systems

MDPI

Article

Synchronization and Patterns in Human Dynamics

Franco Orsucci [1,2,*] and Wolfgang Tschacher [3]

[1] Center for Excellence in Mental Health Sciences, University of Amsterdam, 1012 WX Amsterdam, The Netherlands
[2] Research & Development, Norfolk and Suffolk NHS Foundation Trust, Norwich NR6 5BE, UK
[3] University Hospital of Psychiatry and Psychotherapy, University of Bern, 3012 Bern, Switzerland; wolfgang.tschacher@unibe.ch
* Correspondence: franco.orsucci@nsft.nhs.uk

Abstract: We examine couplings, synchronization, pattern formation, and transformation in human dynamics. We consider intraindividual and interpersonal relations as coevolution dynamics of heterogeneous mixed couplings, synchronizations, and desynchronizations. They form the dynamic patterns of the embodied Self and organize intersubjective dynamics. We critically review various models with differing levels of complexity and degrees of freedom. The Fokker–Planck equation clarifies the balance between determinism and stochasticity. The HKB and Kuramoto models describe complex synchronization and pattern formation dynamics. Chimera states are ubiquitous in the mixed networks of human dynamics. Coupling, synchronization, and patterns form and transform, with gaps in between. We propose a formal model for these complex, mixed, and heterogeneous dynamics. Multidimensional theoretical models can represent the specific nature of human interactions and the dynamic structure of the embodied Self. The embodied Self emerges during a developmental process and retains its dynamical nature by continuously adapting to the ever-changing landscape of affordances of daily life.

Keywords: synchronization; biosemiotics; pattern; information; cognitive neuroscience; psychology; emotions; chimera states; statistical dynamics; coupling

check for updates

Academic Editors: Francis Heylighen and Maurice Yolles

Received: 14 December 2024
Revised: 10 February 2025
Accepted: 8 April 2025
Published: 24 April 2025

Citation: Orsucci, F.; Tschacher, W. Synchronization and Patterns in Human Dynamics. *Systems* **2025**, *13*, 311. https://doi.org/10.3390/systems13050311

1. Introduction, Complex Human Dynamics

The progress of studies on synchronization and coordination dynamics in mammals and humans has created a platform for an integrated science of human dynamics [1–4]. On this basis, further studies on intersubjective synchronization have shown that complex human systems operate through sophisticated coordination mechanisms governed by interconnected biological and semiotic networks. Semiotics studies signs, symbols, and meaning-making processes that are fundamentally integrated with human biological processes [5]. Research demonstrates that coordination occurs across multiple scales, exhibiting stability, instability, and change patterns throughout these systems. These systems display diverse patterns from molecular biology to social dynamics [6]. Unique patterns emerge, evolve, and adapt through coupling and synchronization, filling functional gaps. The dynamic organization of complex systems relies heavily on synchronization and pattern formation processes [7]. Synchronization manifests as time-organized activities that coevolve with spatial patterns, while spatial configurations and boundary structures can influence various forms of synchronization. Information flow within these systems saturates new patterns until transitions occur. The relationship between morphology and synchronization is particularly evident in biological systems [8]. Neural network architecture supports the rhythmic firing of neurons. Concurrently, synchronized activity can lead to new patterns, as evident in developmental processes where coordinated cellular movement contributes to the formation of intricate structures. Within neural networks, synchronized neuronal firing generates oscillatory patterns essential for cognitive functions, such as memory and perception. The connectivity patterns within these networks significantly influence the emerging functional patterns. Similar principles apply to other biological systems. One example is the coordinated contraction of heart muscle cells, facilitating adequate blood circulation. Language plays a crucial role in scaling synchronization dynamics, functioning both as a synchronization medium and a regulatory tool across different communication levels [9]. The study of information dynamics reveals how information flows through these systems over time, including its generation, transfer, storage, and transformation. Considering internal and external interactions, this framework helps explain the emergence, stabilization, and transition of coordination patterns in human dynamics [10]. These complex patterns and interactions are fundamental to understanding human systems across multiple disciplines, from materials science to neuroscience and biosemiotics. Integrating these elements creates a comprehensive framework for studying human dynamics and underlying mechanisms. Integrating diverse expertise in human dynamics is essential for achieving significant advancements in this emerging field of dynamical systems research [11].

The notion that the embodied Self is a complex dynamical system has gained attention in various fields, including cognitive neuroscience, psychology, and philosophy. It suggests that the Self can be understood and described using the principles of complex systems theory [12–16]. Complex dynamical systems refer to systems that exhibit emergent behavior arising from the interactions between their components. Nonlinearity, feedback loops, sensitivity to initial conditions, and self-organization are characteristics of these systems. They often demonstrate adaptability, resilience, and the capacity to transition through phase changes while maintaining system cohesion. When applied to the embodied Self, considering it a complex dynamical system implies that it emerges from the interactions between its various sub-systems, such as neurodynamics, thoughts, emotions, memories, beliefs, social influences, actions, physiology, and biological foundations. These configurations interact with each other in dynamic ways, with a high degree of freedom, leading to the emergence of self-organization and self-regulation. Considering the Self as a complex dynamical system offers a framework for understanding the intricate interplay between internal and external factors, the constant adaptation to environmental change, and the emergent properties that arise from the system's interactions. A formal model of the embodied Self can ground human dynamics in complexity science. We will explore theoretical and empirical research leading to a robust and parsimonious model.

Emotions are particularly relevant in the dynamical integration of the embodied Self. They constitute the bridging matrix that integrates "biological and mental" regions of the PsycheSoma with a pertinent history of theoretical and empirical research [17–19]. An emotional sense of personal identity provides a foundation in everyday life. William James [20,21] defined this nucleus of our Self-identity as "the very sanctuary of our life." In parallel, our biological selves continually regenerate as cells are constantly replaced, while the immune system ensures that our biological identity persists and evolves [22,23]. This view of the integrated nature of the body and the Self echoes Maurice Merleau-Ponty [24,25]. The proto-self may be dynamically centered in a critical brain area, specifically within the center-medial diencephalic midbrain areas, such as the Periventricular and Peri-Aqueductal Gray (PAG), and nearby tectal and tegmental zones [19]. Walter J. Freeman extended this core to other brain areas [26,27], as he located the emotional primary Self within the network of the limbic system. The limbic system, often called the paleo-mammalian cortex, is a collection of brain structures on either side of the thalamus, just below the medial temporal lobe. It works with emotions, intentional behaviors, long-term memory, and olfaction. It is a system that integrates sub-units with different functions, all relevant to the primary Self. Its systemic structure entails neuro-psychological pattern dynamics between areas and functions. Freeman considered the neural populations that compose the limbic system to be the key to understanding the biology of intentionality as the principal agent of action in space and time [27]. Studying and modeling human synchronization and pattern formation can provide crucial insights into the dynamical organization of the embodied human Self.

2. Materials and Methods, Synchronization and Pattern Formation

Terry Marks-Tarlow [28] further developed a perspective of the Self as a dynamical system. In this way, we can understand how the Self is a process of patterns continually formed, destroyed, and reconstructed by local interactions occurring at multiple levels in the brain, emotions, attachment relations, and narrative culture. The Self is an open system, a dissipative structure characterized by metastability, which requires a continuous flow of energy, matter, and information. Marks-Tarlow emphasized its self-organization, degrees of freedom, and continual regeneration while open to the environment. Independently, Tschacher and Rössler [29] conceived the Self as a self-organized system whose attractor-like homeostasis is maintained through repeated calibrations, such as in empathetic social exchange. David Pincus proposed that the Self has an interconnected fractal structure based on self-organization dynamics [30,31]. This complex and dynamic organization fosters systemic resilience.

The self-organizing Self is grounded in relational coordination dynamics. Building on Bowlby's observations [32,33] regarding attachment behavior, psychobiologists explored the mother-infant bond as a significant coupling organization primarily governed by inner emotional signals from its early stages of development. Myron Hofer and other developmental biologists revealed numerous hidden regulatory mechanisms in studies of rodents and primates [34,35]. These concealed factors influence various sensory channels: nutritional, olfactory, tactile, thermal, visual, and vestibular. Evidence for entrainment and coupling in physiological and semiotic domains holds at the emotional level. Research on infants suggests that not only are the emotions and responses of the mother or other primary caregiver critical in shaping the developing baby's sense of self, but the reverse is also true. There is a bidirectional influence, or mutual co-regulation, between the infant and the caretaker, through which they are coupled in coordination dynamics within a bipersonal field. These early dynamics provide the matrix for developing the primary embodied Self.

Most regulatory mechanisms remain hidden from a passive third observer outside the bipersonal fields and can be discovered in controlled settings. Similar hidden regulatory mechanisms in humans persist into adulthood; however, other emotional, cognitive, and social factors also influence their functioning. The interactions between the Self and its primary relations regulate the psychosomatic balance, and the reciprocal influence can be modeled by nonlinear dynamical theory [36,37]. Non-reductionist models delineate complex feedback systems marked by multiple layers and directions of causality. Extensive work on the neurophysiology of development highlights the embodied entrainment and mixed synchronizations between mother and child [38,39]. Emotions are placed as the crucial area of embodiment [40]. They are also shaped through active adaptation to culture, which serves to maintain, regulate, and sometimes challenge the cultural environment to which they are tuned. Multilayered coupling is evidence of a reciprocally interactive relationship between culture and the embodied selves [41]. Each subsystem appears to contain interaction patterns across partially open boundaries and feedback loops operating in bottom-up and top-down directions. This perspective is also taken in the field of network physiology.

The process that supports human selfhood is integrating the PsycheSoma as a biosemiotic complex system. Hoffmeyer presents a semiotic interpretation of biology, suggesting that organic relations are grounded in meaning [5,42,43]. He combines the work of Charles Peirce and the Umwelt theory of Jacob von Uexküll to demonstrate how the interaction, exchange, and development underlying biological order are fundamentally semiotic processes. When animals perceive patterns in their surroundings and use them to guide their actions, they respond to stimuli and interpret signs, coupling with their environment, making it their *Umwelt.* James Gibson referred to this as 'affordance' in his theory of direct perception [44]. Affordance transcends the subjective-objective dichotomy, enabling us to understand the integration of biopsychosocial couplings. An affordance points both ways, to the environment and the subject. Thought exists within us, yet we exist within thought; just as our minds produce language and rely on the brain's mechanisms, we are immersed in language, which predates each of us and shapes our growth and learning. Furthermore, unless we are immersed in language, our brain cannot generate it, and vice versa: if our brain were incapable of developing language, we would not be immersed in it [45]. The conclusion is that the embodied Self is a biosemiotic process that emerges from and within a web of patterns. The PsycheSoma appears to be predisposed to achieve selfhood. Reciprocal and circular causal relations between multiple pattern levels are autopoietic, enabling recovery, repair, and reorganization within the threefold distinction of time scales proposed by Francisco Varela [12,46]. These include the elementary scale (varying roughly from tens to hundreds of milliseconds), the integrative scale (ranging from about 0.5 to 3 s), and the narrative memory scale (exceeding 3 s). Varela characterized these dynamics as having self-generating operational closure. Varela used the term "operational closure" in its mathematical sense, referring to a recursive process not isolated from interactions. Varela's notion of a selfless Self is consistent with Kelso's notion that there is no Self as a substantial controlling agent within the pattern. Our sense of a personal 'I' can be construed as an ongoing interpretative narrative [47] that emerges from the complex coordination of interacting patterns. This way, the embodied Self can be coherent, flexible, and metastable. The uncertainty, consonance, and information entropy levels depend on the fluctuations of synchronizations within their coupling fields. Pattern formation, transitions, and creative destruction and reconstruction processes generate cycles of hybrid, multiscale coupling and decoupling [48,49]. These transitions challenge the systemic flexibility and resilience of the Self. The Self can be categorized as fragile, robust, or antifragile based on its capacity to endure systemic stressors and maintain pattern formation processes [50,51]. Phase transitions between patterns yield free information entropy until a new organization forms into distinct patterns. The coupled inter-subjective organization can withstand temporary states of heightened entropy accompanying decoupling or pattern dissolution and transitions leading to new morphogenesis. Associated risks, such as uncertainty, dissonance, distress, or surprise, may arise, creating challenges and opportunities for positive self-organization. Recent research by Tschacher and Haken [52,53] presents an intriguing view grounded in the Fokker–Planck equation, also called the Kolmogorov forward equation. The Fokker–Planck and Kolmogorov forward equations are mathematically equivalent. While Fokker–Planck developed their version [54,55] to explain Brownian motion, the Kolmogorov forward equation was derived [56,57] to describe random processes. The equation is often referred to as the Fokker–Planck equation in physics and the Kolmogorov forward equation in probability theory.

$$\frac{dP(x;t)}{dt} = \frac{d}{dx}(k(x - x_0)P(x;t)) + Q\frac{d^2P(x;t)}{dx^2} = \mathrm{D} + \mathrm{S} \tag{1}$$

The one-dimensional Fokker–Planck equation encapsulates these concepts: the temporal change in the probability of a state variable x (i.e., the left-hand side) can be modeled by a deterministic term, D, and a stochastic term, S, which contributes to this change. The state variable x may represent a characteristic property of the system of interest. We assume that x is interval-scaled, allowing for the computation of statistics such as averages, variances, and correlations on x. We note that the S term contains d squared; this indicates that we are considering the second derivative of probability P, specifically the diffusion (the variance) of $P(x)$. Q represents the diffusion coefficient parameter, which models the increase or decrease in variable x's variance over time. The D term describes the first derivative, meaning the change in the probability of a given value of x, or $P(x)$. In this context, k and $x - x_0$ represent factors that directly influence P. If a system has a stable equilibrium state (i.e., an attractor), k defines the force that drives the system state x toward this equilibrium state. k is the force that restores equilibrium whenever the system is pushed outside its attractor due to random fluctuations, external forces, or actions. In the Fokker–Planck equation, x_0 typically represents the initial state or condition of the system, serving as the starting point at time $t = 0$ for the probability distribution function $p(x, t \mid x$_0, t_0). This initial condition is crucial for solving the equation, providing the boundary value necessary for a unique solution. The Fokker–Planck equation suggests that behavior change, i.e., the temporal change in the probability of the state variable, depends on the system's current state and time and is commonly a mixture of stochastic and deterministic processes.

Deterministic (causal) and stochastic (random) factors influence human relationships. Deterministic processes establish boundary conditions, while stochastic processes facilitate the exploration of states and possibilities within the interpersonal field state space. Using stochastic dynamics, relational experiences can transcend a limited range of disharmonic, perceptual, and emotional experiences. Stochastic dynamics are associated with the emergence of uncertainty, dissonance, distress, novelty, surprise, opportunities, and sometimes playful humor [58]. In complex systems, the interaction between different causal factors often creates situations where multiple sufficient explanations exist for observed phenomena. This creates emergence, where system-level properties arise from multiple underlying mechanisms that could independently produce equifinality and similar outcomes. It relates to the challenge of attribution in complex causal networks, where numerous causal pathways, all affected by stochastic determinants, can lead to the same system state or behavior. The relationship between indeterminism and overdetermination presents an interesting scientific tension in our understanding of causation in the behavior of complex systems. Indeterminism is the absence of definitive causal determination, where future states cannot be precisely predicted based on current conditions. In quantum mechanics and complex systems, uncertainty and probability play essential roles. Conversely, overdetermination involves multiple sufficient causes for a single outcome, where each cause could independently produce the result. This creates a situation of causal abundance rather than causal uncertainty. In complex systems, these concepts often intersect in subtle ways. A system might exhibit indeterministic behavior at one level while showing overdetermination at another. Understanding overdetermination, equifinality, and indeterminism has essential implications for scientific methodology in challenging the so-called Laplace demon. It suggests that seeking single, definitive causal explanations in complex systems may be less productive than understanding the multiple sufficient pathways through which phenomena can emerge and the multiple opportunities for change. This perspective has influenced approaches to studying everything from climate systems to neural networks [59–61].

3. Results, Modeling Human Dynamics

As a dynamic duo, synchronization and pattern formation are crucial for emerging new structures within the embodied Self. Modern research in synchronization and pattern formation can lay the ground for robust models of the embodied Self. Synchronization refers to the coordinated behavior of multiple individual components. It can also drive pattern formation, as synchronized activity can lead to the emergence of new patterns. Pattern formation, the process of creating organized structures from initially disorganized systems, often serves as a foundation for further dynamics, with patterns typically providing a framework for synchronization. Neurons can fire synchronously, forming oscillatory patterns that underlie cognitive functions such as memory and perception. The connectivity patterns within neural networks influence new emerging patterns [62–64]. For instance, the organized movement of cells during development plays a role in creating intricate structures, such as the alignment of neural networks. Understanding pattern formation and transformations during phase transitions is crucial across diverse disciplines, including materials science, condensed matter physics, chemistry, ecology, biophysics, neuroscience, and biosemiotics. Simultaneously, patterns within individual subjects reflect integrated, complex, and multidimensional networks [65–68]. Patterns in language are involved in scaling synchronization dynamics. A language's sounds are organized into patterns known as phonemes, expressed in morphemes. These patterns can be analyzed in terms of their features, such as voice, place, and manner of articulation. Morphemes form patterns of informational structures, which are studied in information combinatorics [69]. Syntactic patterns of word combinations to form sentences follow specific syntactic rules. These rules can be analyzed in terms of phrase structure, dependency relations, and grammatical categories. The meaning of words and sentences is determined by their semantic relationships, which can be interpreted in terms of semantic features, fields, and networks. The body's physiological processes, such as heart rate, breathing, and hormone levels, exhibit rhythmic or cyclical patterns, including coupling and decoupling, synchrony, and desynchrony, all of which alternate in different yet interconnected streams. Patterns are scaled in pathways, motifs, modules, and networks within the psyche-soma [70].

Scott Kelso suggested that unified coordination dynamics should be seen as a collaboration between established small- and large-scale synchronization models. The former relies on principles from synergetics and nonlinear dynamics, exemplified by the extended Haken–Kelso–Bunz (HKB) model [71,72], while the latter draws from statistical mechanics in groups of many oscillators [73]. Most studies backing the original HKB model have focused on the coordination of two interacting elements, whether two joints of a single limb or two individuals interacting.

$$\phi = -\alpha \sin\phi - 2b \sin 2\phi \tag{2}$$

This is the original HKB interaction dynamic. ϕ is the phase or anti-phase synchronization in a dyadic interaction; a, b are coupling parameters.

In contrast, Kuramoto illustrated the statistical mechanics of large-scale coordination among numerous oscillators. Mathematicians such as Steven Strogatz and Art Winfree quickly adopted Kuramoto's model as a framework for understanding large-scale coordination in complex living systems, which encompasses phenomena ranging from the synchronized flashing of fireflies to the functioning of heart cells and neurons, as well as the behavior of concertgoers [74–76]. This modeling and empirical research indicate that these integrated patterns maintain a dynamic framework of synchronization and coordination, along with multistability and metastability.

$$\frac{d\theta_i}{dt} = \omega_i + \frac{K}{N}\sum_{j=1}^{N} sin\left(\theta_j - \theta_i\right),\ i = 1 \ldots .\ N, \tag{3}$$

The system comprises N limit-cycle oscillators with phase θ_i and coupling K.

Kuramoto and Battogtokh's subsequent research [77] revealed limitations in their initial model, which had assumed uniform synchronization patterns in large groups of oscillators. Their empirical investigations demonstrated a more nuanced reality: networks of identical, nonlocally coupled complex systems of oscillators often exhibited simultaneous coherent and incoherent states. Prior research had established that non-identical coupled oscillators could display diverse behavioral patterns, including frequency locking, phase synchronization, partial synchronization, and incoherence. The prevailing assumption had been that identical oscillators would follow a simpler pattern, either achieving complete phase synchronization or maintaining an incoherent state. However, their groundbreaking discovery showed that even oscillators with identical coupling and similar natural frequencies could develop distinctly different behaviors under specific initial conditions. This phenomenon manifested as a stable state, where some oscillators achieved synchronization while others remained incoherent, challenging the previous understanding of oscillator dynamics.

Kuramoto and Battogtokh later pointed out that their previous model depended on the assumption of perfect homogeneous synchronization within large groups. However, empirical studies frequently reveal that coherence and incoherence can coexist, even among networks of identical, nonlocally coupled oscillators [78]. Coupled oscillators that are not identical are already recognized for demonstrating a range of complex behaviors, including frequency locking, phase synchronization, partial synchronization, and overall incoherence. It was anticipated that identical oscillators would either achieve phase synchronization or drift incoherently. They demonstrated that oscillators with identical coupling and comparable natural frequencies can exhibit diverse behaviors depending on their initial conditions. Some could synchronize, while others maintained a stable, incoherent state.

$$\frac{\partial}{\partial t}\phi(x,t) = \omega(x) - \int G\left(x - x'\right)\sin\left(\phi(x,t) - \phi\left(x',t\right) + \alpha\right)dx' \tag{4}$$

where ϕ is the phase of the oscillator and ω is the natural frequency, with $\omega(x) = \omega$ for all x. This equation corresponds to the continuum limit of the Kuramoto model, with x corresponding to subscript i. The integral kernel $G(x)$ describes the nonlocal interaction, and the phase constant α in the phase-coupling function is related to the original parameters.

Abrams and Strogatz introduced the term "chimera state" to describe this phenomenon of mixed synchronization [79]. Just as the mythological chimera was a creature of different animal parts, this mathematical state describes a system where synchronized and unsynchronized behaviors coexist. Their work provided theoretical foundations for understanding how and why this complex behavioral pattern emerges in oscillator systems. Chimera states are ubiquitous: coupling, synchronization, and patterns emerge and dissipate, with gaps in between. Chimera states were later discovered in limit-cycle oscillators, chaotic oscillators, chaotic maps, and neuronal systems. Initially, chimera patterns were observed in nonlocally coupled networks; subsequently, these states were identified in globally and locally coupled networks and modular networks. The usage of Markov chains for mapping couplings and chimera states was also explored [79,80]. C.R. Laing studied chimera states in heterogeneous networks, examining the influence of mixed-coupling strengths. Of further interest for human dynamics is the emergence of chimera states in multiscale networks that result from coupling different networks [81], a phenomenon commonly observed in biosemiotic dynamics. The dynamic Self emerges from networks of synchronized oscillators linked within fields that include mixed biosemiotic domains [82]. A simplified general mathematical model for heterogeneous mixed chimera networks can be expressed as follows:

$$\frac{dx_i}{dt} = F_i(x_i) + \sum_j K_{ij} G_{ij}(x_i, x_j) \quad (5)$$

where:

x_i represents the state vector of the i-th oscillator.
$F_i x_i$ denotes the intrinsic dynamics of the i-th oscillator, which may differ for various oscillators.
K_{ij} indicates the coupling strength between the i-th and j-th oscillators.
$G_{ij}(x_j, x_i)$ is the coupling function between the i-th and j-th oscillators, which can also differ among distinct oscillators.

This equation is a coupled differential equation, often referred to as an interaction-based differential equation. It represents a generalized version of a coupled nonlinear dynamical system. The overarching structure suggests a system in which each component evolves based on its internal dynamics while being simultaneously influenced by interactions with other components. The coupling enables interaction among multiple variables, each affecting the others while maintaining distinct dynamics. The rate of change relies on both the intrinsic behavior of each variable and its interactions with other variables [83,84]. The prevalence of chimera mapping in synchronization and its diverse typologies has broadened the original definition to encompass phenomena such as human nonidentical coupling oscillators in hybrid networks and multiscale networks that display chimera-like dynamics even before this definition was proposed [10]. Essentially, hybrid chimera networks emphasize the diversity of coupling within a single oscillator type, while heterogeneous mixed-nodes chimera networks delve into the complex interactions among different oscillator types. The dynamical integration of patterns will encompass both rapid and gradual synchronization dynamics. For instance, rapid physiological responses can be observed in emotions, movement, neuro-mediators, breathing, and heart rate, whereas slower responses involve neurotrophic factors, hormones, and attachment dynamics. Speech and cognition can range from rapid to slow, ideally positioned within a mesoscopic dynamic area [85].

4. Discussion: The Dynamics of Self-Organization and Patterns

The coexistence of synchronized and desynchronized behavior within the same network is counterintuitive, as one might expect the oscillators to either synchronize or stay desynchronized. Instead, we can find a coexistence of order and disorder. Chimera states emerge when symmetry in the system breaks down, even when the oscillators are identical and the coupling is uniform. These states are more frequent in human dynamics, where there is coupling between different types of oscillators with varying strengths of coupling and network topologies. Chimera states can be stable or transient, depending on the system parameters and initial conditions.

Chimera states offer numerous systemic advantages, including enhanced resilience, robustness, fault tolerance, and adaptability. By combining synchronized and desynchronized regions, these states improve a network's ability to withstand disturbances and failures. When one part of the network is disrupted, other sections can maintain functionality, preserving overall system stability. Transitioning between synchronized and desynchronized states enables the network to adapt to environmental changes, such as input signal shifts or network topology alterations. This synchronization blend facilitates a reliable information flow across different system components. Synchronized clusters ensure consistent communication, while desynchronized regions provide flexible pathways for alternative signal routing [86,87].

Research on heterogeneous synchronization in the brain reveals complex dynamics across different regions responsible for emotional, motor, and verbal functions. Synchronization patterns play a crucial role in cognitive processing, which requires a delicate equilibrium between neural segregation and integration. The brain's specialized regions efficiently perform segregated computations, while integrated neural systems ensure coordinated performance across multiple areas. Studies indicate that focused cognitive states primarily utilize shorter, local neural connections, whereas integration depends on subcortical regions and cortical hubs that maintain diverse connections throughout the brain [88,89]. Understanding chimera dynamics provides valuable insight into the complex synchronization patterns that emerge during critical cognitive processes. These patterns are particularly relevant when the brain must balance integration and segregation to support adaptive cognition and social interactions [10–12]. The emergence of chimera states in neural networks appears to be influenced by various types of neuronal interactions, including different synaptic mechanisms, varying connection speeds, and neuro-modulatory processes within the nervous system. As distinct brain regions collaborate to execute neurocognitive tasks, they generate variable patterns of partial synchronization. These chimera states manifest repeatedly across various intersubjective interactions, underscoring the complex nature of neural coordination in human cognitive processes. Self-organization, a phenomenon where overall order emerges from local interactions, plays a crucial role in creating spontaneous order in complex systems. This process can occur naturally when adequate information or energy is present without requiring external control. It is frequently initiated by random fluctuations amplified through positive feedback mechanisms. The resulting structure is entirely decentralized, with the organization distributed across all system components. Consequently, this organization is highly adaptable, resilient, and capable of withstanding or self-repairing even after significant disturbances.

The first Kuramoto model is deterministic in its classical form. However, it can be made probabilistic by adding noise terms or considering random initial conditions and coupling parameters. The intrinsic variability in coupling and synchronization patterns across the oscillator population can be regarded as effective stochastic behavior, even without explicit noise terms. The spatial heterogeneity in coupling creates local fluctuations that functionally resemble stochastic effects on system dynamics. Stochastic dynamics can be incorporated into the Kuramoto chimera model by adding noise terms. The most common approach involves adding Gaussian white noise ξi(t) to each oscillator's phase equation as multiplicative or additive. The multiplicative noise term can introduce state-dependent fluctuations, while the additive noise term can provide background perturbations independent of the system state. This combination would account for richer dynamics and can lead to noise-induced transitions in the chimera states [90–94].

The Fokker–Planck and Kolmogorov equations are fundamental for studying stochastic processes and statistical dynamics enmeshed with deterministic processes. They describe how probability distributions evolve in systems subject to random fluctuations. These equations can also be used to analyze mixed synchronization states, particularly in systems where noise or stochasticity plays a role, which is the case in basically all real-life contexts. In systems with coupled oscillators, noise plays a significant role in the emergence and stability of chimera states. The Fokker–Planck equation effectively describes the probability distribution of noise-influenced oscillator phases. For example, noise can disrupt synchronized regions, causing transitions between coherent and incoherent states. The Fokker–Planck framework facilitates the analysis of the noise effect on the coexistence of synchronized and desynchronized groups within chimera states. The backward Kolmogorov equation facilitates the study of the probability of transitions between various states in a system, including shifts between synchronized and desynchronized areas in chimera states. This approach is especially valuable for grasping the stability and duration of chimera states in the presence of noise. Noise can cause transitions between coherent and incoherent states, and the Fokker–Planck equation can describe the probability distribution of these transitions. The Kolmogorov equations can be used to study the stability of chimera states by analyzing the likelihood of transitions between different dynamical regimes [56,62].

5. Conclusions

Human dynamics present network states characterized by the simultaneous presence of multiple distinct synchronization patterns. Subsets of nodes exhibit different degrees or types of phase-locking relationships while maintaining stable global network dynamics. Fundamental advancements in empirical and theoretical research on human synchronization and coordination dynamics pave the way for an integrated complexity science of human dynamical systems.

Author Contributions: Conceptualization, F.O. and W.T.; methodology, F.O. and W.T.; formal analysis, F.O. and W.T.; writing—original draft preparation, F.O. and W.T.; writing—review and editing, F.O. and W.T.; funding acquisition, F.O. All authors have read and agreed to the published version of the manuscript.

Funding: Parts of this research have been funded by the National Institute of Health and Care Research (NIHR) UK, funding the BARTII NSFT project, IRAS ID 316335.

Data Availability Statement: This study did not create or analyze new data, and data sharing does not apply to this article.

Acknowledgments: We are grateful to Walter J. Freeman and Hermann Haken for our past collaborations and some of the inspirations that led to this paper.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Pikovsky, A.; Rosenblum, M.; Kurths, J. *Synchronization a Universal Concept in Nonlinear Sciences*; Cambridge University Press: Cambridge, UK, 2001; Volume 12.
2. Tang, Y.; Qian, F.; Gao, H.; Kurths, J. Synchronization in complex networks and its application—A survey of recent advances and challenges. *Annu. Rev. Control* **2014**, *38*, 184–198. [CrossRef]
3. Winfree, A.T. *The Geometry of Biological Time*; Springer: New York, NY, USA, 1980; Volume 2.
4. Strogatz, S. *Sync: The Emerging Science of Spontaneous Order*, 2nd ed.; Penguin: London, UK, 2004.
5. Sebeok, T.A.; Umiker-Sebeok, D.J.; Young, E.P. (Eds.) *The Semiotic Web 1987*; Mouton de Gruyter: Berlin, Germany, 1988.
6. Barabasi, A.-L.; Frangos, J. *Linked: The New Science of Networks*; Perseus Books: New York, NY, USA, 2003.
7. Kelso, J.A.S. *Dynamic Patterns the Self-Organization of Brain and Behavior*; MIT Press: Cambridge, MA, USA, 1995.
8. Edelman, G.M. Neural Darwinism: Selection and reentrant signaling in higher brain function. *Neuron* **1993**, *10*, 115–125. [CrossRef] [PubMed]
9. Orsucci, F.; Giuliani, A.; Webber, C., Jr.; Zbilut, J.; Fonagy, P.; Mazza, M. Combinatorics and synchronization in natural semiotics. *Phys. A Stat. Mech. Its Appl.* **2006**, *361*, 665–676. [CrossRef]
10. Orsucci, F. Human Synchronization Maps. *Entropy* **2021**, *23*, 1569. [CrossRef]
11. Orsucci, F.; Zimatore, G. Information Entropy in Chimera States of Human Dynamics. *Entropy* **2025**, *27*, 98. [CrossRef]
12. Tschacher, W.; Dauwalder, J.-P. (Eds.) *Dynamics, Synergetics, Autonomous Agents—Nonlinear Systems Approaches to Cognitive Psychology and Cognitive Science*; World Scientific: Singapore, 1999.
13. Damasio, A.R. Emotion in the perspective of an integrated nervous system. *Brain Res. Brain Res. Rev.* **1998**, *26*, 83–86. [CrossRef]
14. Gallagher, S. A pattern theory of self. *Front. Hum. Neurosci.* **2013**, *7*, 443. [CrossRef]
15. Gallagher, S. *The Self and Its Disorders*; Oxford University Press: Oxford, UK, 2024.
16. Gallagher, S.; Shear, J. *Models of the Self*; Imprint Academic: Exeter, UK, 1999; Volume 5.

17. Cannon, W.B. The James-Lange theory of emotions: A critical examination and an alternative theory. *Am. J. Psychol.* **1987**, *100*, 567–586. [CrossRef]
18. Darwin, C.R. *The Expression of the Emotions in Man and Animals*; AMS Press: New York, NY, USA, 1972.
19. Panksepp, J. *Affective Neuroscience the Foundations of Human and Animal Emotions*; Oxford University Press: Oxford, UK, 1998.
20. James, W. *Psychology, Briefer Course*; Harvard University Press: Cambridge, MA, USA, 1985.
21. James, W.; McDermott, J.J. *The Writings of William James a Comprehensive Edition*; Random House: New York, NY, USA, 1967.
22. Tauber, A.I. The immune self: Theory or metaphor? *Immunol. Today* **1994**, *15*, 134–136. [CrossRef]
23. Tauber, A.I. The immune system and its ecology. *Philos. Sci.* **2008**, *75*, 224–245. [CrossRef]
24. Merleau-Ponty, M. *Signes*; Gallimard: Paris, France, 1960.
25. Merleau-Ponty, M. *Phenomenology of Perception*; Humanities Press: London, UK, 1962.
26. Freeman, W.J. *Societies of Brains. A Study in the Neuroscience of Love and Hate*; Lawrence Erlbaum Associates: Mahwah, NJ, USA, 1995.
27. Freeman, W.J. *How Brains Make Up Their Minds*; Weidenfeld & Nicolson: London, UK, 1999.
28. Marks-Tarlow, T. The self as a dynamical system. *Nonlinear Dyn. Psychol. Life Sci.* **1999**, *3*, 311–345. [CrossRef]
29. Tschacher, W.; Rössler, O.E. The self: A processual gestalt. *Chaos Solitons Fractals* **1996**, *7*, 1011–1022. [CrossRef]
30. Pincus, D. Coherence, Complexity, and Information Flow: Self-Organizing Processes in Psychotherapy. 2009. Available online: https://digitalcommons.chapman.edu/psychology_books/9/ (accessed on 16 September 2024).
31. Pincus, D.; Cadsky, O.; Berardi, V.; Asuncion, C.M.; Wann, K. Fractal self-structure and psychological resilience. *Nonlinear Dyn. Psychol. Life Sci.* **2019**, *23*, 57–78.
32. Bowlby, J. Attachment theory and its therapeutic implications. *Adolesc. Psychiatry* **1978**, *6*, 5–33.
33. Bowlby, J. Attachment and loss: Retrospect and prospect. *Am. J. Orthopsychiatry* **1982**, *52*, 664–678. [CrossRef]
34. Hofer, M.A. Early relationships as regulators of infant physiology and behavior. *Acta Paediatr. Suppl.* **1994**, *397*, 9–18. [CrossRef]
35. Hofer, M.A. Hidden regulators: Implications for a new understanding of attachment, separation, and loss. In *Attachment Theory*; Routledge: London, UK, 2013; pp. 203–230.
36. Beebe, B.; Jaffe, J.; Lachmann, F.M. A dyadic systems view of communication. In *Relational Perspectives in Psychoanalysis*; Routledge: London, UK, 2015; pp. 61–81.
37. Schore, A.N. Minds in the making: Attachment, the self-organizing brain, and developmentally-oriented psychoanalytic psychotherapy. *Br. J. Psychother.* **2001**, *17*, 299–328. [CrossRef]
38. Orsucci, F. *Changing Mind*; World Scientific: London, UK; Singapore, 2002.
39. Stern, D.N. *The First Relationship: Mother and Infant*; Harvard University Press: Cambridge, MA, USA, 1977.
40. Trevarthen, C. What is it like to be a person who knows nothing? Defining the active intersubjective mind of a newborn human being. *Infant Child Dev.* **2011**, *20*, 119–135. [CrossRef]
41. Damasio, A. Mental self: The person within. *Nature* **2003**, *423*, 227. [CrossRef]
42. Kyselo, M. The minimal self needs a social update. *Philos. Psychol.* **2016**, *29*, 1057–1065. [CrossRef]
43. Sebeok, T.A. *Biosemiotics: The Semiotic Web 1991*; Walter de Gruyter: Berlin, Germany, 1992.
44. Gibson, J.J. *The Ecological Approach to Visual Perception*; Houghton Mifflin: Boston, MA, USA, 1979.
45. Lotman, Y.M. On the semiosphere. *Σημειωτκή-Sign Syst. Stud.* **2005**, *33*, 205–229. [CrossRef]
46. Varela, F.J. Patterns of life: Intertwining identity and cognition. *Brain Cogn.* **1997**, *34*, 72–87. [CrossRef] [PubMed]
47. Freeman, W.J. On the Nature and Neural Mechanisms of Mind Force. *Chaos Complex. Lett.* **2012**, *6*, 7.
48. Høgenhaug, S.S.; Steffensen, S.V.; Orsucci, F.; Zimatore, G.; Schiepek, G.K.; Kongerslev, M.T.; Bateman, A.; Kjaersdam Telléus, G. The Complexity of Interpersonal Physiology During Rupture and Repair Episodes in the Treatment of Borderline Personality Disorder: A Proof-of-Concept Multimethod Single Case Study of Verbal and Non-Verbal Interactional Dynamics. *Front. Psychol.* **2024**, *15*, 1408183. [CrossRef]
49. Gregorini, C.; De Carli, P.; Parolin, L.A.L.; Tschacher, W.; Preti, E. Potential role of nonverbal synchrony in psychotherapy: A meta-analysis. *Couns. Psychother. Res.* **2025**, *25*, e12885. [CrossRef]
50. Axenie, C.; López-Corona, O.; Makridis, M.A.; Akbarzadeh, M.; Saveriano, M.; Stancu, A.; West, J. Antifragility in complex dynamical systems. *npj Complex.* **2024**, *1*, 12. [CrossRef]
51. Kiefer, A.W.; Pincus, D. Nonlinear Biopsychosocial Resilience: Self-Organization as the Basis for a Common Framework. In *The Routledge International Handbook of Changes in Human Perceptions and Behaviors*; Routledge: London, UK, 2023; pp. 424–436.
52. Tschacher, W.; Haken, H. *The Process of Psychotherapy: Causation and Chance*; Springer Nature: Cham, Switzerland, 2019. [CrossRef]
53. Tschacher, W.; Haken, H. Causation and chance: Detection of deterministic and stochastic ingredients in psychotherapy processes. *Psychother. Res.* **2020**, *30*, 1075–1087. [CrossRef]
54. Hoffmeyer, J. *Biosemiotics: An Examination into the Signs of Life and the Life of Signs*; University of Chicago Press: Chicago, IL, USA, 2008.
55. Fokker, A.D. Die mittlere Energie rotierender elektrischer Dipole im Strahlungsfeld. *Ann. Phys.* **1914**, *43*, 810–820. [CrossRef]

56. Risken, H. *The Fokker-Planck Equation: Methods of Solution and Applications*; Springer: Berlin/Heidelberg, Germany, 1989.
57. Kolmogorov, A.N. Über die analytischen Methoden in der Wahrscheinlichkeitsrechnung. *Math. Ann.* **1931**, *104*, 415–458. [CrossRef]
58. Bogachev, V.I.; Krylov, N.V.; Röckner, M.; Shaposhnikov, S.V. *Fokker–Planck–Kolmogorov Equations*; American Mathematical Society: Providence, RI, USA, 2022; Volume 207.
59. Tschacher, W.; Haken, H. A complexity science account of humor. *Entropy* **2023**, *25*, 341. [CrossRef]
60. Cilliers, P. What can we learn from a theory of complexity? *Emergence* **2000**, *2*, 23–33. [CrossRef]
61. Duchesne, É.; Silve, A. Formal Modelling. In *Research Methods in the Social Sciences: An A-Z of Key Concepts*; Oxford University Press: Oxford, UK, 2021.
62. Gardiner, C. *Stochastic Methods: A Handbook for the Natural and Social Sciences*; Springer: Berlin/Heidelberg, Germany, 2009.
63. Edelman, G.M. Molecular Determinants of Animal Form. In Proceedings of the UCLA Symposium Held at Park City, Park City, UT, USA, 30 March–4 April 1985; A.R. Liss Publisher: New York, NY, USA, 1985.
64. Edelman, G.M. *Neural Darwinism the Theory of Neuronal Group Selection*; Basic Books: New York, NY, USA, 1987.
65. Edelman, G.M. *Topobiology an Introduction to Molecular Embryology*; Basic Books: New York, NY, USA, 1988.
66. Wu, C.W. *Synchronization in Complex Networks of Nonlinear Dynamical Systems*; World Scientific: Singapore, 2007.
67. Gerster, M.; Berner, R.; Sawicki, J.; Zakharova, A.; Škoch, A.; Hlinka, J.; Lehnertz, K.; Schöll, E. Fitz-Hugh-Nagumo oscillators on complex networks mimic epileptic-seizure-related synchronization phenomena. *Chaos* **2020**, *30*, 123130. [CrossRef] [PubMed]
68. Schöll, E. Partial synchronization patterns in brain networks. *Europhys. Lett.* **2021**, *136*, 18001. [CrossRef]
69. Orsucci, F. The paradigm of complexity in clinical neurocognitive science. *Neuroscientist* **2006**, *12*, 390–397. [CrossRef]
70. Oltvai, Z.N.; Barabasi, A.-L. Life's Complexity Pyramid. *Science* **2002**, *298*, 763–764. [CrossRef]
71. Kelso, J.A.S. The Haken–Kelso–Bunz (HKB) model: From matter to movement to mind. *Biol. Cybern.* **2021**, *115*, 305–322. [CrossRef]
72. Kelso, J.A.S.; Mandell, A.J.; Shlesinger, M.F.; Haken, H. Dynamic patterns in complex systems. In Proceedings of the Conference in Honor of Hermann Haken on the Occasion of His 60th Birthday, Fort Lauderdale, FL, USA, 21–23 October 1987; World Scientific: Singapore, 1988.
73. Kuramoto, Y. Self-entrainment of a population of coupled non-linear oscillators. In *International Symposium on Mathematical Problems in Theoretical Physics*; Springer: Berlin/Heidelberg, Germany, 1975.
74. Tschacher, W.; Greenwood, S.; Weining, C.; Wald-Fuhrmann, M.; Ramakrishnan, C.; Seibert, C.; Tröndle, M. Physiological audience synchrony in classical concerts linked with listeners' experiences and attitudes. *Sci. Rep.* **2024**, *14*, 16412. [CrossRef]
75. Sawicki, J.; Berner, R.; Löser, T.; Schöll, E. Modelling tumor disease and sepsis by networks of adaptively coupled phase oscillators. *Front. Netw. Physiol.* **2022**, *1*, 730385. [CrossRef]
76. Berner, R.; Sawicki, J.; Thiele, M.; Löser, T.; Schöll, E. Critical parameters in dynamic network modeling of sepsis. *Front. Netw. Physiol.* **2022**, *2*, 904480. [CrossRef]
77. Kuramoto, Y.; Battogtokh, D. Coexistence of coherence and incoherence in nonlocally coupled phase oscillators. *arXiv* **2002**, arXiv:cond-mat/0210694.
78. Abrams, D.M.; Strogatz, S.H. Chimera states for coupled oscillators. *Phys. Rev. Lett.* **2004**, *93*, 174102. [CrossRef] [PubMed]
79. Afraimovich, V.S.; Shilnikov, L.P. Symbolic—Dynamics in Multidimensional Annulus and Chimera States. *Int. J. Bifurc. Chaos* **2014**, *24*, 1440002. [CrossRef]
80. Vasudevan, K.; Cavers, M.; Ware, A. Earthquake sequencing: Chimera states with Kuramoto model dynamics on directed graphs. *Nonlinear Process. Geophys.* **2015**, *22*, 499–512. [CrossRef]
81. Laing, C.R. Chimera states in heterogeneous networks. *Chaos Interdiscip. J. Nonlinear Sci.* **2009**, *19*, 013113. [CrossRef]
82. Orsucci, F. *Mind Force*; World Scientific Pub Co. Inc.: Singapore, 2009; Volume 12.
83. Omel'chenko, O.E. The mathematics behind chimera states. *Nonlinearity* **2018**, *31*, R121. [CrossRef]
84. Schöll, E. Synchronization patterns and chimera states in complex networks: Interplay of topology and dynamics. *Eur. Phys. J. Spec. Top.* **2016**, *225*, 891–919. [CrossRef]
85. Kahneman, D. *Thinking, Fast and Slow*; Farrar, Straus and Giroux: New York, NY, USA, 2011.
86. Majhi, S.; Bera, B.K.; Ghosh, D.; Perc, M. Chimera states in neuronal networks: A review. *Phys. Life Rev.* **2019**, *28*, 100–121. [CrossRef]
87. Wang, Z.; Liu, Z. A brief review of chimera state in empirical brain networks. *Front. Physiol.* **2020**, *11*, 724. [CrossRef]
88. Bansal, K.; Garcia, J.O.; Tompson, S.H.; Verstynen, T.; Vettel, J.M.; Muldoon, S.F. Cognitive chimera states in human brain networks. *Sci. Adv.* **2019**, *5*, eaau8535. [CrossRef]
89. Chouzouris, T.; Omelchenko, I.; Zakharova, A.; Hlinka, J.; Jiruska, P.; Schöll, E. Chimera states in brain networks: Empirical neural vs. modular fractal connectivity. *Chaos Interdiscip. J. Nonlinear Sci.* **2018**, *28*, 045112. [CrossRef]
90. Zakharova, A.; Semenova, N.; Anishchenko, V.; Schöll, E. Noise-induced chimera states in a neural network. In *Patterns of Dynamics: Berlin*; Springer International Publishing: Berlin/Heidelberg, Germany, 2017; pp. 44–63.

91. Loos, S.A.; Claussen, J.C.; Schöll, E.; Zakharova, A. Chimera patterns under the impact of noise. *Phys. Rev. E* **2016**, *93*, 012209. [CrossRef] [PubMed]
92. Omel'chenko, O.E.; Wolfrum, M.; Maistrenko, Y.L. Chimera states as chaotic spatiotemporal patterns. *Phys. Rev. E—Stat. Nonlinear Soft Matter Phys.* **2010**, *81*, 065201. [CrossRef] [PubMed]
93. Kruk, N.; Maistrenko, Y.; Koeppl, H. Solitary states in the mean-field limit. *Chaos Interdiscip. J. Nonlinear Sci.* **2020**, *30*, 111104. [CrossRef]
94. Kalloniatis, A.C.; Zuparic, M.L.; Prokopenko, M. Fisher information and criticality in the Kuramoto model of nonidentical oscillators. *Phys. Rev. E* **2018**, *98*, 022302. [CrossRef]