditions are represented differently at the neural level (Hebart and Baker, 2018; Bae et al., 2020; Li et al., 2023; Peelen and Downing, 2023; Marsicano et al., 2024; Borst and Anderson, 2024). However, while the level of decoding performance accuracy is typically equated with the size of an effect, it does not reflect a standardized measure of effect size (e.g., Cohen's d; Ku et al., 2008; Christophel et al., 2015; Hebart and Baker, 2018). Instead, decoding accuracies merely provide an intuitive measure of the classifier's ability to predict information content from neural activity (Hebart and Baker, 2018; Bae et al., 2020; Peelen and Downing, 2023; Borst and Anderson, 2024).

Crucially, as the magnitude of the neural activity can be dissociated from the decodable information content (Emrich et al., 2013; Cauchoix et al., 2014; Grootswagers et al., 2017), the differences identified by the decoding classifier can qualitatively and quantitatively differ from those found by univariate analyses (Ritchie et al., 2015; Grootswagers et al., 2017; Fahrenfort et al., 2018), potentially uncovering hidden neural dynamics that otherwise remain difficult to detect. Even in the presence of neural responses where activation does not differ from baseline levels (Bae et al., 2020), it is possible to decode whether and when the information content begins to be represented at the neural level and when it differs between conditions. This allows for the identification of the temporal sequence of information processing and the latency of neural representations by assessing when the classifier's accuracy is above chance at each timepoint (Grootswagers et al., 2017; Fahrenfort et al., 2018; Peelen and Downing, 2023; Borst and Anderson, 2024). For example, as highlighted in a pioneering study conducted by Cauchoix et al., (2012), with respect to univariate approaches, time-resolved MVPA can result in earlier detection of differences in neural responses associated with face processing, revealing the key contribution of intermediate visual areas that is hardly detectable employing univariate techniques. This contrasts with univariate approaches, where each spatio-temporal dimension of the EEG signal is frequently predetermined and assessed separately (Haynes, 2015; Hebart and Baker, 2018; Peelen and Downing, 2023). Assuming that different stages of neural processing can generally be associated with specific time windows may certainly be informative (e.g., ERP components), but there is a risk of obscuring individual neural processing timings, due to the high inter-individual variability typically observed in the latency of the neural activation patterns (Grootswagers et al., 2017; Fahrenfort et al., 2018; Lopez et al., 2023; Nakuci et al., 2023).

Relatedly, a relevant strength of MVPA approach as compared to univariate techniques, in addition to probing classification accuracy on each timepoint (i.e., diagonal decoding; Grootswagers et al., 2017; Fahrenfort et al., 2018), concerns the possibility of computing cross-decoding analysis, training and testing the classifier decoding performance in a different but related set of data, thus allowing to test whether a specific neural code is recurrent in different experimental conditions, groups and timepoints. In this realm, valuable insights are offered by the cross-decoding over time method (i.e., temporal generalization; King and Dehaene, 2014), which allows investigators to examine how the neural representation of information content is unfolded over time, testing whether a pattern of neural activity identified in a specific time window is recurrent over other timepoints (i.e., above-chance cross-decoding). In simple terms, cross-decoding over time offers a way to identify the longevity and stability of the neural representation associated with the information being processed (Fig. 1; King and Dehaene, 2014; Cichy and Oliva, 2020).

1.4. Scope of the present review

Over the past decade such a machine learning decoding technique of EEG data has gained significant traction in the field of cognitive neuroscience. Several studies have identified the neural dynamics

orchestrating low- and high- level cognitive mechanisms, successfully decoding patterns of neural activity associated with the processing and categorization of visual (e.g., Cauchoix et al., 2014; Bae and Luck, 2019; Robinson et al., 2019; Kaiser et al., 2019; 2020; Petit et al., 2023; Meng et al., 2023; Qiu et al., 2023; Stecher and Kaiser, 2024) and auditory stimuli (e.g., Barne et al., 2018; Jensen et a., 2019; Iamshchinina et al., 2022; Jaatinen et al., 2023;Wehrman et al., 2023), decision-making (e.g., Bode et al., 2012; Stokes et al., 2013; Mercier and Cappe, 2020; Liu et al., 2022; Hu et al., 2024) and working memory processes (e.g., van Gerven et al., 2013; Wolff et al., 2015; Bae and Luck, 2018; Adam et al., 2020; Turoman et al., 2024; Shi and Yu, 2024; Li et al., 2024). They further revealed the precise temporal dynamics underlying the formation of perceptual and conceptual neural representations (e.g., Kamitani and Tong, 2005; Schwarzlose et al., 2008; Simanova et al., 2014; Ronconi et al., 2017; 2024), ultimately providing a useful operative tool to probe cognitive theories (for a recent review, see: Peelen and Downing, 2023).

MVPA of EEG data has historically been exploited in the context of cognitive neuroscience in healthy populations. However, over the past few years, the field has witnessed a paradigm shift, and increasing evidence has demonstrated the operative usefulness provided by MVPA of EEG data in decoding hidden dysfunctional neurocognitive dynamics - and compensatory neural mechanisms - in many different clinical conditions, spanning from psychiatric and neurodevelopmental disorders (Bae et al., 2020; Farran et al., 2020; Li et al., 2023; Li et al., 2022; Gomez et al., 2022; Beach et al., 2022; Marsicano et al., 2024), up to acquired (Pfeiffer et al., 2018; Niessen et al., 2020; Defina et al., 2021; Lasaponara et al., 2021; Tzovara et al., 2012; 2015; 2016), genetic (O'Brien et al., 2020) and neurodegenerative conditions (Karimi et al., 2022; Zhen et al., 2023). This initial empirical evidence supports a greater sensitivity of MVPA of EEG data in identifying aberrant neural dynamics as compared to classical univariate methods.

As this approach is gaining traction, in the current review we formalize and propose that the same MVPA technique capable of characterizing neurocognitive dynamics in healthy individuals may also serve as a powerful lens to identify dysfunctional neurocognitive profiles in a wide range of clinical populations, with a special focus to neurodevelopmental, psychiatric and neurological conditions. While previous studies have provided an overview of the MVPA of EEG data approach in the field of basic cognitive neuroscience (Peelen and Downing, 2023; Borst and Anderson, 2024), or its use with other neuroimaging methods in clinical contexts (i.e., fMRI; Bray et al., 2009), the current review represents the first contribution aimed at offering a comprehensive overview of the state-of-the-art of this information-based EEG decoding technique in clinical research.

In detail, we review experimental studies employing MVPA of EEG data in clinical contexts, with the aim of providing an overview of: i) the applicability of this approach in clinical research, ii) whether MVPA of EEG data can provides higher sensitivity of analysis compared to traditional univariate techniques (e.g., ERP analysis), by also examining the differences between the two approaches, and iii) caveats and best practices for implementing the MVPA of EEG data approach in clinical research. We restricted our focus to time-resolved MVPA studies aimed at decoding neural representations of information processing from raw EEG activity (i.e., raw amplitude) in neurodevelopmental (i.e., Autism Spectrum Disorder, ADHD, William Syndrome, Developmental Dyslexia), psychiatric (i.e., Schizophrenia), and neurological conditions (i.e., neurodegenerative conditions and acquired brain damages) across different cognitive domains (perception, attention, memory, consciousness).

In summary, in this review, after introducing the advantages of MVPA over conventional univariate methods, we provide a comprehensive review of studies highlighting its relevance in understanding the neural dynamics of information processing in clinical populations. We conclude by discussing how MVPA, coupled to the high temporal resolution of EEG, may be relevant in providing a new frontier in the future to uncover hidden neural dynamics capable of characterizing the individual neurocognitive profiles in a wide range of clinical populations.

2. Merits and utility of MVPA of EEG data in clinical contexts

Traditionally, different machine learning approaches of EEG data have been employed within the context of clinical research, particularly for the discrimination of membership in different experimental groups (i.e., clinical vs. healthy population) based on specific EEG features (e.g., raw voltage or frequency measures; for example see: Bleich-Cohen et al., 2014; Koch et al., 2015; Haputhanthri et al., 2019, 2020; Brihadiswaran et al., 2019; Jayawardana et al., 2019; Bennett et al., 2019; Kang et al., 2020; Grossi et al., 2021; Alam et al., 2022; Goodspeed et al., 2023; Moreau et al., 2023; Toki et al., 2024; Rahul et al., 2024; Peterson et al., 2024; Li et al., 2024). In this context, the decoder is provided with data from all participants and is trained to discern the group membership of each individual participant, with the ultimate aim of attaining elevated levels of decoding accuracy. For instance, within the context of Autism Spectrum Disorder (ASD), this approach provides a cost-effective and straightforward diagnostic tool for classifying ASD through EEG signal features, which might be beneficial also for early diagnosis, helping to differentiate ASD from other neurodevelopmental disorders and typical development (Haputhanthri et al., 2019; Brihadiswaran et al., 2019; Jayawardana et al., 2019; Haputhanthri et al., 2020; Toki et al., 2024; Li et al., 2024). However, while this group classification approach proves valuable in the development of diagnostic tools, it fails to provide insights into the differences in the information content of neural representations across individuals (Hebart and Baker, 2018; Fahrenfort et al., 2018; Bae et al., 2020).

In more recent years, MVPA has leveraged on the same machine learning classification algorithms with a conceptually different aim, gaining exponential interest in the realm of clinical neuroscience. Indeed, it can provide an operative tool capable of shedding light on the nature of neural representations of information content in its time course, quantifying the information present in each individual's neural signal.

Importantly, considering the complex patterns of neural activity emerging from the interaction between multiple spatio-temporal features of the EEG signal, MVPA allows to extract meaningful information from neural activity even in presence of low level of neural responses magnitude, as the magnitude of neural responses can be independent of the information that can be decoded from neural responses (Emrich et al., 2013; Hebart and Baker, 2018), thus assuming particular relevance in the clinical context (Bae et al., 2020). In the current review, in line with recent empirical evidence (Farran et al., 2020; Bae et al., 2020; O'Brien et al., 2020; Niessen et al., 2020; Defina et al., 2021; Li et al., 2023; Li et al., 2022; Beach et al., 2022; Gomez et al., 2022; Karimi et al., 2022; Zhen et al., 2023; Marsicano et al., 2024), we argue that such a peculiar sensitivity of MVPA to decode patterns of neural activity associated to information processing could make this decoding technique as one of the most suitable and promising tool for characterizing dysfunctional neural dynamics and peculiars neurocognitive profiles in clinical populations, by extending and sometimes surpassing the potentialities offered by classical univariate analysis approaches (Hebart and Baker, 2018; López-García et al., 2022; Peelen and Downing, 2023). Accordingly, MVPA of EEG data can assume paramount significance for decoding individual patterns of neural activity in clinical populations for a multitude of compelling reasons (please, see Fig. 2 for a graphical summary).

A critical aspect in understanding dysfunctional neural dynamics through univariate methods lies on the fact that they aim to investigate significant differences in EEG voltage (or spectral features) elicited under different conditions, assessing the average-based magnitude and latency of the evoked-EEG activity – across trials and for each individual – over predetermined spatio-temporal features with a well-known meaning (e.g., ERPs components or spectral features; e.g., Luck et al.,

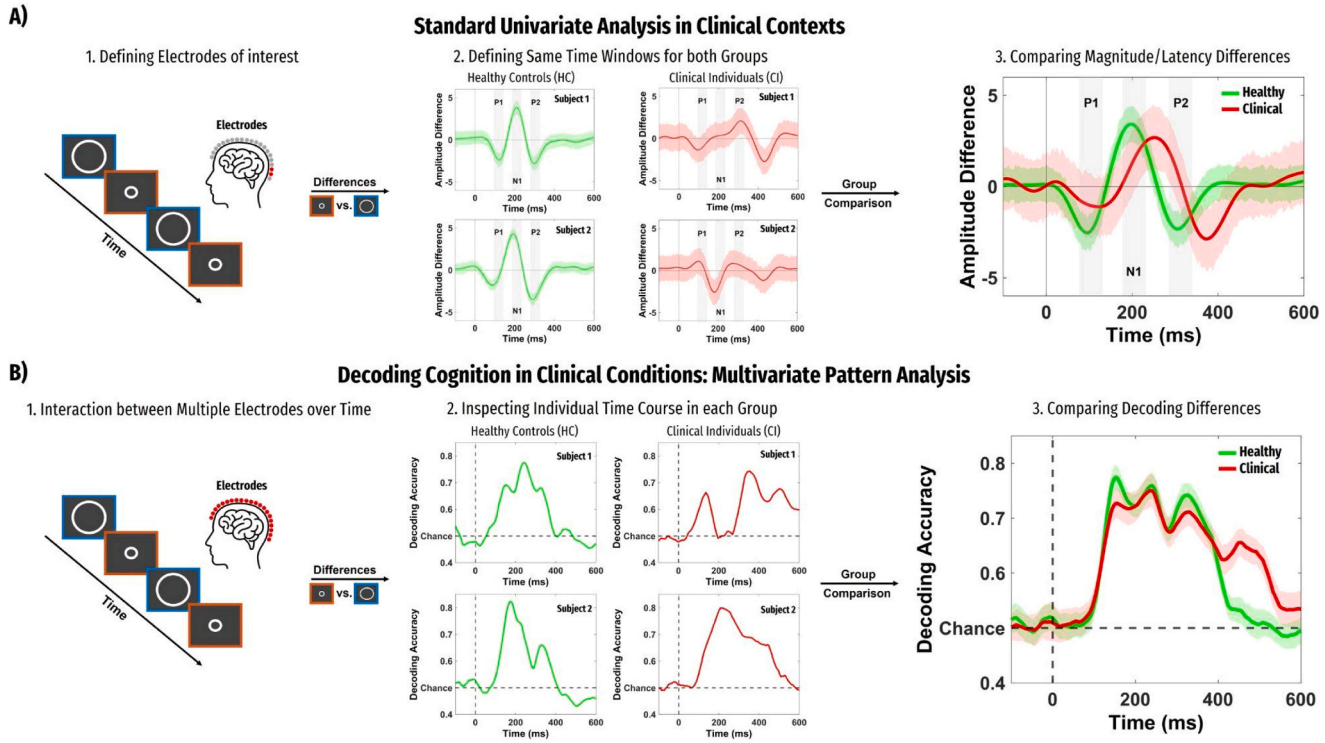

Fig. 2. Schematic illustration depicting methodological and conceptual differences between univariate and multivariate analyses of EEG data in studying neurocognitive dynamics in clinical conditions. **A)** Univariate Analysis. This example of paradigm features the EEG activity differences elicited by two distinct experimental conditions, which are compared between clinical and control groups (A = large circle condition depicted in blue squares; B = small circle condition depicted in orange squares; green line = control participants; red line = clinical participants). In the clinical context, researchers adopt univariate analysis to compare differences between groups in the EEG activity elicited by different conditions over predetermined electrodes and temporal windows, based on the typical neural patterns exhibited by the general population. Here, the EEG activity elicited by Condition A and Condition B at two distinct posterior electrodes is inspected in each group, examining potential intra- and inter-group differences over three different temporal windows (P1, N1 and P2 ERP components). While at the individual participant level the control group shows a clear pattern of differences between conditions on these ERPs components, participants in the clinical group show a qualitatively different pattern of information processing, with more inter-individual variability and differences in the magnitude and temporal latency of effects. Also, subjects in the clinical group show greater intra-individual variability across-trials (red shaded error bar) compared to the control group (green shaded error bar). Averaging the neural activity at the group level assuming uniform scalp distributions and neural timings across individuals in clinical populations, can increase potential differences between groups by mitigating variability among subjects, but dramatically can obfuscates peculiar patterns of neural information processing present at the individual level. **B)** Multivariate Pattern Analysis (MVPA). In the clinical context, MVPA of EEG data is typically computed considering the complex interaction among multiple electrodes and timepoints, with the ultimate aim to identify patterns of information processing present at the individual level. Assessing the consistency of the neural activity across trials for each individual, MVPA decoding accuracy reflects the ability of the decoder to predict whether and when the information content is processed at the neural level, unveiling the uniqueness of neural timing and spatial distribution within each individual. Accordingly, differently from univariate techniques, MVPA demonstrates diminished vulnerability to the increased intra- and inter-individual variability observed within clinical populations. As observable in this example, while the univariate approach constrains the intra- and inter-groups comparisons on specific spatio-temporal features by assuming similar cortical folding patterns for each individual examined, MVPA ascertains whether and at which time the information content has been individually encoded at the neural level within single subjects. This central feature outlines the information-based MVPA approach as a useful operational tool for the identification of dysfunctional and residual/compensatory neurocognitive dynamics in individuals exhibiting clinical conditions. MVPA reveals distinct patterns of neural information processing at the group level within specific clinical populations, which are qualitatively different from those typically observed in the general population, both in terms of the magnitude and latency of neural information processing.

2005; Grootswagers et al., 2017; Hebart and Baker, 2018). Consequently, univariate analyses tend to mitigate variability among subjects, facilitating the emergence of commonalities across individuals to statistically compare the evoked response magnitude as a function of conditions and groups (Luck et al., 2005), with the risk of obfuscating peculiar patterns of neural activity at the individual level (Hebart and Baker, 2018).

On the contrary, MVPA grounds on an information-based data-driven approach (Grootswagers et al., 2017; Bae et al., 2020; Li et al., 2022; 2023; López-García et al., 2022) and is computed at the individual level, by considering within each subject the neural activity derived from distinct subsets of trials for training and testing, thus evaluating the consistency of the neural activity across trials for each participant. Accordingly, the decoding accuracy for a specific subject represents the ability of the neural signal to predict whether the information content is encoded in that individual (Grootswagers et al., 2017; Peelen and Downing, 2023), considering a distinctive pattern of neural activity for each individual (King and Dehaene, 2014; Grootswagers et al., 2017; Fahrenfort et al., 2018). More in detail, MVPA aims to ascertain whether and at which time the information content has been individually encoded at the neural level, informing how neural representations of information content differs between different classes of stimuli (Poldrack, 2006; Poldrack, 2011; Hebart and Baker, 2018). This central feature of MVPA approaches assume considerable significance in clinical populations that can manifest peculiar patterns of neural activity, typically characterized by higher inter-individual variability and noisier neural activity (King and Dehaene, 2014; Dinstein et al., 2015). Grounding on an *atheoretical* data-driven approach (Fahrenfort et al., 2018; Peelen and Downing, 2023), such a decoding technique may represent a valuable operative tool capable to assess whether the phenotype observed in clinical conditions is the product of an alternative, unique neural pathway supported by distinctive neural dynamics (e.g., Thomas et al.,

2009; Farran et al., 2020; Bae et al., 2020; Defina et al., 2021; Li et al., 2023; Marsicano et al., 2024).

Relatedly, while univariate approaches rely on the assumption of relatively uniform scalp distributions and neural timings across individuals for given spatio-temporal components (e.g., ERPs), MVPA of EEG data can reliably decode pattern of neural activity at the individual level, providing a statistical way for addressing the precise spatio-temporal features of neural encoding (e.g., Borrell, 2018; Kroenke and Bayly, 2018; Farran et al., 2020; Marsicano et al., 2024), and uncovering the uniqueness of neural timing and scalp spatial distribution within each individual (Borrell, 2018; Kroenke and Bayly, 2018). This is a crucial point because it has been widely demonstrated that processing speed is often delayed or aberrant in clinical disorders (Key, 2022; Farashi et al., 2023; Marsicano et al., 2024), and constraining the analysis to specific time windows may obscure neural patterns that are evident with different latencies. Thus, being tailored to decode neural information at the individual level, MVPA is less vulnerable to the higher interindividual heterogeneity exhibited by individuals in clinical populations (e.g., Thomas et al., 2009; Dinstein et al., 2015), allowing the identification of potential distinctive, compensatory or residual neurocognitive mechanisms which may establish as a consequence of structural and functional brain anomalies, and that can lead to alternative neural dynamics as compared to those measurable in neurotypical individuals (O'Brien et al., 2020; Dinstein et al., 2015; Farran et al., 2020; Defina et al., 2021; Marsicano et al., 2024).

Although univariate analysis and MVPA of EEG data may be considered conceptually complementary in understanding the neural dynamics orchestrating information processing by addressing different experimental questions (i.e., univariate activation-based vs. multivariate information-based; Grootswagers et al., 2017; Bae et al., 2020; Li et al., 2023; Li et al., 2022; see also below), there is a growing consensus of a greater sensitivity of the MVPA in characterizing the neural representation of information content when compared to traditional univariate analysis techniques (Grootswagers et al., 2017; Hebart and Baker, 2018).

The subsequent section will scrutinize in detail the studies that have leveraged MVPA of EEG data to decode neurocognitive dysfunctions or anomalies of neural encoding in clinical populations, when possible by directly comparing MVPA outcomes with those derived from univariate analysis (see Table 1 for a summary).

3. Decoding cognition in neurodevelopmental and psychiatric populations: the state-of-the-art of empirical evidence

3.1. Decoding cognition in schizophrenia

One of the first attempt in decoding dysfunctional neural patterns of information processing in clinical populations, exploiting MVPA of high-resolution EEG data, was provided by Bae et al. (2020) with the aim to directly determine whether such a decoding technique may be reliably implemented to compare the neural dynamics orchestrating information processing in psychiatric populations. They reanalyzed an EEG dataset previously examined using univariate ERPs analyses (Leonard et al., 2013), in which Schizophrenic (SCZ) individuals showed a higher posterior contralateral delay activity (CDA) during the delay period of a visual working memory task as compared to control (HC) participants. Bae et al. (2020) proposed MVPA of EEG data technique as an information-based decoding approach capable of quantifying in each individual whether and when the information content is encoded by the brain. However, given that the neural signal in individuals with SCZ – and more broadly in clinical cohorts (e.g., Dinstein et al., 2015) - is more variable due to greater noise intrinsically related to variability in neural processes (Smyrnis et al., 2009; Vinogradov et al., 1998; Yang et al., 2014), this could be linked to a lower decoding accuracy in SCZ individuals, posing a crucial issue in the application of this decoding technique in clinical populations. They performed MVPA of EEG data of the time window where the CDA component is typically measured, decoding neural responses elicited by single vs. multiple objects maintained in memory over all electrodes, probing whether such a decoding technique would reveal between- and within-group differences undetected using univariate ERPs analysis. To ensure that differences in decoding performance between groups were not resulting from noise (e.g., Haynes, 2015), Bae et al. (2020) compared the decoding performance between groups (SCZ vs. HC) carefully considering for each individual the strength of task-related neural signal, the extent of neural noise, and the signal to noise ratio (i.e. contrast-to-noise ratio; CNR). First, their results revealed the presence of a greater decoding accuracy in the SCZ group compared to HC subjects, mimicking previous univariate results in which a greater CDA was exhibited by individuals with SCZ (Leonard et al., 2013). Importantly, the decoding performance was predicted by the ratio of the task-related neural signal, its variability across trials, and neural noise (i.e., CNR). While the findings emerging from the univariate analysis allowed to infer only that SCZ allocated more neural activity (i.e. higher CDA) as compared to the HC group, decoding results allowed to conclude that the neural signal contains more task-related information in SCZ as compared to HC individuals, providing a proof-of-concept that MVPA of EEG data can be reliably applied to compare the neural dynamics psychiatric and non-psychiatric populations, highlighting at the same time the importance of carefully considering differences in noise between groups.

In a more recent study, Li et al. (2022) investigated the dysfunctional neural dynamics underlying visual working memory and attentional deficits in first-episode individuals with SCZ. Similar to Bae et al. (2020), the authors employed a visual working memory paradigm while EEG activity was recorded in SCZ patients and HC subjects. Using univariate analyses, the authors identified that SCZ patients showed lower amplitude of N2-posterior-contralateral and CDA components with respect to HC participants. Implementing an information-based MVPA approach they confirmed their univariate results, showing that, despite both groups (SCZ and HC) demonstrated sustained significant decoding of memory loads across time, decoding accuracy was lower in SCZ as compared to HC groups during the time periods of N2pc and CDA. However, such results seem in contrast with previous MVPA findings in which neural activity in CDA time window was decoded with higher accuracy in SCZ patients (Bae et al., 2020), leading the authors to hypothesise that these differences may depend on discrepancies in the experimental paradigm adopted (Li et al., 2022). From a speculative standpoint, such discrepancies may depend on the fact that in this study neural noise in each participant was not considered, potentially leading to a lower decoding accuracy in SCZ where greater noise in the neural signal have been reported (Smyrnis et al., 2009; Yang et al., 2014; Bae et al., 2020; see also Section 4). More interestingly, in contrast to univariate results, only in SCZ individuals, the decoding accuracy of memory load showed a significant positive correlation with their behavioural performance, suggesting that a greater decoding accuracy predicted higher behavioural accuracy. Overall, also in the study by Li et al. (2022), the MVPA of EEG data has proved useful in shedding light on the dysfunctional patterns of neural activity at the individual level in patients with SCZ, which were largely undetectable by using classical univariate ERPs analysis.

3.2. Decoding cognition in neurodevelopmental disorders (Autism, ADHD and Williams syndrome)

To disentangle whether the applicability of this individualized information-based MVPA approach could be extended to neurodevelopmental conditions, the same research group (Li et al., 2023) implemented EEG-decoding technique in school-age children with attention deficit hyperactivity disorder (ADHD), aiming to identify the neural correlates of their visuo-attentional orienting deficits. Specifically, MVPA was implemented for occipito-parietal EEG activity elicited by a classical visual pop-out search paradigm (e.g., Luo et al., 2021;

Table 1
Report of the studies employing time-resolved MVPA of EEG data in clinical populations.

Authors, year, journal	Clinical Condition	Research Domain	Analysis Approach	Univariate Results	MVPA Results
Bae et al., (2020); NeuroImage: Clinical; https://doi.org/10.1016/j.nicl.2020.102179	Psychiatric/ Neurodevelopmental: Schizophrenia (n = 24)	Visual Working Memory	Univariate analysis: ERP MVPA: Diagonal Decoding and CNR (contrast-to-noise ratio)	Higher contralateral delay activity (CDA) in SCZ vs. HC	Higher Decoding Accuracy in SCZ vs. HC. Decoding Accuracy was predicted by CNR
Li et al., (2022); Clinical Neurophysiology; https://doi.org/10.1016/j.clinph.2022.02.001	Psychiatric/ Neurodevelopmental: Schizophrenia (n = 35)	Visual Working Memory and Attention	Univariate analysis: ERP, Alpha Power MVPA: Diagonal Decoding	Lower alpha power, N2pc and CDA in SCZ vs. HC	Lower Decoding Accuracy in SCZ vs. HC. Greater Decoding Accuracy predicted higher behavioural accuracy in SCZ.
Li et al., (2023); Human Brain Mapping; https://doi.org/10.1002/hbm.26115	Neurodevelopmental: ADHD (n = 70)	Visuo-Spatial Perception Target Localization	Univariate analysis: ERP MVPA: Diagonal Decoding	Lower N2pc amplitude in ADHD vs. control	Lower decoding accuracy and a delayed accuracy peak in ADHD vs. HC. Negative association between decoding accuracy and behavioural RTs in ADHD. Negative association between decoding accuracy and standard deviation of RTs.
Marsicano et al., (2024); Autism Research; https://doi.org/10.1002/aur.3062	Neurodevelopmental: ASD (n = 20)	Visual Perception and Attention	Univariate analysis: ERP MVPA: Diagonal Decoding and Temporal Generalization	No difference in P1 and N1 mean amplitude and peak latency between ASD vs. control	Earlier Decoding and a Stronger accuracy in ASD vs. control. Spatially diffuse and temporally prolonged decoding of visual information in ASD vs. control. Higher decoding accuracy of visual information predicted slower RTs at the behavioural level in ASD.
Farran et al., (2020); Neuropsychologia; https://doi.org/10.1016/j.neuropsychologia.2020.107440	Neurodevelopmental: WS (n = 11)	Face Processing	Univariate analysis: ERP MVPA: Diagonal Decoding	No differences between WS and control children in P1 and N170 components	Delayed and sustained decoding for WS vs. control
Gomez et al., (2022); Orphanet J Rare Dis; https://doi.org/10.1186/s13023–022–02395–6	Neurodevelopmental: WS (n = 14), ASD (n = 14)	Face Processing	Univariate analysis: / / MVPA: Diagonal Decoding	/ /	Early time window (~170 ms): lower decoding accuracy in WS, with respect to ASD and control. Late time window (~260 ms): lower decoding accuracy in ASD, with respect to WS and control.
Beach et al., (2022); Frontiers in Human Neuroscience; https://doi.org/10.3389/fnhum.2022.823627	Neurodevelopmental: Dyslexia (n = 24)	Neural Representation of Repeated Standard and Deviant Stimuli	Univariate analysis: / / MVPA: Diagonal Decoding, Temporal Generalization	/ /	No differences in decoding accuracy and latency between DD and control groups. With repetition over time, only in control individuals standards stimuli became increasingly different from deviants
Karimi et al., (2022); Plos One; https://doi.org/10.1371/journal.pone.0264058	Neurodegenerative: MCI (n = 18)	Animacy Processing	Univariate analysis: ERP MVPA: Diagonal Decoding	Decreased P300 amplitude in MCI vs. HC. No neural differences in other timepoints.	Decreased neural speed of animacy information processing in MCI vs. HC evident in different spatial scalp areas and more prolonged over time with respect to ERP analysis
Zhen et al., (2023); The Journals of Gerontology: Series B; https://doi.org/10.1093/geronb/gbad076	Neurodegenerative: aMCI (n = 32)	Visual and Kinesthetic Imagery	Univariate analysis: Mass-univariate Cluster-based Permutation of ERP data MVPA: Diagonal Decoding	Two significant clusters only in visual condition: 130–150 ms; 300–400 ms. aMCI differed in how neural activity was modulated by stimulus orientation	Lower Decoding Accuracy both during kinesthetic and visual imagery in aMCI patients vs. HC. The electrodes that mostly contributed to successful decoding differed between the two groups In both groups significant decoding emerged from global neural patterns, not from specific electrodes. Higher Decoding Accuracy

(*continued on next page*)

Table 1 (*continued*)

Authors, year, journal	Clinical Condition	Research Domain	Analysis Approach	Univariate Results	MVPA Results
					predicted better behavioural outcomes in the executive function domain in aMCI.
Defina et al., (2021); European Journal of Neuroscience; https://doi.org/10.1111/ejn.15387	Chronic Syndrome: CRPS (n = 13)	Pain Perception and Processing	Univariate analysis: / / MVPA: Diagonal Decoding and Temporal Generalization	/ /	Lower decoding accuracy in CRSP vs. HC in the affected side. Pain-related neural responses were delayed and sustained over time in CRSP.
Niessen et al., (2020); NeuroImage: Clinical; https://doi.org/10.1016/j.nicl.2020.102307	Brain Damage: Left Hemisphere (LH) Stroke (n = 24)	Performance Monitoring and Error Detection	Univariate analysis: ERP MVPA: Diagonal Decoding	No differences in ERN amplitude/ latency between LH vs. HC. Aberrant N2 an P3 responses in LH vs. HC	No difference in decoding accuracy between LH vs. HC. Absence of group differences in error-processing neural encoding.
Lasaponara et al., (2021); Neuroscience Letters; https://doi.org/10.1016/j.neulet.2021.136097	Brain Damage: Right Hemisphere Stroke (n = 24) with (N+) and without (N-) left spatial neglect	Posner Task	Univariate analysis: / / MVPA: Single-trial topographical analysis, STTA (De Lucia and Tzovara, 2015)	/ /	Individual level: above-chance decoding of leftward and rightward attentional orienting in five out of the six N+, five out of the six N− patients and in all the six HC. Group level: Significant above-chance decoding level was observed in N+ patients during a later time window (i.e, 400–800 ms) after cue-onset.
Tzovara et al., (2012); Brain; https://doi.org/10.1093/brain/aws264	Brain Damage: Postanoxic Coma (n = 30)	Auditory Deviance Detection	Univariate analysis: Auditory Evoked Potentials (AEPs) MVPA: Diagonal Decoding	23/30 patients on the first day and 20/30 patients during the second day had a consistent AEP. AEPs were not informative about patient's chance of survival	Higher decoding accuracy of auditory processing both in all HC and comatose patients. An increase in decoding accuracy from the first to the second day was predictive of the chance of awakening/ survival at 3 months (100 % predictive value).
Tzovara et al., (2015); Brain; https://doi.org/10.1093/brain/awv041	Brain Damage: Postanoxic Coma (n = 24)	Auditory Deviance Detection at a global (groups of sounds) and at a local (single-sounds) level	Univariate analysis: / / MVPA: Diagonal Decoding	/ /	Detection of global regularities in 10 of 24 patients (above-chance decoding performance). An increase in decoding accuracy from the first to the second day was predictive of the chance of awakening/ survival at 3 months (78 % predictive value).
Tzovara et al., (2016); Annals of Neurology; https://doi.org/10.1002/ana.24622	Brain Damage: Postanoxic Coma (n = 94)	Auditory Deviance Detection	Univariate analysis: / / MVPA: Diagonal Decoding	/ /	The above-chance level decoding between first and second day was predictive of patient's chance of survival (82 %, including all participants; 93 %, excluding patients with epileptiform EEG signal)
Pfeiffer et al., (2018); Annals of Clinical and Translational Neurology; https://doi.org/10.1002/acn3.600	Brain Damage: Postanoxic Coma (n = 66)	Somatosensory Deviance Detection (Auditory and Tactile)	Univariate analysis: / / MVPA: Diagonal Decoding	/ /	Auditory Domain: Above chance-level decoding in 25 patients on the first day and in 31 patients on the second day. Tactile Domain: Above chance-level decoding in 16 patients on the first day and in 23 patients on the second day. Improvement of auditory discrimination, but not tactile, from first to the second day was predictive of patient's chance of survival
O'Brien et al., (2020); Front. Integr. Neurosci.; https://doi.org/10.3389/fnint.2020.00014	Genetic Syndrome: Tuberous Sclerosis Complex (n = 11)	Auditory and Language Processing	Univariate analysis: ERP MVPA Diagonal Decoding	Atypical AEP in TSC vs. HC	Above-chance level decoding accuracy in TSC and HC. No decoding accuracy differences between groups.

Guo et al., 2023), with the aim to decode target localization, as well as to examine a potential association between an inaccurate spatial position encoding and poor behavioural outcomes. The authors claimed that a classical univariate approach may not allow to achieve these aims, since the N2pc (i.e., an ERPs component typically investigated in visual search paradigms; e.g., Woodman et al., 2009) is intricately associated with the process of lateralized attentional selection, but it remains unclear whether it genuinely conveys precise information regarding the target spatial location, or whether it is a mere reflection of attentional shifting. On the contrary, MVPA of EEG data can provide a reliable method to decode neural representations reflecting encoding of spatial localization of target location, as previously demonstrated in healthy individuals (e.g. Foster et al., 2017). Furthermore, an aberrant spatial encoding in ADHD may be related to a higher neural noise (Pertermann et al., 2019; Saville et al., 2015), which might result in a lower decoding accuracy (Deneve and Chalk, 2016; Grootswagers et al., 2017). Li et al. (2023) hypothesised that an increased neural noise, as reflected in a lower decoding accuracy in individuals with ADHD, may be linked to a chaotic neural activity in the visual cortex, which in turn could affect the precision of visuo-spatial attentional localization (e.g., Li et al., 2001). According to these hypotheses, first, they identified a smaller N2pc component elicited in the posterior scalp areas in individuals with ADHD with respect to the control group. In addition, they applied time-resolved MVPA analysis to further explore when and whether the information of target position was decoded. Results showed that decoding accuracy was above chance level starting after the onset of visual search in both control and ADHD groups, but the latter exhibited lower decoding accuracy and a delayed decoding peak, suggesting a more inaccurate and slower target localization in ADHD children. Importantly, correlational analysis among behavioural outcomes, univariate and multivariate neural measures revealed a significant association between N2pc amplitude and decoding accuracy in the control group, but not in ADHD children, who showed a negative association between decoding accuracy and behavioural reaction times (RTs). This suggests that individuals with ADHD encoded target representation with a unique representation not related to N2pc activity, exhibiting a different neural latency. Finally, a negative association between decoding accuracy and standard deviation of RTs at the individual level was found, suggesting that lower level of decoding accuracy in ADHD children predicted higher intra-individual variability in behavioural outcomes. Overall, this pattern of results highlights once again the paramount importance of MVPA in clinical contexts, where individuals show atypical patterns of neural activity and neural processing timings that are often unpredictable, and incomparable with respect to the neural dynamics exhibited by healthy individuals.

Leveraging the same information-based decoding approach, in a recent study (Marsicano et al., 2024) we have adopted MVPA decoding in a sample of individuals with autism spectrum disorder (ASD) with the aim to characterize the dysfunctional neural patterns underlying their atypical visual attention (for a review, see: Palmer et al., 2017), directly comparing the outcomes deriving from univariate and multivariate EEG analyses. Atypical encoding of visual information in individuals with ASD has been widely documented (e.g., Ronconi et al., 2013, 2018; Wang et al., 2015; Lawson et al., 2017; Noel et al., 2021), and in particular their aberrant hyper-focused attention and an inflexibility in the reallocation of attentional resources (Ronconi et al., 2013, 2018; Wang et al., 2015; Lieder et al., 2019; Noel et al., 2021). In our recent study (Marsicano et al., 2024), we hypothesized that such peculiar visual information processing style may be associated with atypically prolonged neural responses and an overrepresentation of visual information at the neural level. To probe these hypotheses, we acquired EEG in age-matched children with ASD and controls (typically developing children) during a visuo-spatial attentional task, where a large or a small circular visual cue preceded the onset of a target at different eccentricities (i.e., centrally or peripherally). MPVA of EEG data was implemented to disclose whether children with ASD showed a prolonged neural representation of visual information, thus comparing neural patterns of ASD and control groups elicited during the modulation of the attentional focus (large vs. small cue trials; cue-locked analysis) and as a function of target location (target-locked analysis). We employed: i) a 'classical' information-based diagonal decoding, where the classifier was trained and tested on the same timepoint; ii) a temporal generalization analysis, using cross-classification across time, a useful method to track whether neural dynamics are stable or transient over time and capable of identifying the longevity of the neural representation of information content (see Fig. 1; King and Dehaene, 2014). 'Classic' MVPA cue-locked analyses highlighted a sustained significant decoding of the cue (large vs. small) in both the ASD and control groups, although an earlier decoding and a stronger accuracy was shown in the ASD group. When the same analysis was performed separately for different clusters of neighbouring electrodes, we found that while in control individuals the neural encoding associated to the visual cue expired at the onset of the target in multiple scalp regions, in the ASD group a significant decoding was present in different scalp regions even after the target onset, thus suggesting a spatially broader and temporally more prolonged processing of visual information, as also confirmed by temporal generalization analyses of cue-related neural responses. Furthermore, an overall significant decoding of target eccentricity was evident in both ASD and control groups, but in the small cue condition (zoom-in condition), children with ASD showed an early onset and a delayed decoding peak with respect to the control group, supporting previous behavioural evidence demonstrating a slower disengagement and hyperfocusing of visual attention (e.g., Ronconi et al., 2013; 2018; Ridderinkhof et al., 2020). Finally, we found that a higher neural encoding of cue-related visual information after target onset predicted slower RTs at the behavioural level only in children with ASD, thus suggesting that an excessive automatic visuo-attentional capture (Palmer et al., 2017; Ronconi et al., 2018; Lieder et al., 2021; Noel et al., 2021), may be linked to a prolonged encoding of visual information at the neural level. Finally, we also performed univariate analysis (for a similar approach, see Luo et al., 2001; Fu et al., 2005; Song et al., 2006; Zhang et al., 2018) on differences between groups in the mean amplitude and peak latency of P1 and N1 ERPs over different scalp areas. Such analyses did not show significant differences between ASD and control groups, strengthening the notion that MVPA of EEG data may be more sensitive in unveiling hidden neural dynamics which might remain largely blind to traditional univariate analysis techniques, which are less sensitive in identifying when the encoding of information content occur over time (Marti and Dehaene, 2017; Mostert et al., 2015; Grootswagers et al., 2017; Fahrenfort et al., 2018; Peelen and Downing, 2023).

Interestingly, despite ASD is associated with higher neural noise and greater intra-individual variability in the neural signal (e.g., Milne, 2011; Dinstein et al., 2015; Pertermann et al., 2019), a greater level of decoding accuracy was found in ASD individuals with respect to the control group. This might reflect, as also suggested in previous MVPA evidence in the context of SCZ (Bae et al., 2020) an aberrant deployment of visuo-attentional and cognitive resources (Luck et al., 2019), with a consequent inflexible hyperfocusing (Luck et al., 2019; Bae et al., 2020; Marsicano et al., 2024). However, additional empirical investigations using EEG-decoding approaches are needed to corroborate this hypothesis.

Shifting the focus to another neurodevelopmental disorder, Farran et al. (2020) successfully provided empirical evidence regarding the higher sensitivity of information-based decoding techniques in unveiling distinctive neural profiles of face processing in individuals with Williams Syndrome (WS). Farran et al. (2020) aimed to characterize the atypical face processing mechanisms and the underlying neural activation profile in WS. Alongside a classical ERPs univariate analysis, they implemented MVPA to explore potential differences between WS and control groups in the neural activation patterns elicited by upright/-inverted faces vs. houses. First, their results showed that both MVPA and univariate ERPs analysis (i.e., N170 ERP component) revealed that both

groups showed a face-specific neural activation profile when compared to houses, suggesting a typical neural activation pattern in classifying faces as a distinct category. Importantly, to unveil potential differences in face-processing masked at the group level, Farran and colleagues (2020) showed that the decoding of face orientation occurred later and was sustained for a longer time in individuals with WS, suggesting hidden atypicalities in the neural response latencies to faces that remained blind to the univariate approach.

Overall, the pattern of results emerging from the aforementioned studies highlighted the operative usefulness of MVPA of EEG data in unveiling dysfunctional and compensatory patterns of neural activity reflecting the neural processing of information content within the realm of neurodevelopmental disorders, which are not easily detectable applying conventional univariate analysis approaches.

3.3. Decoding altered cognition in neurological conditions

An increasing body of empirical findings in this field indicates instances wherein the application of MVPA is not solely a methodological choice for investigators, but it becomes necessary for discerning individual neural responses that are otherwise inaccessible through univariate techniques. For instance, in neurological conditions frequently the brain undergoes a reorganization of its functional architecture, resulting in a pronounced interindividual variability of the neural dynamics underlying information processing. Consequently, there arises a necessity to identify distinctive patterns of neural activity within each individual capable of predicting their neuropsychological profile. As outlined in the overview proposed in following sections, this task proves challenging when approached through univariate analysis methodologies, but can be successfully addressed implementing MVPA (e.g., Tzovara et al., 2012; 2015; Grootswagers et al., 2017; Lasaponara et al., 2021; Karimi et al., 2022).

3.3.1. Neurodegenerative conditions

An explicit empirical illustration of this case was provided in the field of neurodegenerative conditions (Karimi et al., 2022; Zhen et al., 2023), where MVPA has proven useful in providing valuable clinical insights, potentially serving as a biomarker for the early detection of anomalous neurocognitive dynamics in individuals with Mild Cognitive Impairment (MCI). Karimi et al. (2022) implemented MVPA of EEG data to characterize animacy information processing in patients with MCI as compared to a control group. The authors highlighted the need to look beyond a univariate analysis capable of merely indexing activation level of neural responses, applying MVPA with the aim to decode patterns of neural activity reflecting information content in each patient. Applying such a decoding technique, Karimi et al. (2022) identified a decreased neural speed of animacy information processing in MCI patients with respect to control individuals, highlighting a delayed neural encoding latency of the information content. Contrarily, inspecting potential differences of information encoding in the time window where MVPA was capable of discriminating between groups at its maximum, the univariate ERP approach did not reveal significant differences between control and MCI groups. When compared to the ERP univariate results, MVPA differences between groups were evident in different spatial scalp areas and more consistent over time, also showing its usefulness in predicting behavioural outcomes and thus better elucidating individual neurocognitive profiles of information processing.

In a different study, Zhen et al. (2023) investigated the neural correlates of visual and kinesthetic imagery in amnestic MCI (aMCI) patients adopting MVPA to analyze EEG neural dynamics in a data-driven manner. Relying on the evidence of higher inter-individual variability in the spatio-temporal properties of neural responses in aMCI individuals, they highlighted the relevance in this context of examining the patterns of neural activity on large-scale of neural signal, preserving the uniqueness of each patient (Zhen et al., 2023). To ensure a highly comparable confrontation between univariate activation-based and MVPA information-based approaches, in their study the authors employed a data-driven mass univariate analysis (Groppe et al., 2011), allowing the identification of differences between conditions and groups during the entire temporal window of neural processing. Their results showed that while the univariate approach highlighted differences between groups only in the visual imagery conditions, MVPA revealed aberrant processing of both visual and kinesthetic imagery in aMCI patients with respect to control individuals, suggesting a lack of neural representation of information content in both conditions (i.e., lower decoding accuracy). Interestingly, MVPA revealed that spatially the electrodes that mostly contributed to successful decoding differed between the two groups, thus showing that the information processing of kinesthetic and visual imagery was differently represented at the neural level in aMCI and control participants. Furthermore, this decoding analysis revealed that in both groups the ability of the decoder to discriminate kinesthetic and imagery neural processing was not attributable to a specific group of electrodes in the scalp. Thus, the neural encoding of information content was ascribable to patterns of neural activity emerging from the interaction of multiple electrodes across the topographical space, highlighting the importance of MVPA in capturing global patterns of neural activity which are otherwise undetectable by using univariate approaches.

Overall, these findings suggest that MVPA can capture neural patterns of information processing that can provide useful insights in characterizing anomalous neural dynamics of information processing in neurodegenerative conditions.

3.3.2. Acquired brain damages

MVPA approach can yield invaluable insights also in the field of acquired cerebral damage following stroke, where the brain often reorganizes its functional architecture. For instance, Lasaponara et al. (2021) implemented multivariate decoding analysis of EEG neural responses to track the individual profile of left and right endogenous attentional orienting in right-brain damaged patients with (N+) and without (N-) left spatial neglect. Neglect syndrome exhibits notable interindividual variability in its symptomatic profile (e.g., Lasaponara et al., 2018). Consequently, averaging at the group level predetermined spatio-temporal components of EEG signal using a univariate approach could be not effective in providing a reliable characterization of attentional orienting profile at the individual-patient level. Thus, Lasaponara et al. (2021), used a variant of MVPA (Tzovara et al., 2015; single-trial topographical analysis, STTA), analyzing topographical neural responses during leftward and rightward orienting of attention with central cues, comparing N+, N- and controls participants. At the individual level, MVPA successfully decoded EEG signals related to leftward and rightward attentional orienting in right brain-damaged patients and control participants. In particular, in N+ patients, significant individual classifications were mainly observed at a later time window after cue-onset (i.e, 400–800 ms) compared to N- and controls, reflecting an altered and delayed processing of information, but spared voluntary engagement of attentional resources in a later time window. These results highlighted the importance of a decoding approach capable of investigating attentional mechanisms at the individual level and characterising their subtle temporal dynamics.

In a recent investigation, Niessen et al. (2020) adopted MVPA of EEG data to explore the neural dynamics underlying deficits in performance monitoring and error detection (Krämer et al., 2013; Klein et al., 2013) in patients with left hemisphere (LH) stroke affecting the left middle cerebral artery territory, with associated cognitive deficits (i.e., aphasia and apraxia) and executive dysfunction. Alongside the application of univariate ERPs analysis with the aim to investigate neural activity associated with stimulus-processing (i.e., N2 and P3 components) and error-related information (error-related negativity; ERN), they implemented MVPA to track over time whether the pattern of whole-brain activity allowed to decode correct from erroneous responses, thus identifying an individual index of error-related processing. Surprisingly,

although both stimulus-related ERP components (i.e., N2 and P3) were abnormal in patients as compared to controls, no group differences were observed in ERN activity, suggesting that early deficits in stimulus processing were successfully compensated in subsequent response-related ERP components. Also, the MVPA analysis confirmed the absence of group differences in error-related neural processing, as the information contained in the neural activity related to correct and incorrect responses was decodable above chance level in both groups (Niessen et al., 2020), supporting the value of MVPA analyses also in unmasking preserved post-lesional cognitive functions.

3.3.3. *Decoding neural processing of sensory information in neurological conditions*

The application of time-resolved MVPA of EEG data within clinical contexts has proven not only as valuable for decoding high-level aspects of cognition, but also stands as an effective tool for inspecting the integrity of low-level sensory systems and perceptual processes.

A clear empirical evidence in this context was provided by Tzovara and colleagues in a series of different studies (Tzovara et al., 2012; 2013; 2016; Pfeiffer et al., 2018), which demonstrated the ability of MVPA, with respect to univariate approaches, to decode patterns of neural activity associated with auditory information processing even in the absence of explicit measures of cognition in comatose patients. In their first pioneering study, Tzovara et al. (2012) analyzed EEG neural responses related to standard and deviant sounds (i.e., mismatch auditory paradigm) of 30 post-anoxic comatose patients compared to control participants, implementing MVPA at the single patient level at two different times: within 24 h after coma onset and subsequently after 1 day. First, their results revealed a high level of decoding accuracy in discriminating sounds both for all control subjects and all comatose patients, thus showing that also the latter showed, to some extent, preserved neural representations of auditory information. Concomitant with MVPA, they conducted a univariate analysis of auditory evoked potentials (AEPs) across fronto-central electrodes. Nevertheless, given the higher interindividual variability of these patients and the spatio-temporal constraints applied in univariate methodology (i.e., predetermined time window and pool of electrodes analyzed), this analysis revealed consistent AEPs only in 23 patients during the first day and in 20 patients during the second day of EEG recording. Thus, these findings highlighted the enhanced sensitivity of MVPA in capturing global patterns of neural activity reflecting auditory sensory processing, which were undetectable applying standard univariate approaches. Interestingly, an increase in decoding accuracy between the first and second day of EEG data acquisition was also informative of the patient's chance of survival and awakening at 3 months, with 100 % positive predictive value. On the contrary, AEPs univariate analysis did not yield informative insights into the clinical prognosis of individual patients, ultimately highlighting the importance of MVPA in providing paramount insights at the individual level. Following their initial findings, the outcomes derived from MVPA were successfully replicated in a large cohort of individuals in a comatose state (Tzovara et al., 2016) and in response to more complex auditory (Tzovara et al., 2013, 2015) and tactile stimuli (Pfeiffer et al., 2018).

Another interesting contribution in this field was provided by Defina et al. (2021), who highlighted how MVPA of EEG data has proven as a useful tool for exploring dysfunctional neural dynamics underlying tactile perception in individuals with chronic complex regional pain syndrome (CRPS). The authors investigated potential differences in neural responses elicited by touch in the affected and unaffected side of the body between CRPS individuals and controls. Following previous studies in healthy population, which showed the effectiveness of MVPA in decoding the neural patterns associated with pain perception (Schulz et al., 2011; Rosa and Seymour, 2014; Lancaster et al., 2017), the authors exploited this decoding technique in CRPS participants, extracting individual patterns of neural activity related to the pain experience. Implementing an elegant coupling of decoding techniques and computational models (Defina et al., 2021), they found an overall lower decoding accuracy in CRSP patients as compared to the control group in the affected side of the body, with the associated neural code that was delayed and sustained over time, as highlighted, respectively, by diagonal decoding and temporal generalization analysis. In discussing their results, Defina et al. (2021) underlined the importance of using EEG decoding techniques capable of identifying individual patterns of neural information processing related to individual differences in perceptual and sensory processes, ultimately providing a useful tool to obtain individual neurocognitive profiles for a better identification and treatment of CRSP.

To summarize, in acquired neuropsychological conditions, information-decoding techniques facilitate the characterization of residual activities and potential compensatory mechanisms of information processing, elucidating unique spatial localizations and temporal patterns that may emerge in these cohorts as a consequence of functional and structural anomalies.

4. Caveats of MVPA in clinical contexts

Despite its promising utility, MVPA of EEG data is not exempt from some methodological pitfalls that must be considered before the application of this method in clinical populations. Individuals charachterized by clinical conditions often exhibit a noisier neural signal and a higher variability in neural processes (e.g., trial-by-trial variability; Yang et al., 2014; Dinstein et al., 2015; Pertermann et al., 2019; Carment et al., 2020; Turri et al., 2023; Dwyer et al., 2024). In detail, individuals affected by clinical conditions typically show a more 'chaotic' neural signal and variable patterns of neural responses over time, which can mask the physiological neural activity (Smyrnis et al., 2009; Vinogradov et al., 1998; Yang et al., 2014; Dinstein et al., 2015; Turri et al., 2023), ultimately exerting a detrimental impact on MVPA decoding performance (i.e., lower decoding accuracy), whose level of accuracy in predicting neural activity differences between conditions typically relies on effect consistency across trials (Deneve and Chalk, 2016; Grootswagers et al., 2017; Bae et al., 2020; Li et al., 2023). Despite this potential pitfall, as outlined throughout the current review, MVPA has proved to be particularly useful in characterizing neurocognitive profiles in clinical populations exhibiting higher neural noise. Increasing evidence in the domain of neurodevelopmental (ASD: Gomez et al., 2022; Marsicano et al., 2024; WS: Farran et al., 2020; Gomez et al., 2022; ADHD: Li et al., 2023), psychiatric (SCZ: Bae et al., 2020; Li et al., 2022) and in acquired neuropsychological conditions (e.g., Pfeiffer et al., 2018; O'Brien et al., 2020; Niessen et al., 2020; Defina et al., 2021; Karimi et al., 2022; Beach et al., 2022; Gomez et al., 2022; Zhen et al., 2023), demonstrated that MVPA of EEG data is a reliable and enlightening technique to decode how the information content is encoded by the brain in clinical populations with high intra and inter-individual neural variability. For instance, it was documented that a higher neural noise in individuals with attention deficit and hyperactive disorder (ADHD) was associated with a lower decoding accuracy of neural representations of information content, which in turn predicted aberrant behavioural outcomes (Li et al., 2023). On the other hand, addressing visual working memory impairments in schizophrenia (SCZ), carefully accounting for the neural noise in the signal, two different studies recently demonstrated different decoding accuracy in SCZ individuals as compared to healthy control individuals, although the directionality (increased vs. decreased accuracy) remains to be clarified (Bae et al., 2020; Li et al., 2022). Similarly, in the context of autism spectrum disorder (ASD; Marsicano et al., 2024) and William Syndrome (WS; Farran et al., 2020; Gomez et al., 2022), it has been demonstrated a greater decoding accuracy with respect to neurotypical individuals, capable of predicting aberrant behavioural outcomes at the individual level. The mixed pattern of results emerging from these studies suggest that, while the level of decoding accuracy mainly corresponds to the decoder's ability to discriminate differences in how different contents of information are processed at the neural

level, in the clinical context the decoding performance is highly influenced by the intra-individual variability in neurocognitive processes (Deneve and Chalk, 2016; Grootswagers et al., 2017). Given the greater intraindividual neural variability in clinical populations, this point assumes crucial importance, and neural noise must be carefully considered when implementing MVPA approaches (e.g., Bae et al., 2020; Li et al., 2022). To mitigate this noise issue, various strategies have been proposed. One effective approach is to employ robust cross-validation techniques (e.g., Brihadiswaran et al., 2019; Fahrenfort et al., 2017), to ensure the reliability of the decoding results for each individual. This method helps to smooth out the effects of neural noise by training and testing the decoding classifier on different subsets of data, ensuring that the model's performance is not dependent on any particular set of data, which might include noise. This approach reduces the risk of overfitting to noisy data and ensures that the model's performance accurately reflects its ability to generalize beyond the specific data used in training. Additionally, the signal-to-noise ratio (SNR) can be included as a covariate in statistical models to control for noise effects, ensuring that differences in decoding performance are not simply due to variations in neural noise levels. By calculating SNR, it is possible to quantify the amount of noise in the data for each individual. This procedure allows for comparing SNR between groups (e.g., clinical vs. controls) to identify and account for differences in data quality that might affect the decoding results. For example, an EEG-MVPA study in the context of SCZ (Bae et al., 2020) showed that decoding performance was predicted individually by the SNR, thus highlighting the importance of carefully considering differences in noise between individuals and groups in the clinical research.

Also the decoding onset and peak latencies are often distorted by neural noise, and this assumes crucial relevance in clinical contexts where such neural noise is typically greater (Yang et al., 2014; Dinstein et al., 2015; Pertermann et al., 2019). In this context, a reliable method for characterizing temporal dynamics when testing for statistical significance using EEG decoding is to determine the onset latency as the moment when the component attains 50 % of its maximum amplitude (Luck, 2014; Fahrenfort et al., 2018).

Another critical aspect of MVPA, as previously discussed in this review (see Section 1.2), lies in the loss of information regarding the direction of the effect when comparing different conditions or experimental groups (e.g., lower/higher amplitude). This information is, however, of substantial relevance in clinical contexts, where it is typically useful to quantify markers of neural activation (e.g., amplitude, latency), which can be easily compared between groups and experimental conditions. For example, a consistent body of evidence, using an activation-based approach (i.e., ERPs univariate analysis), has revealed that individuals with ASD show a smaller amplitude in the N100 component elicited by non-face stimuli and N170 amplitude elicited by faces (for a recent review see: Farashi et al., 2023). Such comparisons of neural activity differences between groups or experimental conditions are not directly accessible through MVPA, as it is an information-based approach primarily aimed at identifying neural patterns associated with the processing of information content. Accordingly, MVPA provides a percentage-based measure of classifier accuracy in predicting differences in neural activity related to different information content, thus obfuscating the direction (e.g., positive or negative) of neural responses and their relative magnitude. This makes it harder to evaluate whether one group or experimental condition is associated with greater or lesser neural activation compared to another. However, as previously discussed (see Section 1.2), this MVPA limitation can be overcome. Feature weights can be forward-projected onto topographical maps, providing activation patterns at each individual timepoint and electrode, reflecting the mass-univariate differences between the compared conditions (Haufe et al., 2014; Fahrenfort et al., 2017).

When the aim is to compare neural activity associated with an experimental condition between different groups (e.g., ASD vs. control), using the MVPA approach poses additional challenges. This is because the decoding approach primarily aims at discriminating between different neural patterns associated with different information content, which can then be compared between different groups, as described in this review. Despite various methods being proposed to address this MVPA limitation (for example, see: Hebart and Baker, 2018), we suggest an integrated approach of univariate analysis and MVPA in the clinical context. This integrated approach can flexibly adapt to the research needs of the investigator, as both methods can provide insightful information regarding neural processing differences between populations and individuals, addressing different research questions (i.e., activation-based vs. information-based approaches).

5. General discussion and future perspectives

The insights garnered from the empirical investigations examined throughout this review emphasize that the MVPA approach applied to EEG data holds particular promise for investigating both dysfunctional and compensatory neural patterns associated with information processing across diverse cohorts of neurodevelopmental, neuropsychiatric and neuropsychological conditions. An EEG information-based decoding approach, as the one proposed in the aforementioned studies, may provide new valuable insights concerning individual neurocognitive profiles in clinical populations, better accounting for the higher heterogeneity across individuals, while preserving the peculiarities of each subject (e.g., Dinstein et al., 2015; O'Brien et al., 2020; Farran et al., 2020; Bae et al., 2020; Marsicano et al., 2024).

In contrast to the limited sensitivity offered by average-based univariate analysis (e.g., ERPs), which tend to underestimate the substantial interindividual variability of neural activity across individuals in clinical populations, data-driven MVPA approach considers the comprehensive patterns of neural activity for each individual arising from intricate interactions among multiple timepoints and electrodes (Cauchoix et al., 2014; Grootswagers et al., 2017; Holdgraf et al., 2017; Bayet et al., 2018; Peelen and Downing, 2023). In clinical conditions characterized by notable differences in patterns of neural activity, manifesting with unique spatio-temporal localizations, such a decoding approach can assume significant importance, as it facilitates the exploration of dysfunctional neural dynamics and compensatory mechanisms of information processing that may emerge due to functional anomalies (e.g., Grootswagers et al., 2017; Fahrenfort et al., 2018; O'Brien et al., 2020; Bae et al., 2020; López-García et al., 2022; Li et al., 2022; 2023; Marsicano et al., 2024).

Conventional univariate analyses – typically applied to predetermined spatio-temporal components of the EEG signal – are often driven by a theory-driven framework, posing a risk of overlooking dysfunctional patterns and alternative neural dynamics present in individuals with clinical conditions. Conversely, MVPA holds the potential to effectively capture individual patterns of neural activity, without necessitating a priori selection of spatio-temporal EEG components, thus delineating a novel avenue for investigating individual neurocognitive profiles (e.g., Grootswagers et al., 2017; Bae et al., 2020; Li et al., 2023; 2022; Marsicano et al., 2024). Importantly, differently from traditional univariate techniques, where statistical analysis is performed at the group-level, EEG decoding is computed separately for each individual, providing a paramount tool for understanding how information content is individually encoded by the brain. This peculiarity is promising to optimize personalized assessment and intervention in different clinical cohorts (e.g., Bae et al., 2020; Farran et al., 2020; Defina et al., 2021; Li et al., 2022; 2023; Marsicano et al., 2024).

Nonetheless, as discussed in previous sections, we want to emphasize that within the clinical context, the application of MVPA of EEG data does not preclude the concurrent use of conventional univariate approaches. Rather, it enriches the decoding analysis, providing valuable complementary information, such as insights into the magnitude and direction of neural activation differences across different experimental conditions. Indeed, the information content is also inherently present in

the univariate EEG signal, although when the locus of the effect is unclear, experimental differences between groups can be more difficult to discern using traditional univariate approaches (Fahrenfort et al., 2017; Fahrenfort et al., 2018; Bae et al., 2020; Li et al., 2022; 2023; Marsicano et al., 2024). Consequently, we advocate for an integrated approach that combines conventional univariate analysis with MVPA, resulting in a methodology designed to enhance sensitivity in the detection of differences between and within individuals.

An intriguing aspect emerging from this literature review concerns the decoding accuracy differences in identifying neural representations of information between groups (i.e., typical vs. clinical). Although low or moderate levels of decoding accuracy in individuals with clinical conditions can be attributed to their higher neural noise (please, see previous sections and: Dinstein et al., 2015; Pertermann et al., 2019; Turri et al., 2023), interestingly, several studies have shown that neuroatypical individuals can often exhibit higher levels of accuracy compared to control participants. For instance, recent studies revealed that individuals with ASD (Marsicano et al., 2024) and SCZ (Bae et al., 2020) showed an overall greater level of decoding accuracy compared to the typical group. This is counterintuitive, as clinical populations are typically characterized by higher neural noise and greater variability in the neural signal (e.g., Pertermann et al., 2019), which would be expected to result in lower decoding accuracy compared to typical individuals. It has been recently hypothesized that the accuracy of the decoding performance might also indicate a greater representation of information content in neural activity and the extent of neurocognitive resources deployed during stimulus encoding (Bae et al., 2020; Marsicano et al., 2024). Although such functional interpretations of decoding accuracy level in predicting the extent of neurocognitive resources allocated remain speculative at present, we encourage the scientific community to empirically investigate these hypotheses by implementing EEG-decoding techniques in clinical research.

Relatedly, the studies examined in this review suggest that multiple aspects of decoding performance can be informative for characterizing neurocognitive profiles in clinical populations. As employed in recent clinical studies (O'Brien et al., 2020; Farran et al., 2020; Bae et al., 2020; Karimi et al., 2022; Beach et al., 2022; Li et al., 2022; 2023; Zhen et al., 2023; Marsicano et al., 2024), we suggest indexing measures at both individual and group levels that highlight both the accuracy (i.e., percentage of accuracy) and the timing (i.e., decoding latency) of decoding performance. This approach allows for the identification of information related to: i) when information content begins to be decodable in neural activity (*decoding onset*), ii) how prolonged the neural encoding of information is over time (*sustainability of decoding*), iii) the average level of accuracy and the latency peak of the decoding performance (*decoding accuracy* and *peak decoding latency*; for example, see: Farran et al., 2020). Additionally, coupling cross-decoding over time analysis (i.e., temporal generalization) with the diagonal decoding technique (i.e., training and testing at the same time point) can be useful for identifying sequential stages of information processing in individuals with clinical conditions typically exhibiting aberrant neural processing timings, providing valuable information regarding the longevity of neural representations (King and Dehaene, 2014; Defina et al., 2021; Beach et al., 2022; Marsicano et al., 2024).

In the current review, we restricted our focus on evidence employing such a decoding technique within the time domain of EEG data (time-resolved MVPA). Nonetheless, this approach can also be applied to decode information contained in the neural activity by addressing other evoked and spontaneous measures of the EEG signal, such as frequency and time-frequency features (e.g., Jafarpour et al., 2013; Bae and Luck, 2018; Desantis et al., 2020; Zhang et al., 2023). For instance, MVPA was recently employed to ascertain whether raw amplitude and frequency features of the EEG signal reflected different aspects of visual attentional selection, revealing that oscillatory activity in the alpha band may be more associated with the orientation of covert attention, while raw amplitude could be linked to low-level perceptual processes (Bae and Luck, 2018; Desantis et al., 2020). Within this context, as indicated by recent evidence in the clinical domain (e.g., Zhang et al., 2023), it is desirable that future studies will employ decoding of information content by using different EEG measures with the aim to obtain a more comprehensive understanding of the individual neurocognitive profile.

Finally, a noteworthy aspect we wish to emphasize is that, notwithstanding the importance of a basic comprehension of the methodological principles underlying the application of MPVA to EEG data, contemporary tools do not necessitate an advanced programming proficiency. Notably, Matlab-based toolboxes, such as CoSMoMVPA (Oosterhof et al., 2016), ADAM (Fahrenfort et al., 2018), and the latest version of ERPLAB (Lopez-Calderon and Luck, 2014; Luck et al., 2023), required only a modest level of programming knowledge, thereby enabling the implementation of most analyses described in the current review through a user-friendly interface.

We foresee that MVPA of EEG data will be a valuable tool for identifying dysfunctional and compensatory patterns of neural activity in a wide range of neurodevelopmental, neuropsychiatric and neuropsychological conditions, thanks to its potential to identify biomarkers of anomalous cognitive architecture and to tailor treatment for individuals based on their unique neural signatures.

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Declaration of Competing Interest

The authors declare no competing interests.

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