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A measure centrality index for systematic empirical comparison of consciousness theories

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ABSTRACT

Consciousness science is marred by disparate constructs and methodologies, making it challenging to systematically compare theories. This foundational crisis casts doubts on the scientific character of the field itself. Addressing it, we propose a framework for systematically comparing consciousness theories by introducing a novel inter-theory classification interface, the Measure Centrality Index (MCI). Recognizing its gradient distribution, the MCI assesses the degree of importance a specific empirical measure has for a given consciousness theory. We apply the MCI to probe how the empirical measures of the Global Neuronal Workspace Theory (GNW), Integrated Information Theory (IIT), and Temporospatial Theory of Consciousness (TTC) would fare within the context of the other two. We demonstrate that direct comparison of IIT, GNW, and TTC is meaningful and valid for some measures like Lempel-Ziv Complexity (LZC), Autocorrelation Window (ACW), and possibly Mutual Information (MI). In contrast, it is problematic for others like the anatomical and physiological neural correlates of consciousness (NCC) due to their MCI-based differential weightings within the structure of the theories. In sum, we introduce and provide proof-of-principle of a novel systematic method for direct inter-theory empirical comparisons, thereby addressing isolated evolution of theories and confirmatory bias issues in the state-of-the-art neuroscience of consciousness.

1. Introduction

Explaining how consciousness fits in the physical world remains the science's holy grail (Melloni et al., 2021). After a long hiatus, the neuroscientific study of consciousness is experiencing a revival, most likely due to technological advancements that have made it possible to study the human brain non-invasively in real-time. The field is growing (Michel et al., 2019), and over the past 25 years, neuroscientific hypotheses, models, and theories have proliferated while also gaining empirical support (Northoff and Lamme, 2020; Sattin et al., 2021; Seth and Bayne, 2022; Signorelli et al., 2021; Yaron et al., 2022).

However, as theories co-evolved, challenges have emerged. Among the most significant ones is the heterogeneity that hinders direct comparison and adjudication between theories in their explanatory target, theoretical notions, principles, methodology, and postulated mechanisms. Further, a systematic review of the literature of four prominent theories of consciousness revealed parallel co-evolution of the theories, with a confirmation bias, further amplified by methodological preferences, which by itself can significantly predict the theory outcome (Yaron et al., 2022).

Direct comparisons between theories, including an adversarial collaboration format (Kahneman, 2003; Latham et al., 1988; Mellers et al., 2001) testing contradictory prediction and open data sharing, have been suggested to remedy confirmation bias and other challenges in the field (Lepauvre and Melloni, 2021). An open science adversarial collaboration testing contradictory predictions of IIT and GNW has provided the first proof of principle of this approach (Consortium et al., 2023; Melloni et al., 2023, 2021). Going beyond particular insights from adversarial collaborations testing the different theories of consciousness, how can we directly and systematically compare all currently proposed theories of consciousness, including their various empirical measures?

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We currently lack such a systematic methodology. To make headways on this problem, here we present a systematic methodology inspired by conceptual insights from both the philosophy of science (Box 1) and non-reductive neurophilosophy (Box 2). One of our guiding principles is that to be scientific, a theory must be experimentally refutable, at least in principle (Popper, 2002). Following these philosophical lessons, we develop and apply our novel methodology to directly compare three theories in their empirical measures in a systematic and exemplary way: the Global Neuronal Workspace Theory (GNW) (Dehaene and Changeux, 2011; Mashour et al., 2020), the Integrated Information Theory (IIT) (Albantakis et al., 2023; Tononi et al., 2016), and the Temporospatial Theory of Consciousness (TTC) (Northoff, 2018, chaps. 7–8; Northoff and Huang, 2017; Northoff and Zilio, 2022a). That establishes cross-theoretical empirical translations, in which measures proposed by one theory are considered in the context of the other theories. Hence, our systematic methodology creates an arena where theories can directly compete with each other in an adversarial style.

Our approach makes a novel and distinct contribution to the **theory of consciousness science**, an emerging field focused on the empirical, philosophical, and mathematical presuppositions of state-of-the-art approaches to scientifically explaining experience (Bayne et al., 2024; Corcoran et al., 2023; Del Pin et al., 2021; Doerig et al., 2021; Fazekas et al., 2024; Melloni et al., 2021; Michel et al., 2019; Negro, 2024; Storm et al., 2024; Zheng et al., 2024). Here is the paper's outline. **Section 2** briefly introduces the Measure Centrality Index (MCI) methodology, its categories, and challenges. **Section 3** contains the search parameters, inclusion criteria, and the systematic literature review of each theory, with all available measures condensed in Tables 2, 3, and 4, corresponding to GNW, IIT, and TTC, respectively. **Section 4** puts forward cross-theoretic empirical translations for five experimentally tractable divergences using measures from each theory, exemplifying this novel method. **Section 5** addresses the MCI's main challenges and considers response strategies. **Section 6** discusses limitations and prospects.

2. Method for inter-theory comparison: the measure centrality index (MCI)

How can we directly compare the different theories in their respective empirical measures? This section addresses this question by developing a methodological tool, the Measure Centrality Index (MCI), and lists its main intra-theoretical, inter-theoretical, and field-level challenges. We start by defining the concept of "empirical measure" in a general and field-specific scientific context.

Broadly, a scientific measure is a methodologically defined procedure for categorizing or quantifying features or properties of phenomena of interest, facilitating their empirical examination. An empirical measure comprises a symbolic and a physical component (Tal, 2020). The symbolic component involves using formal languages (e.g., mathematical, logical) to define the measurement process, ensuring systematic, reproducible, and rigorous procedures. While natural language is included in the symbolic component, in most cases is complemented or replaced by strictly formal languages because of rigor requirements. Formalism choice is contingent upon the nature of the investigated phenomenon and the research objectives, adhering to coherency, consistency, and relevance principles.

The physical component of a measure involves an experimentally tractable variable that bridges the abstract and the observational domains. It presupposes the possibility of interacting with the world via an algorithm-like procedure, e.g., observation, perturbation, quantification, recording—repetition—reproduction. A variable is called "physical" because it is possible, in principle, for different observers at different times and contexts to engage with it in a procedure-following manner; i.e., the variable is intersubjectively assessable (Tal, 2020).

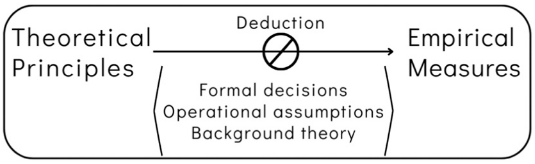
In consciousness science, empirical measures connect "covert," intrasubjective features of experience to "overt," intersubjective investigation procedures. As in other disciplines, they feature symbolic and physical components. However, unlike other scientific phenomena, consciousness is observable only from the first person but not the third person; it is subjective, private, and qualitative (Gallagher and Zahavi, 2021; Goff, 2019). This implies that in the case of consciousness, we

Box 1
Lessons from Philosophy of Science: The Intra-theory Triangulation Requirement.

Developed in the philosophy of science, the Duhem-Quine thesis addresses the complexity of testing scientific hypotheses, highlighting the problem of data underdetermination and the holistic aspect of theory evaluation (Duhem, 1954; Quine, 2011). Data underdetermination means that empirical evidence alone cannot establish a single scientific theory because multiple, potentially conflicting theories can explain an observed dataset. Moreover, since any scientific theory depends on auxiliary hypotheses, assumptions, or frameworks, no single, "crucial experiment" can directly confirm or refute it (Duhem, 1954, pp. 188–90)—holistic theory evaluation. Due to data underdetermination and the inability to test hypotheses alone, science requires subjective judgment, creativity, and theory-dependent interpretation.

These ideas strike the core of theory-building and theory-reduction conundrums in consciousness science. As a start, there is a gap between a theory's principles and experimentally deployable measures. Crucially, this gap must be closed through auxiliary operational assumptions. For example, applying empirical measures involves mathematical formalism and computational decisions, background theory about experimental methodology, and implementation presuppositions—yet currently, none figure explicitly in a consciousness theory's principles. Explicitly defining them creates what we describe as the *intra-theory triangulation requirement*, ensuring the empirical access and testing of a theory's claims about experience.

In other words, theory proponents should expound the process whereby a principle targeting some consciousness aspect is rendered empirically tractable. This is often left unaddressed or, at best, implied without any formal justification. Abiding by the "scientificity" imperative, theoreticians grab any available measure that dovetails their proposal and throw it into the empirical arena. We conjecture that this could contribute to the high prevalence of theory-confirming studies (Yaron et al., 2022) that partially led to the field's current crisis.



Box 2
Lessons from Non-reductive Neurophilosophy: The Inter-theory Coordination Requirement.

Neurophilosophy is an interdisciplinary field that bridges the conceptual and methodological gaps between neuroscience and philosophy. One of its main traditions is non-reductive neurophilosophy (Northoff, 2004, 2014a, 2014b; Zilio, 2020). It resists reducing philosophical concepts, domains, and methodologies to their neuroscientific counterparts, instead emphasizing their reciprocal influence, co-evolution, and pluralism.

Northoff (2014a), Chapter 4) exemplifies the stages of the non-reductive neurophilosophical approach. First, a “conceptual feedforward input” uses a philosophical concept to develop operational criteria for observational-experimental investigation. After, a “conceptual feedback output” redefines the concept empirically. Finally, the redefined concept can be returned to its metaphysical, epistemological, or ethical domain to examine its implications for the respective philosophical questions. More specifically, the concept is redefined within the empirical context of neuroscience, making it an empirical concept that can also be placed within the empirical domain.

These genuine neurophilosophical concepts can be compared to their philosophical counterparts, and one can restart the process and use the concept in observational-experimental studies. “Concept–fact iterativity” captures how concepts and facts constantly modify and redefine each other. An example is the phenomenal-access consciousness distinction (Block, 1995), as heavily debated in current consciousness discussion with its fluctuations between empirical and phenomenal issues/concepts.

In the **Introduction**, we noted the consciousness theories’ heterogeneity in definitions, methodologies, epistemological stances, and prioritizations; hence, comparing them is a complex task called the *inter-theory coordination requirement*. It implies overcoming the challenges in meaningfully comparing architectonically different theoretical frameworks that claim to address similar or overlapping phenomena. Georg Northoff’s (2014) neurophilosophical developments provide an insightful lens to manage the inter-theory coordination problem, explored in more detail in **Section 2** .

The concept-fact iterativity can act as a bridge. The notion that concepts and facts are continuously recursive suggests that theories (laden with concepts) and empirical findings (facts) co-evolve. If we extend this principle to multiple theories, it implies that through iterative engagement with empirical data, theories can refine their concepts in ways that lead to greater alignment or coordination with other theories. Next, Northoff emphasizes the importance of starting from a phenomenological base. In the context of the inter-theory coordination problem, theories might find common ground by anchoring themselves in shared phenomenological descriptions of their target phenomenon or attempting to agree on one.

The iterative nature of concept-fact engagement underscores the idea that theories are refined and evolve. Recognizing this dynamism can determine theorists to adjust, align, or even merge aspects of their theories in light of new evidence or insights. Finally, just as Northoff champions the intersection of neuroscience and philosophy, the inter-theory coordination problem can benefit from interdisciplinary dialogues, where insights from one domain or theoretical tradition can inform and enrich another.

need to link a first-person phenomenon to an empirical measure accessible from a third-person perspective. Nevertheless, how can we know whether the first-person phenomenon is reliably and reproducibly picked up and measured by the third-person measure?

We are, thus, confronted with a gap between first-person access to the phenomenon and the requirement of its third-person measurement (Levine, 1983; see also Chis-Ciure, 2022, 2024; Negro, 2020; Northoff, 2014a, 2014b; Zilio, 2020). The consequence is that methodologically bridging this gap requires explicitly operationalizing experiential phenomena so they can be observed, perturbed, quantified, and recorded, emphasizing reproducibility and intersubjective verification. Thus, when a theory proposes to measure some aspect of consciousness, it must provide an independent argument as to the necessity or, at least, reliable connection between the third-person measure and first-person experience. This marks the difference between a measure of consciousness and a measure of consciousness-related phenomena.

The MCI involves creating a relevance ranking for an empirical measure within a given theory. One quadripartite index could encompass orthogonal, periphery, mantle, and core measures, reflecting a relevance spectrum (Fig. 1).

Orthogonal measures, irrelevant to and outside the boundaries of the theory, do not impact its structure even if predictions based on them conflict with empirical evidence; e.g., they could be measures proposed by competing theories that are incompatible with its tenets.

Peripheral measures contribute additional support without being critical, described as “the auxiliary belt” (Lakatos, 1978); contradictions necessitate adjustments without undermining the theory’s main principles.

Mantle measures, significantly more central, are tied to fundamental principles. Contradictions here may require substantial revisions, but the basic theoretical framework can remain.

Core measures, intrinsic to the theory’s fundamentals, pose a major threat if predictions based on them are experimentally disconfirmed, potentially mandating a new theoretical framework.

The MCI may provide a valuable tool to evaluate the different measures’ intra-theory germaneness, that is, its inner empirical structure. Additionally, the MCI allows ranking the importance of the same empirical measure within and across different theories, thus allowing for empirical translation from one theory to another, which is useful when comparing them. However, MCI’s meta-theoretical approach raises different classes of challenges, summarized in Table 1. While a comprehensive account of how the MCI could face up to all of them is left for future work, we exemplify this methodology in **Section 4** and sketch potential avenues to address those challenges in **Section 5** .

3. Measures-focused reviews of the three theories

3.1. Literature selection criteria

We comprehensively reviewed the theoretical and experimental literature on the Global Neuronal Workspace, Integrated Information Theory (IIT), and Temporospatial Theory of Consciousness (TTC). Subsequently, we selected a variety of measures proposed by each theory in various neuroscientific paradigms and techniques. First, we used the ConTraSt database (Yaron et al., 2022) to navigate the empirical literature on IIT and GNW. We selected theory-driven or theory-mentioning articles from the full database. Second, we searched PubMed for abstracts containing "integrated information theory," "global neuronal workspace," and "temporospatial theory of consciousness." Third, for systematicity, we carefully examined several theoretical papers, meta-analyses, and reviews, either by the theories’ proponents (Dehaene and Changeux, 2011; Koch et al., 2016; Mashour et al., 2020; Northoff and Huang, 2017; Northoff and Lamme, 2020; Northoff and Zilio, 2022a; Tononi et al., 2016) or more general ones on consciousness

Table 1
MCI Challenges.

MEASURE CENTRALITY INDEX (MCI) *CLASSES OF CHALLENGES*		
INTRA-THEORY TRIANGULATION	**INTER-THEORY COORDINATION**	**SOCIOLOGICAL CONSTRAINTS**
Criteria Specification What epistemological and empirical bases should be used to determine the criteria for classifying a measure as orthogonal, peripheral, mantle, or core? Who will be the key stakeholders in this decision-making process?	**Inter-theory Definitional Differences** What mechanisms can the MCI implement to navigate scenarios in which theories offer contradictory or non-overlapping definitions for the same pre-theoretical construct or phenomenon?	**Proponents' Agreement and Coherence** Is a consensus among theory proponents essential for the legitimacy of measure classification within their theory? If not, what are the minimal levels of agreement required to establish a compelling classification?
Operationalization Once the measures are classified, what challenges arise in establishing theory-specific operational protocols and assumptions that allow for empirical testing? How can interdisciplinary expertise be integrated effectively?	**Inter-theory Empirical Non-overlap** How can the MCI possibly facilitate meaningful comparisons between theories that propose entirely distinct empirical methodologies or measures with no obvious overlap while professing to address the same phenomenon?	**Conflict Resolution Mechanisms** What formal or informal methodologies are available to resolve disagreements on the classification of measures?
Validation, Reliability, and Adaptability How can the classifications within the MCI be periodically and rigorously reassessed to remain current with ongoing research and data? What mechanisms must be in place to ensure the MCI remains adaptive to the evolving theoretical landscape?	**Cross-Theoretical Empirical Translations** How can the MCI manage the complexities of accurately translating empirical measures across theories, especially when those measures receive different classifications in different theoretical contexts?	**Subjectivity, Bias, and Neutrality** While the aim is for an unbiased and objective MCI classification, what checks and balances can be implemented to mitigate the influence of individual convictions or preferences on the classification process?

Table 2
Empirical and Theoretical Measures and NCC Candidates in GNW.

GNW PARADIGM/TECHNIQUE-INDEXED MEASURES AND CANDIDATE NCC				
EEG/MEG/ECoG	**TMS-EEG**	**fMRI**	**Formal Modeling**	**NCC**
P3b (sudden late ignition) (Dehaene et al., 2003b; Dehaene and Changeux, 2011, 2005; Mashour et al., 2020) PFC Activation (Dehaene et al., 1998; Dehaene and Changeux, 2011; Dehaene and Naccache, 2001; Mashour et al., 2020) PFC Decoding (Bellet et al., 2022; Kapoor et al., 2022; King et al., 2013; King et al., 2016; Marti and Dehaene, 2017; Salti et al., 2015) Error-Related Negativity (ERN) (Charles et al., 2013; Wessel, 2012) Weighted Symbolic Mutual Information (wSMI) (King et al., 2013) Post-250msec Bifurcation Dynamics in the Global Playground (Sergent et al., 2021) EEG-based Consciousness Index (EEG-CI) (Sitt et al., 2014)	PFC Activation/ Inhibition (Dehaene et al., 1998; Dehaene and Changeux, 2011; Dehaene and Naccache, 2001; Mashour et al., 2020)	Dynamic Coordinated Pattern (Demertzi et al., 2019; Tasserie et al., 2022) Functional Hub Global Workspace (Baars et al., 2013; Deco et al., 2021) Intrinsic Ignition (Deco et al., 2017)	Computer Simulations (Connor and Shanahan, 2010; Dehaene et al., 2003b; Dehaene and Changeux, 2005, 2000; Shanahan, 2008) Kolmogorov Symbolic Complexity (KSC) (Sitt et al., 2014)	Dorsolateral prefrontal and inferior parietal cortex; also temporal cortex, anterior and posterior cingulate cortex, and precuneus (Dehaene and Changeux, 2011; Mashour et al., 2020)

science topics like NCC, complexity, information-theoretic, or EEG measures, etc. (Mediano et al., 2022; Nilsen et al., 2020; Sarasso et al., 2021; Sattin et al., 2021; Seth and Bayne, 2022; Signorelli et al., 2021; Storm et al., 2017). We included all references that either (i) proposed/updated the theory, (ii) proposed/updated at least one theoretical or empirical measure associated with the theory, or (iii) experimentally supported/contradicted at least one theory prediction. IIT had 107 citations, GNW 94, and TTC 63.

While numerous theories of consciousness exist, we have chosen to focus on three to illustrate how inter-theory comparisons can be conducted. However, our methodology can be applied beyond these theories, providing broad applicability across different contexts and frameworks.

We have selected these three theories for several reasons. First, limiting ourselves to three enables a detailed analysis of their literature and theoretical structures, which is crucial for identifying empirical discrepancies. Second, we have chosen theories that aim to comprehensively explain various aspects of consciousness, such as the level or state of consciousness, its content, as well as other aspects like connectedness and structure, while also diverging in their explanations. It is precisely this divergence that necessitates inter-theoretic comparisons and requires a methodology to address this issue. Finally, we have selected theories based on our expertise, as some claims made below presuppose a nuanced understanding of their conceptual tenets. Additionally, we have included an emerging theory, TTC, to complement the focus on the major frameworks of GNW and IIT.

3.1.1. *A GNW empirical review*

GNW defines a conscious state experienced subjectively as “the global availability of information” (Dehaene and Naccache, 2001, p. 1), equates consciousness and conscious access, and denies non-self-reported experiences (Dehaene, 2014; Mashour et al., 2020). Importantly, accessibility requires preconscious processing, while access requires conscious processing (Dehaene et al., 2006; Sergent, 2018). Self-reports need neither be overt behaviors nor verbal. A report is “an active internal process that solicits many high-level cognitive functions […], [i]n particular, interpretative, narrative, belief-construct, and belief criticism,” being the “core content of our subjective experience” (Naccache, 2018, p. 4). Self-report is a “conscious comment on an inner mental representation,” and any conscious item “is accessible for report”

Table 3
Empirical and Theoretical Measures and NCC Candidates in IIT.

IIT PARADIGM/TECHNIQUE-INDEXED MEASURES AND CANDIDATE NCC				
EEG/MEG/ECoG	**TMS-EEG**	**fMRI**	**Formal Modeling**	**NCC**
Phi-Autoregressive (Φ_{AR}) (Barrett and Seth, 2011; Isler et al., 2018; Kim, 2019; Nazhestkin and Svarnik, 2022) Mean Regional Integrated Information (Φ_{R}) (Kim et al., 2018) Phi-Star (Φ^*) (Afrasiabi et al., 2021; Haun et al., 2017; Oizumi et al., 2016a) Integrated Information Structures (IIS) (Leung et al., 2021)	Lempel-Ziv Perturbational Complexity Index (LZ-PCI) (Casali et al., 2013) State Transitions Perturbational Complexity Index (ST-PCI) (Comolatti et al., 2019) Explainable Consciousness Indicator (ECI) (Lee et al., 2022)	Multivariate Integrated Information (Sasai et al., 2016) Phi-Information Decomposition (ΦID) (Luppi et al., 2021; Mediano et al., 2022; Rosas et al., 2020)	Φ-family (Albantakis et al., 2023; Barbosa et al., 2021, 2020; Haun and Tononi, 2019; Oizumi et al., 2014; Tononi et al., 2016) Phi-atomic (Φ_{atomic}) (Edlund et al., 2011; Joshi et al., 2013; Sheneman et al., 2019) Phi-Stochastic Interaction (Φ_{SI}) (Ay, 2015) State Differentiation (D) (Marshall et al., 2016) Geometric Integrated Information (Φ_{G}) (Cohen et al., 2020; Leung and Tsuchiya, 2022; Oizumi et al., 2016b) Informational Structures (IS) and Fields (IF) (Esteban et al., 2018; Kalita et al., 2019) Compression-Complexity (Φ^{C}) (Virmani and Nagaraj, 2019) Causal Information Integration (Φ_{CII}) (Langer and Ay, 2020) Phi-Information Decomposition (ΦID) (Luppi et al., 2021; Mediano et al., 2022; Rosas et al., 2020) Simplification/generalization procedures: approximate factorizations (Tegmark, 2016), Queraynne's algorithm (Hidaka and Oizumi, 2018; Kitazono et al., 2018), graph clustering (Toker and Sommer, 2019), shared transitions in Process Algebras (Bolognesi, 2019), and self-organized criticality (Aguilera, 2019; Aguilera and A. di Paolo, 2019; Aguilera and di Paolo, 2021; Kim and Lee, 2019; Popiel et al., 2020; Walter and Hinterberger, 2022)	Posterior temporo-parietal-occipital "hot zone" (Boly et al., 2017; Koch et al., 2016; Siclari et al., 2017; Tononi et al., 2015)

Table 4
Empirical and Theoretical Measures, Mechanisms, and NCC Candidates in TTC.

TTC PARADIGM/TECHNIQUE-INDEXED MEASURES, MECHANISMS AND CANDIDATE NCC				
EEG/MEG/ECoG	**TMS-EEG**	**fMRI**	**Formal Modeling**	**NCC**
Expansion: Trial-to-Trial Variability (TTV) (Braun et al., 2022; Huang et al., 2015; Wainio-Theberge et al., 2021; Wolff et al., 2021) Alignment: Intrinsic Neural Timescales (INT) (Chaudhuri et al., 2015; Chen et al., 2015; Golesorkhi et al., 2021a, 2021b; Honey et al., 2012; Murray et al., 2014; Raut et al., 2020; Wolff et al., 2022) Alignment: Temporal Receptive Windows (TRW) (Hasson et al., 2015; Yeshurun et al., 2021) Alignment: Autocorrelation Window (ACW) (Golesorkhi et al., 2021a, 2021b; Honey et al., 2012; Meisel et al., 2017; Northoff et al., 2021; Zilio et al., 2021) Nestedness: Power-Law Exponent (PLE) (Lendner et al., 2020; Meisel et al., 2017; Northoff et al., 2021; Zilio et al., 2021) Alignment: Power Spectral Density (PSD) (Zilio et al., 2021) Nestedness: Detrended Fluctuation Analysis (DFA) (Hardstone et al., 2012; Linkenkaer-Hansen et al., 2001; Meisel et al., 2017) Globalization: Post-250msec Bifurcation Dynamics in the Global Playground (Sergent et al., 2021)	Expansion: Trial-to-Trial Variability (TTV) (Huang et al., 2015) Nestedness: Dynamic Repertoire (Casali et al., 2013; Hudetz et al., 2015)	Expansion: Trial-to-Trial Variability (TTV) (He, 2013; Huang et al., 2015) Alignment: Intrinsic Neural Timescales (INT) (Huang et al., 2021, 2018a) Alignment: Autocorrelation Window (ACW) (Chaudhuri et al., 2015; Huang et al., 2021, 2018a; Ito et al., 2020; Raut et al., 2020) Alignment: Temporal Receptive Windows (TRW) (Hasson et al., 2015; Yeshurun et al., 2021) Nestedness: Global Signal (GS) + GS-topography (Huang et al., 2016; Tagliazucchi et al., 2016a, 2016b; Tanabe et al., 2020; Zhang et al., 2020) Nestedness: Power-Law Exponent (PLE) (Huang et al., 2018b, 2016, 2015; Klar et al., 2023a; Meisel et al., 2017; Zhang et al., 2020)	Expansion: Category Theory (Northoff et al., 2019) Nestedness: Scale-free Topology (Chialvo, 2010; He, 2014; He et al., 2010)	Region-specific representation of global activity and non-additive pre-post-stimulus interaction occurrence in every region, to different degrees, and involving both longer and shorter timescales (Northoff and Huang, 2017; Northoff and Zilio, 2022a)

(Naccache and Dehaene, 2007, p. 519). "Our conscious perception incorporates a process of fictionalization," as Capgras syndrome and other neuropsychological conditions show (Naccache, 2016, p. 289).

GNW is a mechanism-first approach. First, a global computational workspace selects and broadcasts for flexible cognitive manipulation information received from specialized networks of local processors (Baars, 1988). While distinct cortical domains subsume the dedicated processors with local connections encoding specialized information, the

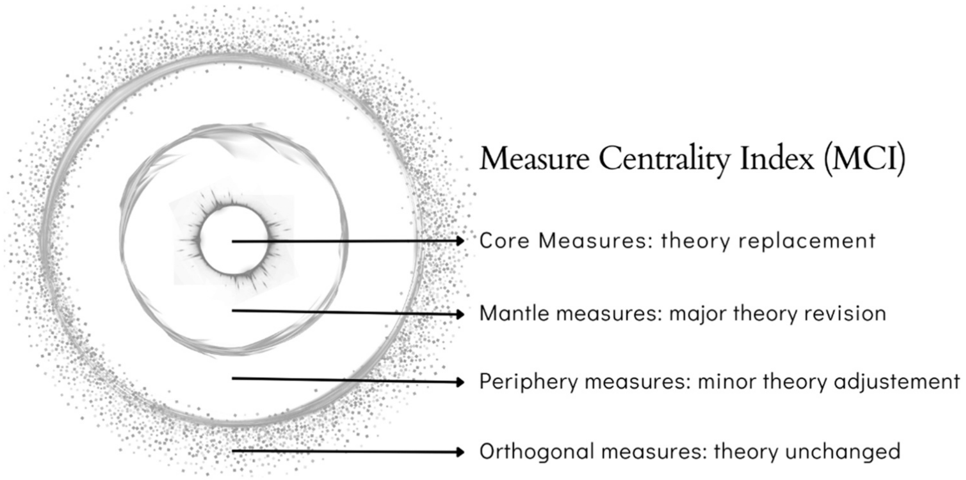


Fig. 1. Measures Centrality Index (MCI). MCI is a categorical index expressing an impact gradient a theory would have when facing disconfirmatory evidence. The gradient extends from no changes to the theory to substantive changes leading up to a theory replacement. Orthogonal measures are those non-central to the theory, as such empirical data conflicting with predictions based on the measurement do not affect the theoretical structure. Peripheral measures are marginally more central and provide extra support without being essential; contradictions call for adjustments without undermining the theory's main tenets. Mantle measures, are significantly more central to the theory. If experimentally disconfirmed, they may call for substantial revisions without necessarily affecting the fundamental theoretical foundation of the theory. Core measures, as the name implies, reflect central aspects of a theory. Disconfirming predictions resting on core measure, lead to a significant challenge to the theory, requiring the development of a new theoretical framework. The MCI also allows evaluating the relevance of another's theory measure when formulating experimentally deployable predictions within a "home" theory.

global workspace consists of long-range excitatory neurons that receive bottom-up input and top-down output to specific processor neurons. Pyramidal cells of layers II/III and deeper layer V are distributed GNW neurons, along with other cortical and subcortical cells (Changeux and Dehaene, 2008; Dehaene et al., 2003a; Mashour et al., 2020). Second, computer simulations of global workspace architecture (Dehaene et al., 2003b, 1998; Dehaene and Changeux, 2005, 2000) revealed global ignition, a stochastic phase transition of neuronal dynamics depending on stimulus-related and spontaneous activity, as the neurophysiological signature of conscious access (Dehaene et al., 2014; Dehaene and Changeux, 2011; del Cul et al., 2007; Polich, 2007). This self-sustained reverberation broadcasts the stimulus-relevant signal to all workspace processors, marking the current consciousness content (Dehaene et al., 2017, 2011). GNW equates consciousness as self-reported experience with the global availability of information—"the contents of the workspace *is* what we subjectively experience as a conscious feeling or experience" (Panagiotaropoulos et al., 2020, p. 1)—and searches for its neural underpinnings (Dehaene, 2014).

Theoretical measures. GNW's repertoire of theoretical measures comprises, first, computer simulations of a hierarchical cognitive workspace architecture, whether by its proponents (Dehaene et al., 2003b, 1998; Dehaene and Changeux, 2005, 2000) or other groups (Connor and Shanahan, 2010; Shanahan, 2008). Second, it includes different information-theoretic measures, e.g., weighted symbolic mutual information (wSMI), which evaluates the extent to which two EEG signals present non-random joint fluctuations, suggesting that they share information (King et al., 2013) or Kolmogorov signal complexity (KSC), which involves lossless compression of the time series and quantification of compression size—both measures have been used to determine an EEG-based consciousness index (CI) (Sitt et al., 2014). Third, based on PFC's workspace neurons, conscious content can be decoded (King et al., 2013, 2016; Marti and Dehaene, 2017; Salti et al., 2015) in different paradigms, e.g., no-report (Bellet et al., 2022; Kapoor et al., 2022).

Empirical measures. PFC activation and the "late-positive" (P3b) component of the P300 scalp-ERP indexing ignition are two empirical markers (Dehaene et al., 2011; Dehaene and Changeux, 2011; Dehaene and Naccache, 2001; Mashour et al., 2020; Sergent and Dehaene, 2004). Conscious access relies on long-distance cerebral connectivity to allow a global all-or-none neuronal ignition coding for conscious contents, especially in temporal and prefrontal cortices. The PFC integrates and diversifies cognitive operations through its workspace neurons, underscoring conscious access as a sudden, non-linear neural activity phase transition (Mashour et al., 2020; van Vugt et al., 2018). Thus, unlike IIT, GNW considers frontoparietal areas, cortical hubs, and the late all-or-none ignition (P3b) as proper anatomical and physiological NCC (see Table 2 in the main text).

Noel et al. (2018) found ~>300 msec evoked potentials, or sudden late ignition, to be the only common EEG signature across visual, auditory, and audiovisual consciously accessed trials, while other markers like between-trial variability and EEG complexity differed for unisensory and multisensory conditions. Sanchez et al. (2020) reported similar results across multimodal modalities, further establishing the P3b component as GNW's most robust neural marker of conscious access across different methodologies (Dehaene and Changeux, 2011; Kouider et al., 2013; Mashour et al., 2020; Moutard et al., 2015); see Deco et al. (2017) for a complementary concept of ignition. This only adds to the significant theoretical research and experimental evidence supporting the global workspace framework (Arthuis et al., 2009; Asplund et al., 2014; Baars et al., 2021; Bartolomei and Naccache, 2011; Barttfeld et al., 2015; Berkovitch et al., 2021; Deco et al., 2021; Demertzi et al., 2019; Faugeras et al., 2012; Fisch et al., 2009; Gaillard et al., 2009, 2007; Hesselmann et al., 2013, 2011; Joglekar et al., 2018; King et al., 2014; Kouider et al., 2007; Kreiman et al., 2002; Logothetis, 1998; Mashour et al., 2021; Mei et al., 2022; Michel, 2017; Munoz Musat et al., 2022; Nieuwenstein et al., 2009; Noy et al., 2015; Panagiotaropoulos et al., 2012; Quiroga et al., 2008; Reuter et al., 2009; Rohaut et al., 2015; Schurger et al., 2015; Sergent et al., 2005; Tasserie et al., 2022; Uhrig et al., 2016a; Vul et al., 2008; Wessel, 2012).

Nevertheless, GNW's candidate physiological NCC, the P3b component, has been debated, with some claiming that it reflects post-perceptual processes (Almeida, 2022; Andersen et al., 2016; M. Cohen et al., 2020; Förster et al., 2020; Koivisto et al., 2016; Koivisto and Revonsuo, 2010; Lamme, 2018, 2010; Northoff and Lamme, 2020; Pitts et al., 2014a, 2014b; Rutiku et al., 2016, 2015), being thus a post-NCC rather than NCC proper (Aru et al., 2012; de Graaf et al., 2012; Northoff, 2013; Northoff and Heiss, 2015). In light of these debates, Sergent et al. (2021) reassessed the P3b's role without report relying on inter-trial variability. Thus, the P300 ERP reflects conscious access-related decision processes rather than conscious access itself. They claim that the global playground, a subset network of the global workspace, mediates task-free "covert" conscious access. "Overt" conscious tasks require the full global workspace. NCC-wise, bilaterally positive late 250–300 ms and 600–700 ms bifurcation dynamics in the global playground are a general neurophysiological signature of conscious access, supplemented by a central positivity component corresponding to GNW's canonical P300 during decisional processes (Sergent et al., 2021).

3.1.2. An IIT empirical review

IIT defines consciousness as subjective experience (Albantakis et al., 2023; Oizumi et al., 2014; Tononi et al., 2016), and uses phenomenology-first introspection and reasoning to isolate the essential phenomenal properties of experience (Ellia et al., 2021; Tononi et al., 2022). These are subjectivity, specificity, unity, definiteness, and structuredness, and the axioms express them. It then posits one-to-one explanatory correspondences between phenomenal properties and physical substrate cause-effect properties captured by the postulates. They explain our experience by operationally equating it with an intrinsic, specific, unitary, and definite cause-effect structure (Albantakis, 2020; Albantakis et al., 2023; Barbosa et al., 2021; Haun and Tononi, 2019; Tononi, 2017; Tononi and Koch, 2015). "Unfolding" is the algorithm for revealing cause-effect power, and a candidate substrate must satisfy all postulates to be a "complex," i.e., to be conscious—axioms, operationalization, main complex identification, and unfolding lead to measures.

Theoretical Measures. IIT's theoretical model is the Φ-structure and the mathematical measures of Φ (big Phi) and φ (small Phi), which involve partitioning the candidate system, its mechanisms, and their overlap. The Φ-family quantifies integrated existence: an entity or part thereof is one if and only if it cannot be reduced to causally separate parts by partitioning its substrate. IIT formalism improved from 1.0 (Tononi, 2004) to 2.0 (Balduzzi and Tononi, 2009, 2008) to 3.0 (Mayner et al., 2018; Oizumi et al., 2014) to 4.0 (Albantakis et al., 2023) versions. IIT attempts to find a universal mathematical formula for consciousness by identifying an experience with a global maximum of irreducible, specific, intrinsic, and structured cause-effect power. However, the full formula for computing Φ-structures is non-deployable except in "toy" systems with 4–30 binary elements (Albantakis et al., 2014; Albantakis and Tononi, 2015; Farnsworth, 2021; Fischer et al., 2020; Grasso et al., 2021; Hoel et al., 2016, 2013; Marshall et al., 2017; Mayner et al., 2018), recently extended up to 8 states (Gomez et al., 2020), with a practical limit of ~10–12 elements (Nilsen et al., 2019). Moreover, some argue that the Φ formula is not well-defined (Barrett and Mediano, 2019) or needs clarification and expansion (Kleiner and Tull, 2021). Thus, such theoretical measures are not immediately experimental.

Empirical Measures. Φ-proxies constitute IIT's empirical repertoire of measures. For instance, the Lempel-Ziv Perturbational Complexity Index (LZ-PCI) (Casali et al., 2013) provides an empirically tractable method of objectively assessing consciousness in clinical contexts (Ferrarelli et al., 2010; Massimini et al., 2009, 2005; Nilsen et al., 2020; Sarasso et al., 2021, 2015, 2014); for reviews on consciousness and complexity measures, see Nilsen et al. (2020) and Sarasso et al. (2021). LZ-PCI was designed with IIT's first principle in mind: Consciousness requires an optimal balance between functional differentiation, which follows from the second axiom and postulate, and integration, which follows from the third. Giulio Tononi's early work with Gerald Edelman on neural complexity measures (Tononi, 2001; Tononi et al., 1996, 1994; G. Tononi and Edelman, 1998) explored this principle, which IIT later incorporated and developed (Balduzzi and Tononi, 2008; Oizumi et al., 2014; Tononi, 2004). However, it is only an indirect proxy derived from two of the five postulates (Mediano et al., 2022). This index is the normalized Lempel-Ziv complexity of a direct TMS perturbation's spatiotemporal cortical activation pattern (Casali et al., 2013). LZ-PCI can distinguish between consciousness and unconsciousness in healthy people and brain-injured patients, as well as graded consciousness changes. Comolatti et al. (2019) introduced the State Transition Perturbational Complexity Index (ST-PCI) to speed up brain signal complexity estimation.

The neural correlates of consciousness (NCC) research paradigm exhibits a well-known debate between phenomenology-driven theories like IIT and cognition-driven ones like GNW. IIT posits the posterior cerebral cortex, more precisely, the temporo-parietal-occipital "hot zone," for full and content-specific NCC (Boly et al., 2017; Koch et al., 2016; Siclari et al., 2017), while the anterior brain, particularly the prefrontal regions, contributes "possibly sensations of thought, reflection, effort, volition, and motion" (Tononi et al., 2015, p. 435) (see Table 3).

Two decades of theoretical and experimental research across paradigms and techniques support the hypothesis that consciousness and the integration/differentiation balance motif of neural dynamical complexity, especially in cortico-cortical and cortico-subcortical (thalamic and striatal) circuits, are necessarily connected (Afrasiabi et al., 2021; Chang et al., 2012; Deco et al., 2015; Demertzi et al., 2019; Fujii et al., 2019; Hashmi et al., 2017; Hudetz et al., 2016, 2015; Hutchison et al., 2014; Kung et al., 2019; Lee et al., 2022, 2009; Marshall et al., 2016; Mikulan et al., 2018; Monti et al., 2013; Nir and Tononi, 2010; Noirhomme et al., 2010; Rosanova et al., 2018, 2012; Sanders et al., 2018, 2012; Schartner et al., 2017, 2015; Shin et al., 2013). Furthermore, regarding the structure of phenomenological space (Haun and Tononi, 2019), there is some empirical support for IIT's predictions about the role of lateral connectivity (Song et al., 2017) and the need for differentiation and integration of neural responses across individual locations in the visual field (Song and Rees, 2018). In addition, Φ-measures have successfully been applied to characterize group dynamics (Engel and Malone, 2018; Niizato et al., 2020a, 2020b), and the recent discovery of electron transport in catecholaminergic neurons has been hypothesized as a physical substrate and action selection mechanism consistent with IIT's emphasis on the integration of neural signals (Rourk, 2022). On top of that, "weak" IIT has been proposed as a complementary research program to "strong" IIT, focusing on pragmatic hypotheses linking consciousness to a wider range of information measures (Mediano et al., 2022). Finally, to make Φ-based measures empirically tractable, IIT researchers use different operationalizations and heuristics (see Table 3 for overview and references).

3.1.3. A TTC empirical review

TTC emphasizes temporal continuity, intentionality, qualia, ipseity, transparency, unity, and other phenomenological aspects of experience (Northoff, 2014b; Northoff and Huang, 2017; Northoff and Zilio, 2022a). It aims to determine how these relate to brain features. Dynamics—change patterns over time and space—guide its approach. Consciousness and its phenomenological features depend on how the brain creates its own inner time and space as distinct from the world's. The brain's inner time-space construction relates to phenomenology (Northoff, 2014b; Northoff et al., 2020a; Northoff and Zilio, 2022a, 2022b). Time-space manifests in the world, the brain, and consciousness (Northoff, 2018; Northoff and Zilio, 2022a); therefore, mental phenomena are nothing special or mysterious. Time-space features are the necessary (Northoff, 2018, chap. 10) "common currency" of neural and mental levels (Northoff, 2021; Northoff et al., 2020a, 2020b). Topography describes the brain's neural activity across regions and networks. TTC is a global approach since it examines the brain's neural activity as a whole and how it forms temporospatial relationships and organizes regions and networks. It investigates the structure and organization of frequencies and timescales, such as in scale-free activity.

Theoretical Mechanisms and their Empirical Measures. Taking a global view of time and space, TTC distinguishes four main temporospatial mechanisms or ways the brain constructs its inner time-space: temporospatial nestedness, alignment, expansion, and globalization (Northoff and Huang, 2017; Northoff and Zilio, 2022a). They refer to different purely neuronal mechanisms and relate to distinct phenomenal features of consciousness. The four temporospatial mechanisms can dissociate and are complementary neuronally and phenomenally, being the origin of TTC's empirical measures summarized in Table 4.

Temporospatial Nestedness. This mechanism refers to the structure's self-similarity across spatial and temporal organizations, including larger/longer and smaller/shorter ones (Northoff and Tumati, 2019). On the temporal side, the power law exponent (PLE) and detrended fluctuation analysis (DFA) have been used in EEG and fMRI to discriminate among altered states of consciousness like anesthesia (Tagliazucchi et al., 2016b; Zhang et al., 2018; Zilio et al., 2021), sleep (Meisel et al., 2017; Tagliazucchi et al., 2016a; Zilio et al., 2021), and unresponsive wakefulness (Zilio et al., 2021). The global signal (GS) and its representation in local-regional activity measure spatial nestedness. A large-scale fMRI study with all the groups above found a direct relationship between GS-indexed brain activity and consciousness, with lower GS levels corresponding to lower consciousness levels (Tanabe et al., 2020).

Temporospatial Alignment. This mechanism measures how well the brain's activity matches the body's and the environment's. Entrainment—the brain's neural phase shifting to the external rhythm—measures temporal alignment (Lakatos et al., 2019). Brain-environment synchrony may be necessary for consciousness (Northoff and Huang, 2017; Northoff and Zilio, 2022a). The signal's autocorrelation window (ACW) is another temporal measure that reflects the brain's intrinsic neural timescales (Chaudhuri et al., 2015; Chen et al., 2015; Golesorkhi et al., 2021a, 2021b; Honey et al., 2012; Ito et al., 2020; Murray et al., 2014; Northoff et al., 2021; Raut et al., 2020; Wolff et al., 2022). ACW is abnormally long in consciousness loss (Huang et al., 2018a; Zilio et al., 2021). The gradients or transitions of the transmodal core and unimodal periphery (Golesorkhi et al., 2022, 2021a) or the sensory input streams' regions (Çatal et al., 2022) can be used to measure spatial alignment. Notably, the dynamics and topography converge, providing the brain with an integrated time-space coordinate system in its neural activity (Golesorkhi et al., 2022, 2021a, 2021b) that, following TTC and its assumption of "common currency," should be manifest on the phenomenal level.

Temporospatial Expansion. Temporospatial nestedness and alignment focus on the brain's spontaneous or ongoing activity, including resting state and pre-stimulus activity, while expansion focuses on their interaction. How do they interact to make an input conscious? TTC asks how pre-stimulus activity's spatial and temporal dynamics provide a neuronal context or envelope for incoming input, which may "decide" whether it becomes conscious. Prestimulus-stimulus interaction is measured by prestimulus variability, poststimulus trial-to-trial variability, poststimulus intertrial phase coherence, and pre-poststimulus differences in all these measures (Arazi et al., 2017a, 2017b; Baria et al., 2017; Braun et al., 2022; Churchland et al., 2011, 2010; Dehaghani et al., 2022; He, 2013; Huang et al., 2015; Northoff and Zilio, 2022b; Schurger et al., 2015; Wainio-Theberge et al., 2021; Waschke et al., 2021; Wolff et al., 2021, 2019). Changes in consciousness alter these measures (Bai et al., 2016; Dinstein et al., 2015; Huang, Zhang, et al., 2018; Northoff and Lamme, 2020; Northoff and Zilio, 2022a, 2022b).

Temporospatial Globalization. This mechanism is both neural and phenomenal: a particular temporospatial feature dominates neural and phenomenal activity, which can be thought of as a continuation of expansion by linking cognitive functions to the latter. In TTC, globalization is spatially and temporally determined by the brain's topography and dynamics, encompassing all timescales. GNW's globalization is similar (see differences below). Thus, the GNW's updated bilaterally positive late 250–300 ms and 600–700 ms bifurcation dynamics in certain global workspace subsets may be a candidate measure (Sergent et al., 2021).

4. Applying the MCI: intra-theory measures ranking and cross-theoretical empirical translations

This section examines five divergence points between GNW, IIT, and TTC, highlighting empirically tractable conflicting predictions or promising future research. Cross-theoretical translations are proposed to compare empirical measures from the three theories, summarized below:

- Autocorrelation Window (ACW) is a core measure in TTC but, at best, peripheral in GNW and IIT;
- Mutual Information (MI) variants are, at best, peripheral in all;
- Lempel-Ziv Complexity is roughly a mantle measure in all, closer to IIT's core (but not included in it) and to GNW's and TTC's periphery (possibly included in it);
- region-specific activity as NCC is roughly mantle in GNW via the PFC, closer to the core (possibly included in it), and mantle in IIT via the posterior "hot zone," but at best peripheral, if not orthogonal, in TTC, which has global activity as a mantle NCC instead;
- late event-related potentials (e.g., P3b) are mantle in GNW, closer to the core (possibly included), while early event-related potentials (e.g., VAN) are peripheral in IIT, with both orthogonal in TTC, which has non-additive pre-poststimulus interaction as mantle measure.

4.1. *Intrinsic neural timescales and autocorrelation window (ACW)*

The brain's intrinsic neural timescales—short, intermediate, and long—are measured by the autocorrelation window (ACW) mainly in the brain's spontaneous activity, e.g., during the resting state (Golesorkhi et al., 2021a, 2021b; Ito et al., 2020; Raut et al., 2020; Wolff et al., 2022; Yeshurun et al., 2021). Related to these intrinsic timescales, the more task-based temporal receptive windows (Hasson et al., 2015) in the ACW can promote temporal integration and segregation of input sequences depending on their size (Golesorkhi et al., 2021a, 2021b; Wolff et al., 2022; Wolman et al., 2023).

Intrinsic neural timescales are a core TTC measure because they provide temporal windows for the temporospatial alignment mechanism, allowing the brain to relate to its environmental context (Northoff et al., 2023; Northoff and Huang, 2017; Northoff and Zilio, 2022a). Evidence shows intrinsic timescales are necessary for becoming or being conscious in both fMRI (Huang et al., 2018a) and EEG (Buccellato et al., 2023; Zilio et al., 2021); see Northoff et al. (2023) for a summary. ACWs are important for consciousness because they allow temporal integration and segregation of inputs across different timescales (Fig. 2). If these timescales shift abnormally toward longer periods, as when consciousness is lost (Buccellato et al., 2023; Huang et al., 2018a; Zilio et al., 2021), the various inputs cannot be segregated and specified anymore, making consciousness of specific contents blurry and ultimately non-existent (Northoff and Zilio, 2022a).

Intrinsic timescales do not play a prominent role in IIT, which predicts shorter 50–300 ms consciousness timescales and does not consider a variety of temporal windows relevant to experience (Northoff and Zilio, 2022a). However, IIT may attribute information integration to the ACW: longer ACW mediates more temporal integration (Wolff et al., 2022) and presumably higher Φ values. Hence, IIT might expect information integration and consciousness to increase with longer ACW. A necessary caveat here is that, according to IIT's exclusion axiom and postulate, the spatial and temporal grain of experience and its empirical substrate's size and update grain should be definite. Given the current state-of-the-art, the computational unfeasibility of finding the maximally irreducible substrate, i.e., the complex, and unfolding its cause-effect structure should mitigate but not dissipate the epistemic weight put on the "early" (50–300 ms) empirical extrapolation above.

According to TTC, consciousness requires a balance of temporal integration and segregation with a medium ACW duration rather than a

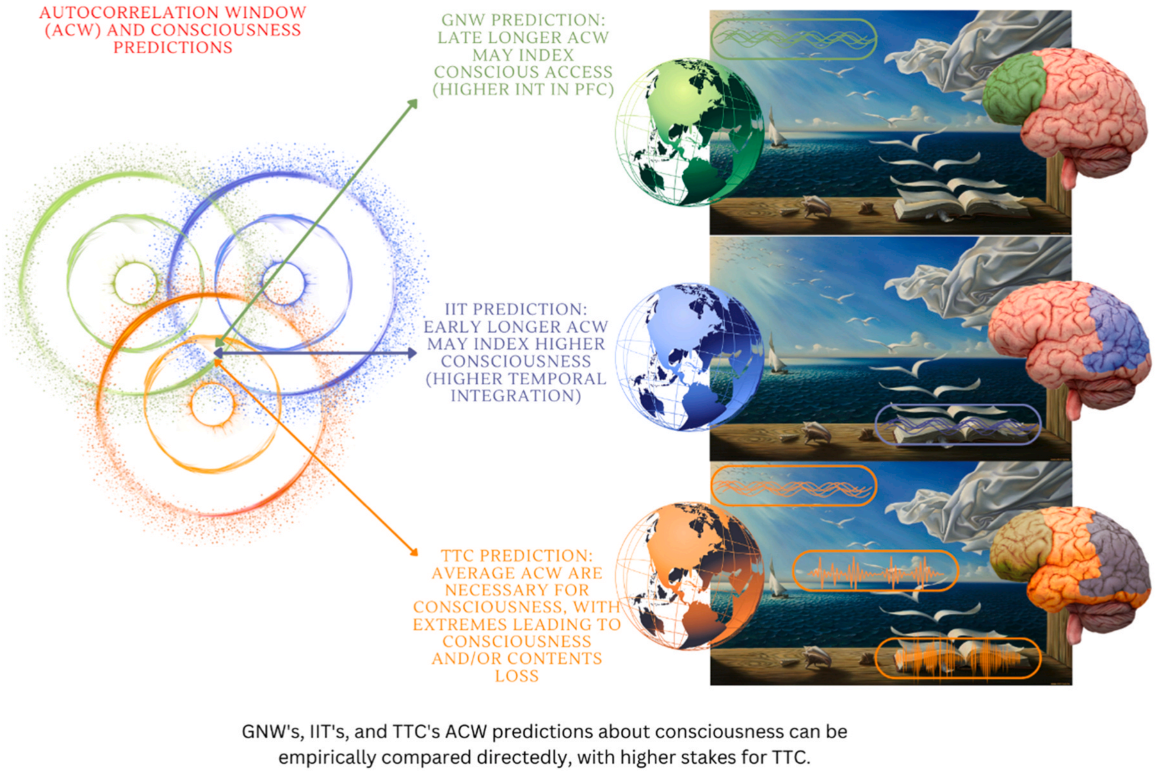


Fig. 2. Direct empirical comparison of the three theories based on the Autocorrelation Window (ACW). TTC predicts that a balance between longer and shorter ACW is necessary for consciousness, consistent with its emphasis on the foreground-background structure of phenomenology, which in the figure is represented as the different frequencies of the waves. Extrapolating ACW to GNW and IIT, a plausible inference is that they would associate longer ACW with the presence of consciousness due to the specifics of their proposed mechanism (i.e., workspace ignition and information integration), possibly differing in the latency of the increase (i.e., later in GNW and earlier in IIT).

maximally long one. By medium ACW, TTC means a balance across different regions, with sensory ones having shorter ACW and transmodal regions having longer ACW (Golesorkhi et al., 2021b; Wolff et al., 2021). Moreover, TTC also intends a balance within each region, targeting the relation of shorter and longer timescales within a power spectrum to slower and faster frequencies (Northoff and Tumati, 2019). This balance must be preserved in an equilibrium neighborhood, which, once transgressed, leads to psychopathologies (Lechner and Northoff, 2023; Northoff and Gomez-Pilar, 2021; Northoff and Tumati, 2019) and neurological deficits (Buccellato et al., 2023; Tanabe et al., 2020; Zilio et al., 2021). Northoff and Tumati (2019) express this as the “average is good, extremes are bad” principle for relating neural mechanisms and mental features. Thus, since IIT and TTC arguably predict intrinsic timescale duration and consciousness differently, they can be directly compared.

GNW and TTC are also comparable. GNW may connect consciousness to longer ACW because the longer intrinsic timescale-PFC mediates complex cognitive operations in resting and task states (Barrett and Seth, 2011; Isler et al., 2018; Kim and Lee, 2019; Nazhestkin and Svarnik, 2022). Like IIT, GNW would likely hypothesize that longer ACW is associated with conscious access given the theory-driven research on local and global auditory novelty processing (El Karoui et al., 2015; Marti et al., 2014; Uhrig et al., 2016). Hence, this indicates another empirically tractable divergence from TTC.

TTC’s temporospatial alignment mechanism, as one of the four mechanisms driving consciousness, relies on intrinsic timescales, which ACW measures. ACW is thus a core or at least a mantle measure for TTC. Showing that ACW is unrelated to consciousness and its contents would be a major challenge to, if not a partial falsification of the TTC. ACW is, at best, a mantle but likely a peripheral measure in both IIT and GNW because it only indirectly expresses their mechanisms. Accordingly, ACW-indexed intrinsic timescales allow for a reasonably direct and valid comparison of TTC with GNW and IIT, with TTC having much higher stakes (**Fig. 2**). There is also room for convergence: the ACW may be related to the measures focused on in IIT, like LZC (Çatal et al., 2022; Zilio et al., 2021), and in GNW, like the post-stimulus measures (Buccellato et al., 2023; Lechner and Northoff, 2023).

4.2. *Mutual information (MI)*

All three theories use mutual information (MI) and its extensions as information-theoretic measures but attribute differential importance to it. Imaging studies in GNW used MI to measure the degree of shared information in time series among regions (Kim et al., 2021; Kim and Lee, 2020; King et al., 2013; Sitt et al., 2014). The more globalized the workspace, the more regions/networks with high MI, and the higher the consciousness—a three-fold relationship indexing global workspace capacity (Kim et al., 2021; King et al., 2013; Sitt et al., 2014).

Tononi and colleagues used MI in their neural complexity measures (Tononi, 2001; Tononi et al., 1996, 1994; Tononi and Edelman, 1998) and the effective information-based IIT 1.0. (Tononi, 2004; Tononi and Sporns, 2003), but they replaced it after 2.0 (Balduzzi and Tononi, 2008). One could surmise that information integration across large regions/networks boosts MI, but its relationship to 4.0 Φ-based measures (Albantakis et al., 2023) requires investigation.

TTC extends MI to the environment, that is, to the degree of information shared between the environment and the brain. Better temporospatial alignment with the environment increases consciousness (Northoff et al., 2023). Such alignment implies higher MI degrees between environmental and neuronal stochastics, as indexed by higher inter-trial phase coherence, inter-subjectively shared topography, and lower inter-individual variability in ACW during task states (compared to rest) (Klar et al., 2023a, 2023b; Northoff et al., 2023). However, measuring MI between neuronal and environmental stochastics/stimuli still needs to be done in the context of alignment and consciousness TTC studies. Higher temporospatial alignment should lead to higher MI of environmental and neuronal stochastics and, thus, higher consciousness.

In conclusion, MI is a somewhat peripheral measure in all three theories, but for different reasons. GNW and IIT consider MI in brain regions as an index of workspace capacity and integrated information, respectively, while TTC emphasizes its key role in measuring brain-environment alignment. Hence, MI is measured within the brain itself, e.g., among its different regions within the context of GNW and IIT, while it is conceived to measure the shared information of the brain and environment in TTC. That currently hinders direct MI-driven empirical comparisons, although there is a future promise.

In earlier work with Gerald Edelman, Giulio Tononi emphasizes the importance of neuronal-environmental complexity matching for consciousness (Tononi et al., 1996; Tononi and Edelman, 1998), indirectly implying the importance of alignment and MI. Besides being pursued in some studies in humans (Boly et al., 2015; Mensen et al., 2018, 2017) and mice (Gandhi et al., 2023; Mayner et al., 2022), a new 4.0 Φ-based (Albantakis et al., 2023) matching measure is currently being developed (Tononi, personal communication). Therefore, there could be a fertile comparison with TTC's MI-based brain-environment alignment. Moreover, it is worth noting that the degree of brain-environment MI, as focused on in TTC, may relate to and shape the degree of shared mutual information among the regions/networks within the brain itself, as postulated in GNW and IIT.

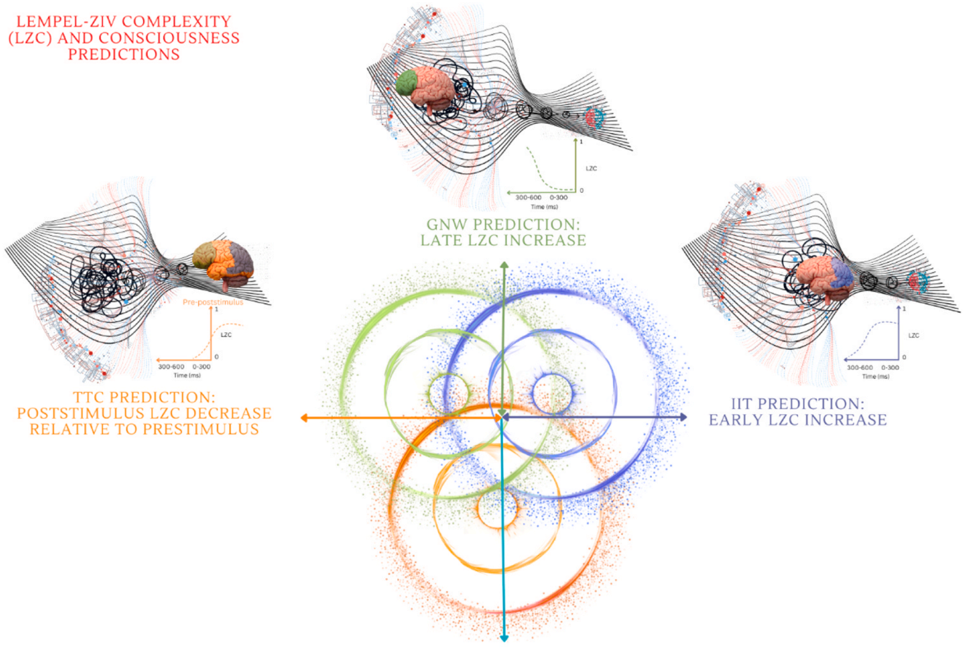
4.3. Lempel-Ziv complexity (LZC)

Empirical studies interpreted under IIT show that Lempel-Ziv Complexity (LZC)—a component of the Perturbational Complexity Index (PCI)—increases with consciousness level, requiring maximal integration in the early (0–300 ms) poststimulus period (Casali et al., 2013; Comolatti et al., 2019; Sarasso et al., 2021, 2015). Studies have shown that higher LZC is associated with higher levels of consciousness (Casali et al., 2013; Sarasso et al., 2021, 2015). Thus, it is a mantle measure but not a core IIT measure because it is only derived from two of its postulates (see the IIT review above). Empirical studies interpreted under GNW also indicate LZC increase, but later (300–600 ms) as related to the P3b and cognitive processes supporting conscious access, making it a mantle measure, too (Dehaene et al., 2011; Dehaene and Changeux, 2011; del Cul et al., 2007; Gaillard et al., 2009; Mashour et al., 2020; Sergent et al., 2005).

Unlike IIT and GNW, TTC considers how the prestimulus activity relates to both the early and late poststimulus activity (see Fig. 3). One EEG study found that the poststimulus LZC is lower than the prestimulus (Wolff et al., 2021, 2019). As the TTV, LZC decreases during the poststimulus period relative to the prestimulus period (He, 2013; Huang et al., 2015; Wainio-Theberge et al., 2021; Wolff et al., 2021). However, whether such poststimulus LZC decrease (relative to prestimulus) is related to the contents of consciousness remains yet unknown. If so, it would contradict IIT's and GNW's claim of increased LZC serving as NCC.

Thus, LZC comparisons of IIT, GNW, and TTC are valid. LZC is, arguably, a mantle measure in all theories—more central in IIT but not a core measure. If, as a function of conscious content, LZC is found to increase (while not decreasing in the early and/or late poststimulus period), it would significantly support IIT and GNW over TTC. However, if LZC decreases (relative to prestimulus) as a function of conscious content, that would be supporting evidence for TTC.

There are, though, some obstacles in comparing the theories via this measure. For example, LZC calculations in IIT and GNW only consider the poststimulus period, making it impossible to determine whether the observed LZC increases in the TMS-EEG studies (Casali et al., 2013; Sarasso et al., 2021, 2015) are increases or decreases relative to the prestimulus period (see **Fig. 3**). Nevertheless, it bears stressing that there is a distinction between the methodological focus on the latency of poststimulus activity and the one on pre-poststimulus interaction that could be valuable for consciousness theory design. Moreover, one would



Despite some conceptual differences, GNW's, IIT's, and TTC's LZC predictions about consciousness can be empirically compared directly.

Fig. 3. Direct empirical comparison of the three theories based on Lempel-Ziv Complexity (LZC). Arguably a mantle measure in all theories (but more important for IIT), a later (> 300 ms) increase in LZC might correlate with consciously accessing an experienced content in GNW, while this increase might happen earlier (< 300 ms) in IIT as a correlated of phenomenal consciousness. TTC differs in its approach and predicts that the non-additive interaction between the prestimulus and the stimulus-induced activities should lead to an early (< 300 ms) LZC decrease rather than an increase for experienced contents.

need to apply task-based paradigms probing conscious vs. unconscious content with an intertrial interval design that would allow measuring the prestimulus duration for at least 500–1000 ms. Finally, IIT uses LZC as a proxy of information integration (because it measures complexity); in contrast, TTC regards it more as a measure of time-series compression (which is not the same as information integration) (Golesorkhi et al., 2022; Wolff et al., 2021).

4.4. NCC: anterior vs. Posterior cortex and local vs. Global approaches

The prefrontal cortex (PFC) is thought to participate in the global workspace through neurons with specific cytoarchitecture. PFC activation as NCC is a core GNW hypothesis and prediction supported by various lines of evidence (Baars et al., 2021; Bellet et al., 2022; Dehaene and Changeux, 2011; Kapoor et al., 2022; Mashour et al., 2020; Noel et al., 2018; Odegaard et al., 2017). Based on other findings, IIT claims that a posterior temporal-parietal-occipital "hot zone" is necessary and sufficient for the state and content of consciousness and its phenomenal features, e.g., NCC as distinct from access mediated by the PFC, which could be an NCC for specific consciousness contents like volition, thought, or affect (Boly et al., 2017; Koch et al., 2016; Siclari et al., 2017; Storm et al., 2017; Tononi et al., 2016, 2015). Thus, GNW hypothesizes PFC activation as NCC but not IIT (Consortium et al., 2023). Moreover, GNW associates the PFC with access consciousness, which "may be all there is to consciousness" (Naccache, 2018, p. 3).

More abstractly, both IIT and GNW presuppose explanatory localizationism: they share the assumption of a particular region or network as the guiding thread to the NCC, whereas they differ in pinpointing it. In contrast to this localizationist focus in IIT and GNW, TTC assumes the whole brain with all its regions and networks is key for NCC—a global approach (see Fig. 4). While regions/networks are also considered in TTC, they derive their importance only from and relative to the global brain's topography (and its dynamics), which shapes the organization or structure of consciousness as in meditation (Cooper et al., 2022) and dreams (Northoff et al., 2023). Indeed, as predicted, topography (as measured by the global signal in fMRI) is highly differentiated with different weightings among different regions/networks in awake, conscious states, whereas it remains undifferentiated in unconscious states (Huang et al., 2021, 2018a, 2018b, 2015; Tanabe et al., 2020; Zhang et al., 2019, 2018).

Despite also assuming a global component, GNW postulates a local-to-global integration because the PFC and connected regions locally constitute the global neuronal workspace. This, however, does not mean that PFC activity is sufficient by itself; the workspace needs inputs from specialized processors, e.g., V1, for broadcasting to happen. Instead, the point of the "local-to-global integration" is that the former holds explanatory priority over the latter: the frontal "local" does more to account for consciousness than the whole "global." In TTC, global

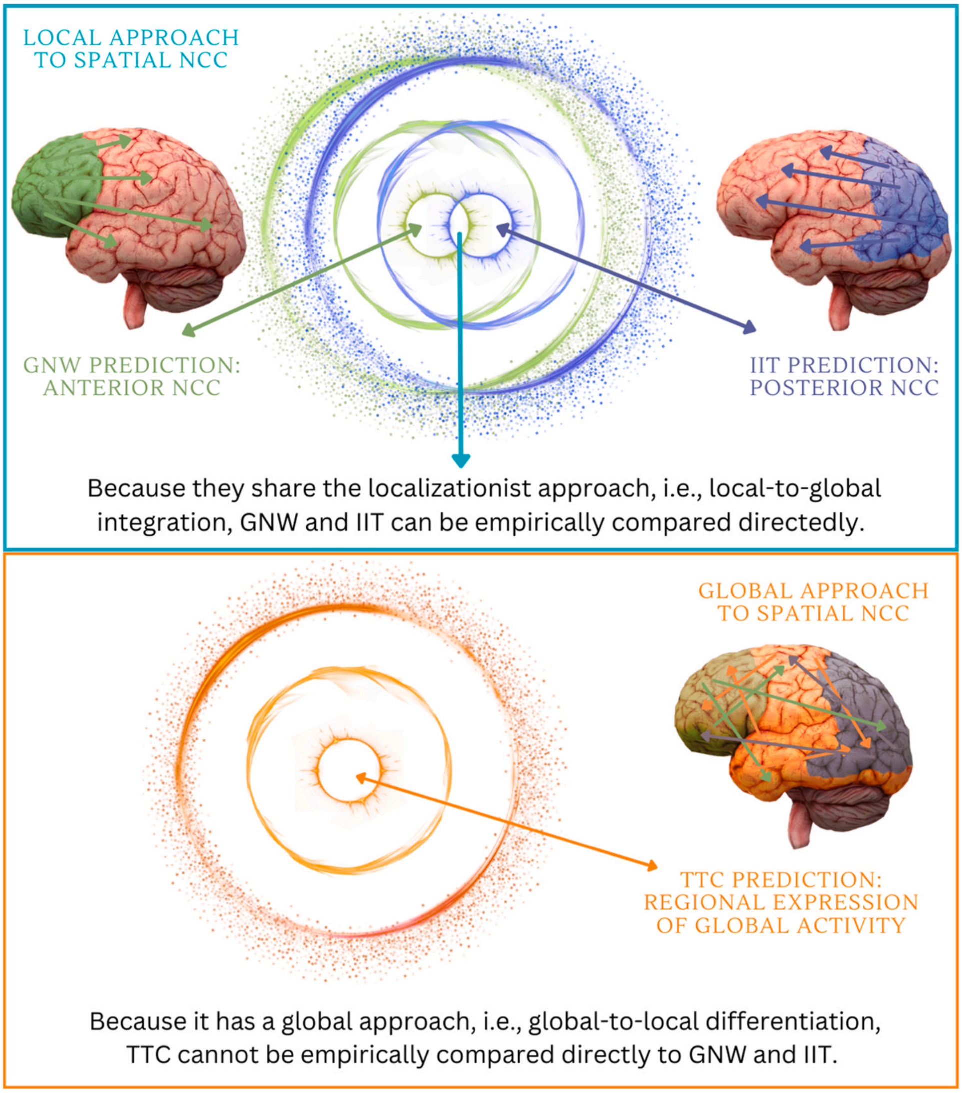


Fig. 4. Direct empirical comparison of the three theories relative to the anatomical NCC.

activity throughout the brain is differentiated topographically with different weightings of the regions within that global topography—a global-to-local differentiation (Northoff and Zilio, 2022b). Here, the explanatory priority is reversed.

Spatial NCC differences affect the weighting of empirical measures. Falsifying NCC predictions like the posterior cortical "hot zones" and/or the prefrontal cortex would have a larger bearing on IIT and GNW. Hence, activity in these regions is likely a mantle measure within IIT and GNW, probably closer to core for the latter. In contrast, neither region/network alone is important by itself and isolated from the brain's global activity for the TTC—they are only, at best, peripherally relevant for the TTC relative to the global or whole brain topography. Thus, unlike GNW and IIT, their falsification would not affect TTC significantly; at best, neural activity in these regions is a peripheral, if not orthogonal, measure.

The consequence is that comparing and falsifying GNW, IIT, and TTC by investigating their spatial NCCs would be uninformative because TTC is based on different assumptions about the brain: a global approach with global-to-local differentiation as distinguished from IIT's and GNW's localizationist approach with local-to-global integration. By these characterizations, we do not mean that either GNW or IIT are old-fashioned "localizationist," i.e., attempting an explanation at a modular (local) rather than network (global) scale—both would be "globalist" in this interpretation.

More specifically, the inference from theoretical principle to plausible neurobiological substrate (NCC) is carried out at a higher abstraction level. In GNW, the inference goes from the postulation of a cognitive workspace coupled with biophysical properties of pyramidal neurons to the frontoparietal networks as loci of experience. In IIT, the inference goes from the explanatory identification of experience with maximally irreducible cause-effect structures coupled with formal knowledge about which network architectures maximize integrated information to the posterior "hot zone" of pyramids of grids.

In other words, the difference concerns the spatial or topographic extension of the neural truth-maker (i.e., what makes true) for each inferential schema, which dictates the explanatory direction. The theory-driven locality in GNW and IIT means explaining why consciousness is associated with a specific region/network and extrapolating to why it is not associated with others or the entire brain—an explanatory integration of the global into the local. In contrast, the theory-driven globality in TTC means explaining why consciousness depends on the entire brain and extrapolating how this is differentially expressed on a regional level—an explanatory differentiation of the local within the global. TTC's inferential schema goes from temporospatial dynamics as a "common currency" between the neural and phenomenal domain coupled with the emphasis on ongoing spontaneous neural activity to the regional differentiations of global brain activity as the full NCC.

This is how we use the local-global distinction here instead of the more common one of modules vs. networks. Naturally, the "local" and "global" qualifiers are defined relatively, and there is no sharp separation independent of an analytic perspective. Nevertheless, the difference is significant for experiment construction, as this meta-theoretical disparity in explanatory trajectories and truth-makers engenders potentially non-overlapping empirical outcomes, such that, for example, in an adversarial experiment, both GNW and TTC are confirmed, meaning it is not a productive one on this specific topic.

Therefore, one substantive takeaway of this sub-section is that the global vs. local distinction in the NCC search has consequences for the empirical comparison and discrimination of consciousness theories, including their potential falsification. However, there is room for convergence: the global brain activity may be represented to different degrees in more local regions like the posterior cortex or PFC. If such global-to-local representation could be linked to the contents of consciousness, TTC could be connected to either GNW or IIT (see Fig. 4).

4.5. Event-related potentials (ERPs) (P3b/VAN), trial-to-trial variability (TTV), and latency of poststimulus activity vs. Pre-poststimulus interaction approaches

GNW associated the P3b component, a late positivity ERP in the ~300–600 ms post-stimulus interval, as a marker of conscious access, which caused much controversy (Almeida, 2022; Andersen et al., 2016; Cohen et al., 2020; Förster et al., 2020; Koivisto et al., 2016; Koivisto and Revonsuo, 2010; Lamme, 2010, 2018; Northoff and Lamme, 2020; Pitts, Metzler, et al., 2014; Pitts, Padwal, et al., 2014; Rutiku et al., 2015, 2016). Despite its NCC status, empirical evidence and theoretical modeling suggest that the P3b component might be associated with cognitive processes like attention (Kropotov, 2009a; Polich, 2007), engagement operations, salience monitoring (Foss-Feig et al., 2012; Kropotov, 2009b), and decision-making (Rac-Lubashevsky and Kessler, 2019). Thus, the P3b component appears associated with multiple cognitive processes, suggesting it may not be specific to conscious access. Another unproven possibility is that all cognitive processes involve conscious access. Thus, P3b's presence in many cognitive tasks argues against it being an NCC for conscious access; rather, it could index a neural consequence (Aru et al., 2012; de Graaf et al., 2012; Northoff, 2013; Northoff and Heiss, 2015)

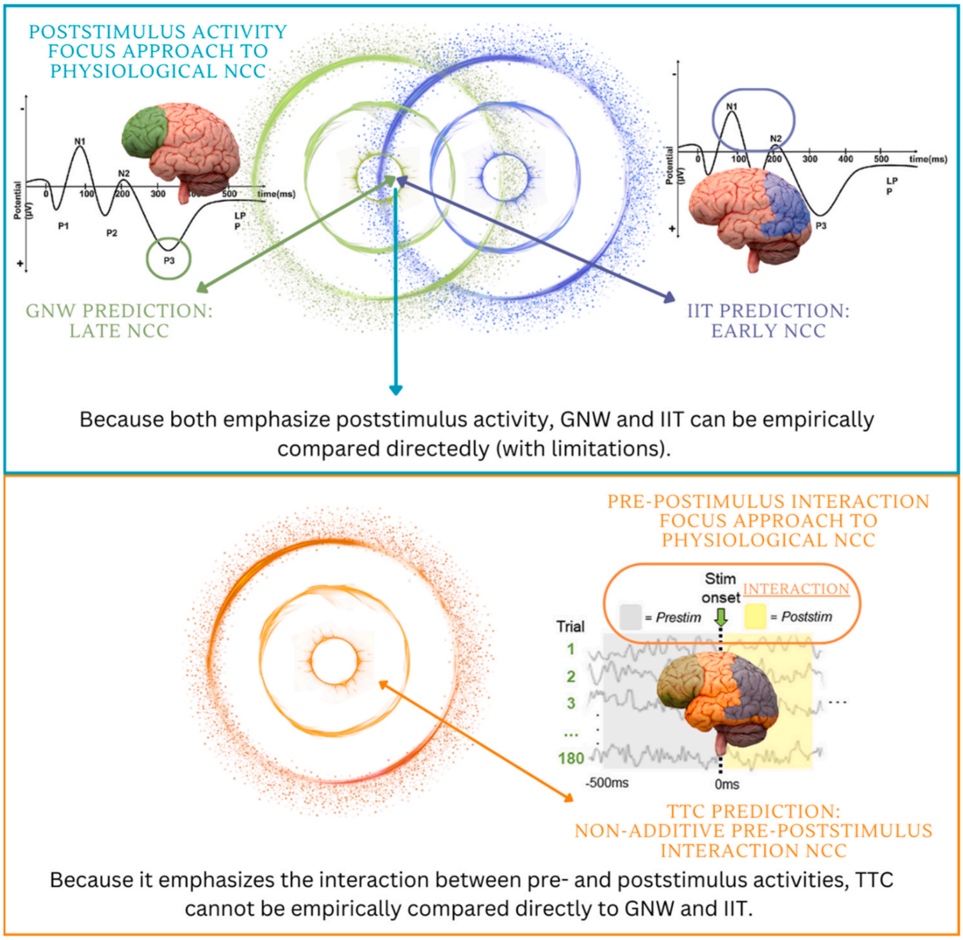
Unlike GNW, IIT associates earlier event-related potentials (Boly et al., 2017; Koch et al., 2016; Siclari et al., 2017; Tononi et al., 2015) like the early negativity N200 component, known as visual awareness negativity (VAN) in the visual perception paradigm (Förster et al., 2020; Koivisto and Revonsuo, 2010; Storm et al., 2017), with visual consciousness. Moreover, the earlier ERPs like N200 (and N100; see Railo et al. 2011) appear to be associated with phenomenal consciousness rather than access consciousness as the P3b (Koch et al., 2016; Storm et al., 2017).

Despite their differences in early vs. late event-related potentials, IIT and GNW prioritize poststimulus activity as NCC candidates despite not completely ignoring prestimulus activity. TTC differs here as it postulates that the prestimulus period and its non-additive interaction with the external stimulus is a necessary aspect of an NCC (Braun et al., 2022; Huang et al., 2015; Northoff and Huang, 2017; Northoff and Zilio, 2022b, 2022a; Wainio-Theberge et al., 2021) (see Fig. 5). One measure of such non-additive pre-poststimulus interaction is trial-to-trial variability (TTV) (i.e., the variance in the amplitude in response to the same stimulus over several trials), whose degree of poststimulus quenching (i) depends on prestimulus variance (Wainio-Theberge et al., 2021; Wolff et al., 2021) and (ii) is associated with conscious contents (Arazi et al., 2017a, 2017b; Huang et al., 2018b, 2015; Schurger et al., 2015; Wainio-Theberge et al., 2021; Waschke et al., 2021).

In sum, as physiological NCCs, the late ERP (P3b) is a mantle to GNW measure, but the early ERP (N200; VAN) is likely peripheral for IIT; both are orthogonal to TTC. TTV, which measures the degree of non-additive pre-poststimulus interaction, is a mantle measure of TTC but only peripheral or, likely, orthogonal in IIT and GNW since neither considers the prestimulus period, including its non-additive interaction with the external stimulus, as an indispensable piece of the NCC. Thus, one could compare IIT and GNW regarding early- and late poststimulus activity. Moreover, in an empirically meaningful sense, GNW and IIT cannot be directly compared with TTC since neither GNW nor IIT considers the TTV-indexed non-additive pre-poststimulus interaction (see Fig. 5). That does not exclude their future convergence, though: the TTV-indexed pre-poststimulus non-additive interaction highlighted in TTC may predict the early and/or late post-stimulus ERP changes that GNW and IIT focus on.

5. Addressing MCI's challenges: intra-theory triangulation and inter-theory coordination

The complex landscape of consciousness research, with its methodological, epistemological, and ontological intricacies, challenges multi-



Because both emphasize poststimulus activity, GNW and IIT can be empirically compared directedly (with limitations).

Because it emphasizes the interaction between pre- and poststimulus activities, TTC cannot be empirically compared directly to GNW and IIT.

Fig. 5. Direct empirical comparison of the three theories relative to the physiological NCC.

theory classification interfaces like the MCI. Addressing intra-theory issues outlined in **Section 2** 's Table 1 is essential to avert reductive or fragmentary approaches. Here, the concept of "relevance" stands for the impact measures-driven predictions have on theoretical constructs if disconfirmed. How can relevance be rigorously categorized? Who decides a measure's relevance, and based on what evidence? How can those measures be empirically deployed? How can the ranking be adjusted to theory change?

Conceptual and computational strategies

Firstly, we consider the general relevance classification—the 'criteria specification' challenge. The core–mantle–peripheral–orthogonal nomenclature is a non-formal, conceptual attempt at expressing the idea of an impact gradient ranging from no change to theory rejection. One approach to explore could be to use computational models, e.g., machine learning, applied over extensive datasets, e.g., Yaron et al. (2022), to determine optimal classification boundaries or best criteria for classifying measures within the MCI.

This approach raises some technical considerations we briefly address. Applying machine learning models to classify the relevance of measures in consciousness research necessitates rigorous validation protocols beyond traditional k-fold cross-validation (Hastie et al., 2009). Given the field's interdisciplinary complexity, as illustrated by Yaron et al.'s (2022) dataset, k should be adaptively set to suit data size and diversity (Kohavi, 1995). Interpretability issues also loom large (Doshi-Velez and Kim, 2017); ensemble methods like Random Forest could offer a more transparent approach (Breiman, 2001; Chen and Guestrin, 2016).

Consensus-building and open-science strategies

Intra-theoretical triangulation (Box 1) commences with theory proponents offering an initial measure ranking, thus constructing a foundation in line with the original theoretical intent. Subsequent external expert review, ideally solicited via a call for contributions, fortifies the system's validity and academic rigor, further answering the 'criteria specification' and 'operationalization' challenges (Fig. 6A). This step can be done in a collaborative forum to bootstrap inter-theory coordination (Box 2), also addressing the 'definitional' and 'empirical no-overlap' challenges (Fig.6B). Complementary mechanisms such as symposia, virtual meetings, or online platforms facilitate this mutual understanding without enforcing uniformity but aiming for clarification on theoretical overlaps and divergences

However, potential disagreements among stakeholders or between them and experts can create implementation bottlenecks or syncopate the entire process—the 'proponents' agreement and coherence' and 'conflict resolution mechanisms' challenges. To mitigate such possible conflicts, a structured approach like the Delphi method can be employed (Dalkey and Helmer, 1963; Hasson et al., 2000). Utilizing anonymized surveys, theory proponents and experts categorize measures using a core–mantle–peripheral–orthogonal framework. Iterative rounds could promote consensus and counteract bias, ensuring that the classification accurately represents a shared, field-wide comprehension of the theory's fundamental principles.

Theory proponents could pre-register their conflicting predictions, methodologies, and empirical measures like Melloni et al. (2023) did. This should promote transparency and robustness in comparing theories while reducing the primarily confirmatory and method-specific accumulation of evidence that the field exhibits (Yaron et al., 2022).

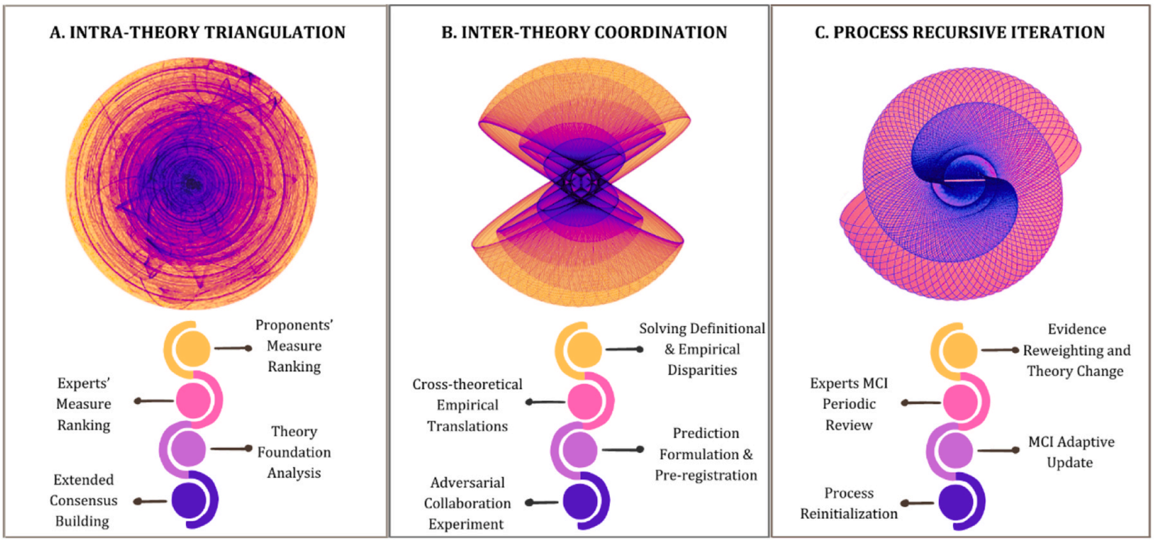


Fig. 6. A. Intra-theory triangulation. Intra-theoretical triangulation involves collaboration between theory proponents and external experts to establish a foundational ranking of measures. This process involves inviting experts to review and provide feedback on the proponent's initial classifications. Interdisciplinary analysis can reveal the deep structure of a theory, clarifying its phenomenological starting point, foundational principles, epistemological commitments, operational assumptions, and explanatory goals. This collaborative understanding helps determine which measures are central to achieving the theory's epistemological goals, generating consensus beyond the theory proponent group. B. Inter-theory coordination. The coordination begins by addressing definitional and empirical differences between candidate theories in an extended and transparent process. Cross-theoretical empirical translations involve systematically transposing a theory's empirical measures into the conceptual framework of another, adaptively reclassifying their centrality. These not only make empirical contrasts starker but might expose latent weaknesses and contribute to potential theory unification and pruning. Theory proponents agree upon and sign off divergent predictions, and the adversarial experiment is pre-registered. Then, a theory's measures-driven predictions are pitted against another's in an adversarial collaborative experiment. C. Process recursive iteration. The experiment's theory-related results are assessed, and the credence given to the theory is reweighted. In light of such changes, periodic expert review panels recalibrate the MCI's measures ranking, ensuring its accuracy and responsiveness. The entire process can be reinitialized for different, potentially overlapping, sets of theories.

5.1. Philosophical strategies

In addition to theory proponents and experts, interdisciplinary philosophical analysis elucidates a theory's deeper structure, including its phenomenological, epistemological, operational, and ontological facets (**Fig. 6 A**). To illustrate, it can shed light on a theory's epistemological foundations: What kind of knowledge it aims to provide, how it views the relationship between theoretical constructs and empirical reality, and what it posits as the limits of its own explanatory power.

Addressing the 'operationalization' challenge, this angle aims at revealing the assumptions through which a consciousness theory faces the intrinsic challenge of translating subjective experiences—private, unique, and qualitative by nature—into objective, quantitative measures that can be systematically studied and compared. Revealingly, the falsifiability and empirical character of some (Doerig et al., 2019) or most (Kleiner and Hoel, 2021) consciousness theories recently came under fire because objectively explaining a subjective phenomenon remains an unresolved methodological problem in consciousness science.

This phase is mandatory, as a theory's epistemological foundation significantly shapes the types of empirical measures considered central or relevant (see also theory meta-classifications below). This determines what set of 'data' is deemed necessary or relevant.

In some frameworks, subjective reporting or phenomenological analysis could be considered central, while others could emphasize

Box 3
Galilean vs. Nagelian Objectivity: Does Phenomenological Data Exist?.

In consciousness studies, discerning reliable data sources is pivotal. Central to this are the divergent epistemological foundations of theories directing the choice and use of empirical measures.

Galilean objectivity prioritizes data triangulation among observers, generally sidelining subjective experiences. This approach heralds a "purely" objective pathway, a third-person perspective grounded in physical manifestations observable externally, emphasizing neurobiological, computational, or behavioral metrics and marginalizing subjective narratives in data landscapes.

In contrast, Nagelian objectivity, inspired by Nagel's (1974, 1986) work, upholds the centrality of the "what it is like to be" narrative from within, emphasizing the primary role of subjective experiences in consciousness studies (Frank et al., 2024; Gallagher and Zahavi, 2021; Goff, 2019). Despite acknowledging the scope and signal limitations of subjective data, it affirms their indispensable value in capturing the complexity and depth of phenomenal experience.

A unified objectivity paradigm to study subjective experience appears necessary for progress. Consciousness researchers should find common ground and navigate these dichotomous objectivities. Non-reductive neurophilosophy (Northoff, 2014a; Zilio, 2020); see Box 2) provides a nuanced pathway for reconciling these two objectivity paradigms without reducing the experiential-subjective to the neuro-objective but instead finding a "common currency" between them and keeping a method and domain pluralism (rather than eliminativism) and brain-based (rather than -reductive) stance.

neurobiological, computational, or behavioral measures that can be subjected to rigorous empirical testing without the "interference" of subjective experience (see Box 3).

Beyond elucidating foundational elements within a single theory, it serves as a toolkit for disentangling inter-theory semantic intricacies that may appear trivial but are often grounded in deep-seated theoretical disagreements. The rigorous employment of this toolkit within a collaborative forum thus leads to conceptual and empirical interoperability, enabling the identification of incommensurable assumptions causing definitional and empirical divergences.

Establishing common ground could imply, for instance, unraveling that the different theories, e.g., illusionist and phenomenology-driven, share a commitment to the notion that consciousness necessarily involves or is a product of information processing, albeit interpreted differently within their respective epistemological frameworks. In this way, the philosophical toolkit enables us to disentangle what seems like mere semantic discordances to uncover areas where the theories can be made commensurable or at least comparable. It allows for a higher degree of conceptual and empirical interoperability, identifying the specific aspects in which, e.g., the illusionist and phenomenological frameworks can engage in meaningful dialogue without diluting their respective theoretical essences. Such an endeavor does not merely aim at compromise but seeks to enlarge the explanatory scope of each theory by integrating insights from the other.

If repeated recursively (**Fig. 6 C**), one significant outcome of this process is the generation of theory meta-classifications, which serve as interpretive layers facilitating discourse between different theoretical frameworks. Such meta-classifications act as a Rosetta Stone, translating the terms of one theory into the context of another. They sharpen the idea that a theory's semantic and epistemological commitments decisively constrain the types of empirical measures deemed pertinent. Thus, we treat the 'inter-theory definitional differences and empirical no-overlap' (Table 1) as a two-faced challenge.

5.2. *Experimental strategies*

The proposed approach increases informativeness when comparing a given theory's measures-driven predictions against another's in an adversarial collaborative experiment (**Fig. 6B**). In particular, the concept of *cross-theoretical empirical translations* stands as a useful methodological dimension of the current proposal. To elucidate, consider two distinct theories, *A* and *B*, each with unique conceptual tenets—*A–C* and *B–C*—and empirical measures, denoted as *A–E* and *B–E*. The goal is not merely to deploy *A–E* into *B–C* but to undertake a nuanced mapping that accounts for each theory's methodological, epistemological, and ontological intricacies. When theory *A*'s empirical measures (i.e., *A–E*) are interpreted within the conceptual framework of theory *B* (i.e., *B–C*), a *systematic* empirical translation emerges. This facilitates meaningful comparisons and contrasts between theories without destroying the particularities that make each theoretical approach unique.

We showed this in **Section 3** by taking an IIT-popularized measure, the LZC, and cross-theoretically translating it to GNW and TTC in a way that dovetails with their theoretical and empirical apparatus. We argued that if an LZC increase is observed in the early or late poststimulus periods in connection with a conscious percept, this finding would support IIT and GNW, depending on the timing, as opposed to TTC. On the other hand, if a decrease in poststimulus LZC, relative to prestimulus levels, is associated with conscious content, this would tip the scales in favor of TTC. Notwithstanding the results, the nuanced difference between zeroing in on poststimulus latency and investigating pre-poststimulus interactions is already a fruitful result of the MCI-driven methodology that could inform future theory-building and adversarial collaboration design.

An unavoidable stumbling block when translating empirical measures across theories is the difference in within-theory relevance. For instance, what is deemed "core" in theory *A* might only occupy a "peripheral" status in theory *B*. The MCI approach tackles this by adaptively reclassifying the translated measure based on the cumulative knowledge garnered. As shown, upon importing a measure from one theoretical context to another, this process critically evaluates the measure against the definitional and empirical criteria inherent to the receiving theory. This adaptive reclassification is a dynamic mapping: It reconciles the imported measure with the receiving theory's existing categorizations, ensuring conceptual fidelity while accommodating differences in measure centrality.

The benefits of cross-theoretical empirical translations extend beyond methodological innovation. First, such translations enable the examination of a theory's robustness by placing its empirical measures within the purview of an alternative theoretical construct. This facilitates more rigorous and nuanced evaluations and exposes latent weaknesses or gaps in each theory. The adversarial nature of these translations sharpens the experimental contrasts, rendering them starker and more insightful.

Moreover, these translations present an avenue for weighing the falsification of various theories, thus helping decide which adversarial collaborations are informative. For instance, if a core measure-based prediction of theory *A* is falsified, it provides robust evidence against the theory rather than if a peripheral measure is falsified. MCI then provides a tool to more rigorously evaluate the evidence against a theory but also contribute to potential theory unification and pruning, a highly sought-after yet elusive goal in consciousness studies. When empirical measures from theory *A* are coherently integrated and tested within the conceptual architecture of theory *B*, this creates the potential for cross-fertilization of ideas that might benefit both theories.

5.3. *Dynamic adaptive strategies*

To address the 'validation, reliability, and adaptability' challenge, we propose a dynamic adaptive framework for MCI's relevance schema. The intra-theory schema would be continually updated through periodic reviews conducted by panels of experts, both theorists and experimentalists. This step also encourages additional feedback from the broader research community. To formalize this process, Bayesian reasoning can be employed to update the classification of empirical measures in the MCI based on emerging evidence. Transparent documentation of these periodic reviews and adjustments will be maintained, in line with open science policies, to show that classifications are non-dogmatic and adjustable.

To make this process formally rigorous, we can use Bayesian reasoning to adjust beliefs (or probability estimates) based on new evidence (Hanti, 2022; Howson and Urbach, 1989). As a simple example, the classification of empirical measures within the MCI (whether core, mantle, peripheral, or orthogonal) at the second step can be seen as our prior belief about the relevance of those measures to a theory. As new empirical evidence emerges that might elicit theory change at the fourth step, it provides an opportunity to update the measure ranking, even the relevance classification at step 1, by acting as the likelihood in Bayesian terms. By combining prior beliefs with new evidence, a posterior belief about the classification of an empirical measure can be derived, reflecting an update. To illustrate, if a previously mantle measure met disconfirmatory experiments and the theory changed, the confidence in its relative centrality decreases and is downgraded to peripheral if not replaced as not relevant anymore.

Corcoran et al. (2023) provide a nuanced Bayesian account of adversarial experiments designed to compare theories in a Bayesian belief updating framework. Arguably, our approach is methodologically antecedent and complementary to theirs, as the MCI delineates explicit steps and strategies for designing informative experiments based on conceptually deep assessments of the competing frameworks' theoretical structures. With this initial theoretical step in place, the results of Bayesian comparisons become more easily interpretable and informative as the measure's status with respect to the theory is known (e.g., orthogonal, periphery, mantle, and core). Therefore, we regard the MCI as an initial tool for bringing methodological clarity.

6. Conclusion—looking back and looking forward

The process described in the previous section is designed to be applied recursively (**Fig. 6 C**), much like Northoff's (2014) concept-fact dynamic (Box 2). Altogether, the comparison process with intra-theoretical triangulation leads to inter-theory coordination, where each theory's core, mantle, peripheral, and orthogonal measures are designated, resulting in a theory-specific MCI. Definitional and empirical disparities between theories are identified and systematically reconciled through consensus-building and pre-registration, supported by philosophical scrutiny that reveals their deeper structural commitments. This culminates in an adversarial collaborative experimental paradigm involving sophisticated translation of empirical measures across theoretical frameworks. Ultimately, this framework anticipates subsequent cycles of theory revision and MCI updating, enriched by adaptive reclassification and Bayesian reasoning, in a dynamic and responsive feedback mechanism.

We gave a proof-of-concept of this process by comparing the empirical measures of three theories: IIT, GNW, and TTC. Applying our methodology, we observed that direct comparison among all three theories may be possible only for a handful of measures like ACW, LZC, and maybe MI. For most others, their direct comparison remains uninformative, e.g., anatomical and physiological NCCs, due to their different weightings within and relative to the theoretical and empirical frameworks of the theories. The proposed methodology brings to light both the opportunities and limitations of such comparisons.

Rather than being static or monolithic, the MCI strategy is predicated upon an evolving dialogue that intertwines theoretical postulations with empirical validations. Such a cyclical process—comprising classification refinement, empirical scrutiny, feedback assimilation, and belief recalibration—guarantees an ever-enhancing alignment of MCI categorizations with the field's foundational theoretical constructs and empirical revelations. As the field progresses, our methodology aspires to ensure that the MCI remains a rigorously grounded and adaptable instrument for the working consciousness researcher.

In grappling with the complexity of consciousness and the various theories aiming to elucidate it, a concerted, collaborative approach has become paramount—one that takes interdisciplinarity seriously at both scientific and institutional levels. Consciousness research needs a unifying framework capable of facilitating empirical inter-theoretic comparison. This paper proposes such a framework, distilling direct, testable predictions and pitting them against each other. By engaging in this method of cross-theoretical empirical translation, the field can leverage the strengths of individual theories, encourage direct comparison, reduce idiosyncrasies, and specify possible convergence and divergence pathways among different theories. This initiative emphasizes accuracy over inclusivity, suggesting that the future growth of consciousness science lies in the deliberate, detailed exploration of theoretical and empirical measures. It invites consciousness researchers worldwide to engage in this empirical dialogue, challenge and refine their theoretical constructs, and participate in the collective pursuit of understanding consciousness.

Declaration of Generative (AI) and AI-assisted technologies in the Writing Process

During the preparation of this work the author(s) used Grammarly and Chat-GPT in order to improve the text's readability and grammar. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Data availability

No data was used for the research described in the article.

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