Akademik İncelemeler Dergisi
Journal of Academic Inquiries

e-ISSN : 2602-3016
Publisher : Sakarya University

Cilt/Vol. 21, Sayı/No. 1, 169-188, 2026
DOI: https://doi.org/10.17550/akademikincelemeler.1811877

Research Article

Dynamic Rationality: Bridging Neuroeconomics and Dynamical Systems in the Study of Choice

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Received: 27.10.2025
Accepted: 09.02.2026
Available Online: 13.02.2026

Abstract: This paper develops a neurodynamic theory of economic decision-making, reframing preference, rationality, and choice as emergent properties of a nonlinear dynamical system. It argues that traditional and behavioral economic models remain fundamentally static, describing outcomes rather than the evolving processes that generate them. Integrating insights from neuroscience and dynamical systems theory, the study formalizes decision-making as a competition among neural populations within an attractor network. Preferences are conceived not as pre-existing utilities but as transient cognitive equilibria - momentary stabilizations within a continuously self-organizing neural field. The model explains behavioral anomalies such as framing and attraction effects as lawful bifurcations - topological shifts in the decision landscape induced by contextual perturbations and cognitive noise. Conceptually, it redefines rationality as metastability: the adaptive balance between coherence and flexibility in cognitive dynamics. By bridging micro-level neural mechanisms and macro-level economic behavior, the paper proposes a unified framework - Homo dynamicus-that situates economics within the broader science of complex adaptive systems.

Keywords: Neuroeconomics, Dynamical Systems, Preference Reversals, Attractor Networks, Cognitive Equilibrium, Metastability, Dynamic Rationality

1. Introduction

For decades, the edifice of modern economics has been constructed upon a core axiom of human rationality: that individuals possess stable, well-defined, and transitive preferences, which they express consistently through their choices (Von Neumann & Morgenstern, 1944). This postulate of *Homo economicus* provides the bedrock for normative decision theory and elegant mathematical models, from expected utility to general equilibrium. The agent is conceived as a utility-maximizing engine, whose preferences are revealed through choice, independent of the context or the method of elicitation. This vision of human nature, while powerful and parsimonious, offers a profoundly static depiction of the decision-making process, one that assumes the conclusion-the preference-exists prior to and independent of the act of choice itself.

1.1. The limits of static models: Empirical challenges and theoretical gaps

Yet, sustained and robust empirical evidence has steadily eroded this foundational axiom, revealing a landscape characterized not by stability, but by profound malleability. The landmark work of Tversky and Kahneman (1981) on framing effects demonstrated that logically equivalent descriptions of a problem, whether framed in terms of gains or losses, could systematically reverse preferences, a finding fundamentally at odds with the invariance principle of rational choice. This was not an isolated anomaly but rather a manifestation of deeper cognitive architecture. Subsequent experimental work has consistently shown that preferences are not merely revealed but are actively constructed during the decision process (Slovic, 1995).

The classic attraction effect, or asymmetric dominance, offers a compelling illustration: introducing a dominated “decoy” option can shift choice shares between two other alternatives, effectively reshaping the decision landscape in ways that violate the regularity condition of rational choice (Huber, Payne, &

Cite as(APA 7): Kahraman, Ü. O. (2026). Dynamic rationality: Bridging neuroeconomics and dynamical systems in the study of choice. *Journal of Academic Inquiries*, *21*(1), 169-188. https://doi.org/10.17550/akademikincelemeler.1811877

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Puto, 1982). These phenomena extend beyond laboratory settings, permeating real-world domains from financial investing to public policy, which suggests that preference instability is not a marginal curiosity but a central feature of human judgment (Camerer, 1999). Collectively, this evidence poses a formidable challenge to the neoclassical paradigm, compelling a critical reexamination of its core assumptions and calling for a theoretical framework that treats preference reversals not as noise, but as central phenomena to be explained through a dynamic model of choice (Roe, Busemeyer, & Townsend, 2001).

In response to this empirical challenge, behavioral economics mounted a formidable response, most notably through Prospect Theory (Kahneman & Tversky, 1979). By replacing the standard utility function with an S-shaped value function and a nonlinear probability weighting function, it provided an elegant descriptive account of documented anomalies, particularly those involving risk and loss. Its success is undeniable, and it remains a cornerstone of modern behavioral science. However, from the perspective of explaining the dynamic construction of preference, Prospect Theory and its descendants share a fundamental limitation with the neoclassical model they sought to supplant: they remain essentially static. They substitute one fixed function for another, offering a more accurate yet still cross-sectional "snapshot" of decision outcomes; a sophisticated map of behavioral biases, but not a model of the cognitive journey that generates them (Bhatia, 2013).

This static nature becomes particularly limiting when examining the instability and reversal of preferences over time. A value function, however well parameterized, cannot capture the moment-to-moment cognitive conflicts and competitions that characterize real-time choice. It may describe the end state of a framing effect but cannot trace the neural or cognitive trajectory that leads a decision-maker from one preference state to another. While the theory elegantly describes what happens, preferences shift under different frames, it offers little insight into how such shifts occur: the mechanistic process by which a subtle contextual cue triggers a fundamental reorganization of cognitive states. In this sense, it continues to treat the decision-maker as a "black box", albeit with a more complex input-output mapping, without elucidating the dynamic interactions within (Caginalp & Doiron, 2017).

Thus, although Prospect Theory adeptly catalogs systematic departures from rational choice, it leaves a theoretical vacuum at the heart of the preference reversal phenomenon. It does not formally account for the competition between neural representations of options, the role of stochastic noise, or the critical temporal dimension of deliberation. To move beyond cataloging anomalies and toward explaining their genesis, a theory is needed that explicitly models the time-evolving, competitive, and often unstable dynamics of the cognitive system as it approaches a choice; a theory capable of naturally accommodating bifurcations, in which small changes in input produce qualitative shifts in output (Shadlen & Shohamy, 2016). The following section contends that such a theory lies not in refining static functional forms, but in adopting the formal language of dynamical systems.

1.2. Decision-making as a dynamic system: From revealed preference to emergent outcome

The limitations of static models point toward a more profound theoretical shift: a move from an economic logic of revelation to a cognitive and computational logic of emergence. This paper is predicated on the core thesis that the brain is not a passive storehouse of pre-computed preferences, but an active, dynamical system whose states evolve continuously in a high-dimensional neural space. Within this framework, a "preference" is not a hidden input to be revealed by a choice experiment; it is the transient output-the emergent attractor state-of a nonlinear process of competition and integration among simultaneously active, conflicting neural representations (Hunt & Hayden, 2017).

This reconceptualization provides the necessary theoretical machinery to directly address the phenomena that static models can only describe. If the mind is a dynamical system, then a preference reversal is not an irrational contradiction but a natural consequence of the system's evolution, such as

a bifurcation where a small change in a control parameter (e.g., contextual frame, time pressure, or the introduction of a decoy) qualitatively alters the landscape of attractors, guiding the system's trajectory toward a different final state. This view elegantly reframes the entire problem: the question is no longer "Why are preferences inconsistent?" but rather "What are the dynamics that govern the transitions between coherent, but competing, cognitive states?".

This perspective is powerfully supported by recent work in neuroeconomics, which seeks to ground economic theory in the biological reality of the brain. It aligns with the view that value-based choice is fundamentally a process of evidence accumulation, where noisy evidence for each option is integrated over time until a critical threshold-a decision boundary-is reached. Crucially, this process can be formally modeled as a stochastic dynamical system, directly linking the abstract mathematics of dynamics to both observable choice behavior and its underlying neural correlates (Rustichini & Padoa-Schioppa, 2015). By adopting this language, we can construct a formal model where the documented anomalies of choice are not exceptions to a rule, but predictable, lawful manifestations of the intrinsic dynamics of a complex cognitive system moving toward a decision.

1.3. The contribution of the article

This article contends that to truly resolve the theoretical impasse presented by preference reversals, we must transcend descriptive, static models and adopt a formal language capable of capturing the intrinsic dynamism of cognition. Our central contribution is to propose a unified neurodynamic framework that models the decision-making apparatus as a continuous attractor network, formalized through a system of nonlinear differential equations. Within this model, choice options are conceptualized as competing attractors in a neural state space, and preference reversals are explained not as errors, but as bifurcations-qualitative shifts in the system's trajectory induced by deformations of the underlying cognitive landscape. This approach provides a parsimonious and mechanistic explanation for a wide spectrum of choice anomalies, from framing and attraction effects to decisions under time pressure, situating them as emergent properties of a single, coherent dynamic process.

2. Theoretical Foundations: Decision-Making as a Dynamical System

The transition from static to dynamic conceptions of decision-making marks more than a methodological evolution-it represents a profound reorientation in how we conceive the architecture of human choice. Where classical and behavioral models alike have treated preferences as fixed coordinates within a stable representational space, recent developments in cognitive neuroscience invite us to view decision-making as a time-evolving process unfolding across a complex neural manifold. Within this view, the act of choosing is not the revelation of a latent preference but the emergent stabilization of a transient cognitive trajectory. The dynamical perspective thus reframes economic behavior as the output of a continuously self-organizing system-one in which valuation, attention, and contextual inputs interact nonlinearly to produce coherent yet context-sensitive outcomes. This section develops the theoretical and empirical groundwork for such a framework, situating decision-making within the broader language of dynamical systems and elucidating how cognition, rather than computing utilities, dynamically constructs them in real time.

2.1. Neurocognitive foundations of dynamic valuation

Value has long served as the cornerstone of decision theory, yet its conventional treatment as a static construct overlooks the inherently temporal and interactive nature of cognition. Traditional models assume that agents evaluate alternatives by mapping them onto a stable utility function, a pre-existing and context-independent representation of desire. However, growing neurocomputational evidence indicates that valuation is not a retrieval process but a dynamic construction, emerging through the iterative integration of sensory, affective, and mnemonic signals (Balewski et al., 2023).

Rather than a fixed scalar, value manifests as a trajectory: a temporally extended pattern of neural activation that reflects ongoing negotiation among competing representations.

This reconceptualization replaces the classical utility function with a dynamic valuation process, a set of transformations that evolve toward transient attractor states corresponding to provisional preferences. Within this framework, preference reversals and contextual dependencies arise not as anomalies but as lawful consequences of the system's nonlinear dynamics. Recent computational models show that value-related signals in regions such as the orbitofrontal and ventromedial prefrontal cortices exhibit time-dependent variability consistent with attractor-like dynamics, where subtle perturbations in attention or framing can induce bifurcations in decision trajectories (Wang et al., 2023a). Moreover, high-resolution neuroimaging and recurrent neural modeling studies support the view that economic decisions unfold as temporally extended competitions within recurrent cortical circuits, rather than as instantaneous computations of static worth.

Thus, dynamic valuation reframes the decision-maker not as a calculator optimizing a pre-existing function, but as a self-organizing system that continuously shapes its own representational landscape. Utility is reconceived not as a number, but as a process, a momentary equilibrium within a perpetually evolving cognitive field.

If dynamic valuation describes the process of preference formation, the neural architecture of choice reveals the substrate on which this process unfolds. Decision-making is not localized to a single brain region, but emerges from the coordinated dynamics of distributed circuits spanning the orbitofrontal cortex (OFC), ventromedial prefrontal cortex (vmPFC), anterior cingulate cortex (ACC), and striatum. These regions form an interconnected network that encodes, integrates, and updates subjective value representations over time. Critically, their interactions are recurrent rather than feedforward, enabling continuous feedback between valuation, conflict monitoring, and action selection. In this view, the brain functions less as a serial calculator and more as a dynamical system, a network of attractors whose states evolve through mutual excitation, inhibition, and stochastic noise until a decision boundary is reached.

Recent advances in neuroeconomics provide compelling evidence for this distributed and temporally dynamic organization. High-resolution single-neuron recordings in non-human primates demonstrate that OFC and vmPFC neurons do not encode static value signals, but dynamically shift their representational geometry during deliberation, reflecting transient competitions between choice options (Imaizumi et al., 2022). Similarly, human intracranial and fMRI studies reveal that choice-related neural activity propagates across large-scale networks along identifiable temporal gradients: valuation signals emerge in vmPFC, are modulated by conflict monitoring in the ACC, and culminate in motor preparation circuits as the system stabilizes toward a final choice (Gore et al., 2023).

This evidence substantiates the theoretical claim that preference is not a pre-existing input, but an emergent outcome of network dynamics. Neural populations continuously negotiate value, context, and uncertainty until the system settles into an attractor state corresponding to a behavioral decision. Consequently, the architecture of choice is not a static map of regions and functions, but a living, temporally orchestrated system, a neural choreography that transforms cognitive conflict into coherent commitment.

2.2. The attractor network framework: Formalizing dynamics and noise

To move from metaphor to mechanism, the theory of decision-making as a dynamical system requires a formal framework capable of capturing how transient, competing cognitive states evolve over time. The attractor network model provides precisely this formalism, serving as a mathematical and conceptual bridge between neurobiological processes and observed behavioral dynamics. This approach represents decision-making as the trajectory of a high-dimensional system moving through a landscape of potential cognitive states.

Within such networks, each possible choice corresponds to an attractor basin, a region in state space toward which neural activity converges over time. A decision, therefore, is not a discrete event but the stabilization of the network within one such basin following a period of stochastic exploration and competitive interaction.

The elegance of this framework lies in its capacity to explain both stability and variability within a unified structure. When the attractor landscape is steep and well defined, the system settles quickly and consistently, yielding stable, seemingly rational choices. Conversely, when the landscape is shallow or perturbed by contextual inputs such as framing, emotional salience, or cognitive load, identical initial conditions may lead to divergent trajectories and different choices. These bifurcations encapsulate the essence of preference reversals: minor contextual perturbations can shift the system from one attractor to another, generating qualitatively distinct outcomes from nearly identical starting points (Luo et al., 2025). At the neural level, this formalism aligns with the known architecture of cortical decision circuits. Recurrent excitatory-inhibitory networks, such as those in prefrontal and parietal cortices, exhibit the bistable and multistable dynamics necessary for attractor-based behavior (Rostami et al., 2024).

Competing neural populations represent alternative options. Through mutual inhibition and self-excitation, their collective activity drifts toward one stable pattern, the chosen option, while suppressing others. This dynamic competition unfolds continuously, shaped by intrinsic neural noise and contextual modulations. Computationally, the system can be described by a set of coupled nonlinear differential equations governing how activation levels evolve as functions of synaptic input, internal coupling, and time. The solutions to these equations define the system's attractor landscape, its stability, and its susceptibility to bifurcation.

What distinguishes the attractor framework from classical decision theories is its focus on process rather than outcome. Rather than treating choice as an endpoint that reveals preference, it models how preferences emerge from the dynamic interplay of neural and contextual forces. It naturally incorporates the temporal dimension of deliberation, including how evidence accumulates, uncertainty fluctuates, and cognitive noise can propel the system between competing states. Moreover, it provides a unified mathematical language to connect multiple scales of analysis, from synaptic activity and neural firing rates to cognitive phenomena and economic behavior. This scalability allows the model to integrate diverse findings across disciplines, linking psychophysical reaction times, population-level neural recordings, and macroeconomic anomalies within a single coherent system.

In essence, the attractor network framework transforms decision-making from a computation over static values into an emergent process of self-organization within a dynamic neural field. It captures how coherence arises from competition, how stability emerges from noise, and how the brain's intrinsic dynamism gives rise to the richly contextual nature of human choice. This formalism not only bridges cognitive theory and neural implementation but also lays the foundation for a generative, predictive model of preference formation, one capable of explaining why human choices are simultaneously structured and fluid, rational yet profoundly dynamic.

If the attractor network framework explains the structural organization of decision dynamics, then incorporating cognitive noise and temporal competition illuminates the source of their variability. Human decision-making is rarely a smooth convergence toward equilibrium; it is a turbulent process driven by fluctuations in attention, perception, and neural activity that introduce stochastic perturbations. These fluctuations, collectively termed cognitive noise, are not merely sources of error. Instead, they are functional components that endow the cognitive system with flexibility, enabling it to explore multiple trajectories before stabilizing on a decision. Within the dynamical framework, noise operates as both a destabilizing and generative force, capable of pushing the system across attractor boundaries and enabling transitions that deterministic dynamics alone could not produce (Ye & Li, 2021).

Temporal competition arises naturally in this noisy environment. As alternative representations of choice options evolve concurrently, they engage in continuous mutual inhibition and recurrent excitation. The decision process thus unfolds as a time-dependent race among neural populations vying for dominance. This competition is inherently dynamic; its outcome depends not only on the relative strength of initial inputs but also on the temporal structure of neural fluctuations. Minor timing differences in activation can cascade into large qualitative divergences, leading to early commitment, delayed resolution, or oscillatory indecision. Such temporal sensitivity offers a mechanistic basis for well-documented psychological phenomena, including hesitation, preference reversals under time pressure, and the instability of nearly indifferent preferences (Rostami et al., 2024).

Cognitive noise and temporal competition together create conditions ripe for bifurcation under uncertainty, a regime in which the system's trajectory becomes highly sensitive to micro-level perturbations. When the neural landscape is shallow, as in ambiguous or low-stakes decisions, noise can amplify small differences into divergent outcomes, producing experiences of apparent randomness in choice. Conversely, in high-stakes or well-learned contexts, deep attractor basins constrain these fluctuations, leading to stable, rapid decisions (Ashwin et al., 2023). This dynamic balance between determinism and stochasticity is central to adaptive cognition, enabling the decision system to remain both responsive and resilient, capable of exploration in uncertain environments and exploitation when confidence is high.

The temporal dimension also imposes a critical constraint: decisions must be made not only correctly but also timely. As deliberation proceeds, neural evidence accumulates toward a decision boundary, competing with temporal costs such as fatigue, environmental demands, or social pressure. The brain must therefore solve a dynamic optimization problem, balancing the precision of information accumulation against the opportunity cost of delay. Within the attractor framework, this trade-off manifests as a deformation of the potential landscape over time. As pressure increases, attractor basins narrow, noise becomes more influential, and the system transitions more readily to a decision state. Time, in this sense, is not a passive parameter but an active variable shaping the topology of choice.

By integrating cognitive noise and temporal competition, the dynamical model captures the essential tension at the heart of human decision-making: the interplay between structured computation and spontaneous emergence. Noise is not the antithesis of rationality but the substrate from which adaptive rationality arises. Through its interaction with temporal constraints, noise transforms decision-making from a deterministic computation into a living, evolving process, one capable of generating the full spectrum of human choice behavior, from consistency and confidence to hesitation and reversal. This synthesis completes the theoretical foundation for a neurodynamic theory of preference, preparing the ground for its empirical articulation in the modeling and simulations that follow.

3. The Model: A Neurodynamic Framework for Preference Reversals

Having established the theoretical and neurobiological foundations of decision-making as a dynamical process, we now turn to the formal implementation of this perspective. The preceding section developed the conceptual architecture: decision-making as a competition among neural populations evolving through a landscape of attractor states, modulated by noise and temporal constraints. Yet, theory attains its full explanatory power only when formalized into a model that can generate observable behavior. In this section, we construct such a model-a neurodynamic framework designed to capture the mechanistic underpinnings of preference reversals. The model operationalizes the principles articulated earlier, translating them into a system of coupled nonlinear equations that represent the evolution of cognitive states over time. Through this formalization, we move from descriptive analogy to computational precision, allowing the dynamic properties of cognition to be simulated, visualized, and empirically tested.

3.1. Model specification and parameters

At the heart of the proposed framework lies a recurrent neural network that embodies the essential ingredients of dynamic decision-making: competition, feedback, and stochasticity. The model represents each choice option as a neural population with a continuous activation level, denoted $x_i(t)$, which evolves over time according to both external input and internal dynamics. The general form of the model can be expressed as:

$$\frac{\tau dx_i}{dt} = -x_i + f\left(I_i + \sum_j w_{ij}\, x_j\right) + \eta_i(t)$$

Here, τ represents a temporal constant governing the speed of neural integration; I_i denotes the external input reflecting the contextual and sensory salience of option i; w_{ij} encodes the excitatory and inhibitory couplings between populations, capturing the mutual competition among options; $f(\cdot)$ a nonlinear activation function (typically sigmoidal), translating synaptic input into neural output; and $\eta_i(t)$ represents Gaussian noise, modeling intrinsic neural fluctuations and attentional variability.

This formulation allows the system to exhibit a range of dynamical behaviors-steady states, oscillations, or bifurcations-depending on parameter configurations. Stable decision outcomes correspond to attractor states where one population's activation dominates while others are suppressed. The transitions between these states, induced by small perturbations in inputs or noise, correspond to *preference reversals*. Thus, reversals emerge naturally as state transitions within the same dynamical architecture, requiring no exogenous "error" term or ad hoc assumption.

Several key parameters govern the system's behavior:

Activation time constant (τ): Determines how rapidly the system integrates evidence and approaches stability. Short τ values produce impulsive, context-sensitive decisions; larger τ values correspond to deliberative, slow-evolving trajectories.

Mutual inhibition coefficient (w): Controls the strength of competition between options. High inhibition sharpens categorical decisions and stabilizes outcomes; moderate inhibition allows coexistence and increased susceptibility to reversals.

Noise amplitude (σ): Governs the magnitude of stochastic fluctuations. Low σ values yield stable, deterministic dynamics; high σ values induce volatility and frequent attractor switching.

Input asymmetry (ΔI): Represents contextual bias-such as framing or the introduction of a decoy-that deforms the attractor landscape and can precipitate bifurcation events.

Nonlinearity shape parameter (β): Controls the slope of the activation function, tuning the system's sensitivity to incremental input changes.

The interplay among these parameters determines whether the decision process converges smoothly toward a single attractor or oscillates between competing alternatives before resolution. Importantly, the model allows for *parametric manipulation* of contextual variables-such as time pressure, attentional noise, or value framing-thereby generating testable predictions about when and how preference reversals are likely to occur.

In conceptual terms, this system formalizes the decision-maker as a *dynamic equilibrium-seeking agent*: a network perpetually driven toward local stability, yet inherently poised for transition. Each decision corresponds to a temporary stabilization in the network's state space; each reversal, to a reorganization of that landscape. The model thus captures the paradoxical nature of human choice-its coherence within moments and its fragility across contexts-by grounding it in the mathematics of dynamical self-organization.

3.2. Analytical properties of the model: Stability, bifurcation, and cognitive equilibrium

Having formalized the neurodynamic architecture of choice, we now turn to its analytical properties-those structural features that endow the system with both coherence and flexibility. While the model is expressed through a set of coupled nonlinear differential equations, its essence lies not in numerical simulation but in the qualitative geometry of its solution space. The following analysis elucidates how stability, bifurcation, and equilibrium emerge as the mathematical signatures of cognitive organization. These properties transform decision-making from a computational function into a dynamic field phenomenon, governed by topological transitions rather than static preferences (Sergent et al., 2021).

3.2.1. Stability and bifurcation: The dynamics of equilibrium and transition

At the heart of the system are its fixed points-the steady states of neural activation where the rate of change in all populations approaches zero. Each fixed point corresponds to a candidate decision state, a potential cognitive equilibrium representing a provisional commitment to one option over others. The local stability of these equilibria is determined by the Jacobian of the system, whose eigenvalues dictate whether small perturbations decay or amplify over time.

In the cognitive interpretation, a stable fixed point represents a coherent preference-a state resilient to minor fluctuations in attention or neural noise. Conversely, instability signifies cognitive indecision or volatility: even infinitesimal disturbances can push the system toward a different attractor. This analysis captures, in mathematical form, the phenomenology of deliberation itself: the mind oscillates among possible commitments until one equilibrium basin proves sufficiently deep to absorb ongoing perturbations (Ma et al., 2024).

The model thus redefines rationality as a form of dynamic stability. Rather than a precondition of choice, coherence is an emergent property of the system's local geometry. Decision confidence corresponds to the curvature of the attractor basin-the steeper the curvature, the faster the convergence, and the stronger the subjective sense of certainty.

A defining feature of nonlinear systems is their capacity for bifurcation: qualitative shifts in equilibrium structure induced by continuous parameter changes. Within the neurodynamic model, such bifurcations offer a formal account of preference reversals. Parameters like contextual bias (ΔI), inhibitory coupling (w), or noise amplitude (σ) serve as control variables shaping the topology of the decision landscape. As these parameters vary, the system may transition from a monostable regime (a single dominant attractor) to a bistable or multistable configuration, in which multiple cognitive equilibria coexist (Klatzmann et al., 2025).

A small contextual perturbation-such as a reframing of outcomes or the introduction of a dominated decoy-can then act as a catalyst for a topological shift, transforming the system's geometry and redirecting its trajectory toward a different attractor. From this perspective, a preference reversal is not a logical inconsistency but a lawful phase transition: the spontaneous reorganization of a cognitive field in response to a subtle deformation of its underlying parameters (Guo & Vetschera, 2022).

This dynamical account reframes anomalies traditionally viewed as violations of rationality. The framing effect, the attraction effect, and temporal instability in choice all correspond to bifurcation phenomena in the neural manifold. Just as a small change in temperature can induce a phase change in matter, a minute contextual cue can precipitate a discontinuous transformation in cognitive state space (Spektor, Bhatia, & Gluth, 2021). The model thereby provides a mechanistic bridge between micro-level neural perturbations and macro-level behavioral discontinuities.

3.2.2. Cognitive topology and the emergence of preference

The bifurcation structure of the system gives rise to what may be called cognitive phase transitions: discrete reorganizations in the qualitative architecture of thought. In regions of parameter space where multiple attractors coexist, the system exhibits hysteresis and path dependence-its trajectory becomes contingent on initial conditions and prior states. This provides a mathematical foundation for the psychological observation that decisions are history-dependent: once a preference is formed, it reshapes the cognitive landscape, making certain reversals more likely and others less accessible (Fuscà et al., 2023).

The topology of this landscape-the number, depth, and connectivity of attractor basins-defines the repertoire of possible cognitive equilibria available to the system. Shallow landscapes promote exploration and flexibility; deep basins promote stability and commitment. Optimal decision-making thus arises not from eliminating noise or bias but from maintaining the appropriate balance between exploration and exploitation, between the capacity to stabilize and the potential to reorganize (Wang et al., 2023b).

In this light, cognitive flexibility emerges as a topological property of the mind. The human decision system is poised near criticality, delicately balanced between order and chaos. This critical regime confers adaptiveness: it allows rapid stabilization when coherence is required and sensitivity to contextual nuance when flexibility is advantageous (Tian et al., 2022). The analytical structure of the model formalizes this intuition, showing that the brain's decision dynamics operate near the edge of bifurcation-a regime where small causes can yield profound effects.

The mathematical properties described above suggest that what we call a "preference" is, in fact, a temporary cognitive equilibrium-an emergent attractor state within a continuously self-organizing field (Ye & Li, 2021). Equilibrium is not an assumption but a momentary achievement: the result of recurrent interactions among valuation, competition, and noise (Klatzmann et al., 2025). The equilibrium is dynamic, perpetually open to perturbation, yet locally coherent while it persists.

This conception allows for a unification of classical decision theory and neurodynamics under the broader notion of cognitive equilibrium. The classical "utility maximization" condition becomes a special case of dynamical stabilization: the point at which the system's internal forces balance (Dennison, Sazhin & Smith, 2022). Preference reversals, inconsistencies, and framing effects cease to be anomalies; they become manifestations of the lawful dynamics of equilibrium formation and dissolution.

In summary, the analytical properties of the model articulate a new vision of choice as a process of dynamic stabilization within a nonlinear cognitive landscape. Rationality, in this view, is not static consistency but metastability-a poised equilibrium, robust yet revisable, reflecting the brain's evolutionary adaptation to a volatile world. The next section deepens this analysis by exploring the conceptual implications of this formal structure for theories of mind, rationality, and economic behavior.

3.3. Parametric foundations and analytical robustness: Theoretical justification and sensitivity analysis

The dynamic system presented in the preceding section aims to formalize the qualitative structure of decision-making processes. As the reviewer rightly points out, the explanatory power of a model stems not only from the structure of its equations but also from the theoretical and empirical grounding of its parameters, as well as from an examination of the system's sensitivity to these parameters. This subsection aims to substantiate the proposed framework as both a conceptual and an analytical tool by explaining the neuroscientific and behavioral economic roots of the model parameters and presenting a foundational sensitivity analysis.

3.3.1. Theoretical and empirical grounding of parameter choices

Each parameter in the model can be linked to concrete findings and theoretical assumptions from the relevant literature.

The time constant (τ) reflects the speed of neural integration and, consequently, decision time. Research in experimental psychology on decision reaction times (e.g., drift-diffusion models) and the characteristic time scales of neural activity in the prefrontal cortex (ranging from hundreds of milliseconds to seconds) inform the typical value range for τ. Short τ values model impulsive or time-pressured decisions, while long τ values represent complex scenarios requiring deeper deliberation.

The mutual inhibition coefficient (w) controls the intensity of competition between options. Neuroscientific studies indicate that the competitive dynamics in prefrontal and parietal regions involved in decision-making are driven by circuits featuring high levels of mutual inhibition. Experimentally, decision difficulty and indecision when option values are similar can be modeled with moderate w values, whereas clear preferences correspond to high w values.

The noise amplitude (σ) represents stochastic fluctuations within the system. These fluctuations originate from sources such as the inherent volatility of attention, randomness in neural firing, and perceptual uncertainty. The neuroeconomics and decision neuroscience literature documents that decision processes are invariably influenced by such intrinsic noise, which contributes to a portion of non-optimal choices. The σ parameter allows for the systematic incorporation of this phenomenon into the model.

Input asymmetry (ΔI) represents the additional activation or bias provided to the neural representation of one option by contextual factors such as framing, emotional labeling, or the addition of a decoy. This can be directly linked to experimental manipulations like the gain/loss frames of Prospect Theory or the "asymmetric dominance" effect in behavioral economics.

The nonlinearity parameter (β), which determines the slope of the activation function, controls the sensitivity of neural populations to inputs. In neural network and computational neuroscience models, such parameters determine how the network implements decision thresholds and whether it exhibits “soft” or “sharp” decision transitions.

3.3.2. Parameter Sensitivity and Stability Analysis of Model Behavior

To strengthen the model's explanatory claim, it is essential to map the system's qualitative behavior across critical regions of the parameter space. The analysis presented here aims to reveal the model's fundamental dynamic regimes.

Monostability Regime: Under conditions of high mutual inhibition (w) and low noise (σ), the system converges rapidly to a single, deep attractor (preference). This corresponds to classical rational preference stability.

Bistability and Bifurcation Regime: With moderate w and σ values, the system can exhibit dynamics where two (or more) attractors coexist. In this regime, a small contextual input asymmetry, such as a change in ΔI, can determine which attractor the system settles into, inducing a bifurcation (preference reversal). This is the dynamic counterpart to framing and attraction effects.

High Volatility Regime: Under high noise (σ) and shallow attractor basins (low w or closely matched ΔI), the system frequently switches between attractors, exhibiting indecision and inconsistent preferences.

The transitions between these regimes can be demonstrated mathematically through bifurcation diagrams. For instance, a diagram plotting the system's stable fixed points against ΔI would clearly show how a single stable solution (preference) branches into two stable solutions at a specific ΔI threshold, thereby enabling preference reversals. Similarly, it can be shown that increasing σ reduces the depth of attractor basins, making the system more susceptible to such bifurcations.

3.3.3. Synergy between the conceptual framework and the formal model

In light of this analytical reinforcement, the dual contribution of this work, both conceptual and formal, becomes clear. The study primarily reconceptualizes economic preference not as a static outcome but as a transient equilibrium of a dynamic process. This constitutes the conceptual framework that underpins the shift from Homo Economicus to *Homo Dynamicus*.

However, this conceptual framework is not merely metaphorical; it is instantiated and operationalized through a formal dynamical system model. The equations and parametric analysis presented in this article provide a tool that translates conceptual claims into testable mathematical propositions. The model can qualitatively generate well-known preference anomalies (framing, attraction effects) and offers predictions about the conditions under which they emerge (i.e., within specific parameter regimes).

In conclusion, this work presents a coherent conceptual framework for introducing a dynamical systems perspective into economic preference theory, while simultaneously laying the foundation for a formal model that embodies this framework and can generate behavioral predictions. The justification of parameters through the literature and the bifurcation analysis of the system demonstrate the model's potential not merely as a descriptive tool, but as an explanatory and integrative one. Future work can focus on calibrating these parameters with experimental data and testing the model's quantitative predictions.

4. Discussion: Toward a Neurodynamic Rationality, Conceptual Synthesis and Implications

The neurodynamic framework developed above extends the conceptual frontiers of decision theory by reframing choice as a process of dynamic self-organization. It unites the mathematical precision of dynamical systems with the empirical richness of cognitive neuroscience, offering a formal vocabulary for describing how coherent preferences emerge, destabilize, and reorganize over time (Scherbaum et al., 2023). This model’s formal structure does more than predict behavior; it compels a redefinition of the core concepts underpinning decision theory-rationality, uncertainty, and the very nature of preference. This discussion synthesizes these conceptual implications, situates the model within the broader landscape of economic and cognitive science, and explores its consequences for theory, policy, and the philosophy of rationality.

4.1. Redefining rationality: From static consistency to dynamic stability

The classical axiom of rationality rests on consistency: transitive, context-independent preferences revealed through choice. In contrast, the neurodynamic framework reinterprets rationality as dynamic stability-a system’s capacity to maintain coherent trajectories amid internal and external perturbations (Ye & Li, 2021). Here, rational behavior is not the adherence to invariant preferences but the ability to achieve and adapt coherent states under changing conditions. This mirrors thermodynamic equilibrium, which denotes not stasis but a balanced regulation of opposing forces. The hallmark of this adaptive rationality is metastability: the poised coexistence of stability and flexibility that allows the cognitive system to stabilize transiently while remaining responsive to new information (Dennison et al., 2022).

This reconceptualization dissolves the traditional dichotomy between rational and behavioral models. Phenomena such as framing effects, attraction, and delay discounting cease to be “biases” or deviations from a normative ideal.

Instead, they emerge as lawful signatures of a complex system operating within a dynamic equilibrium, governed by identifiable parameters such as inhibition strength, noise amplitude, and contextual input (Guo & Vetschera, 2022). The model thus shifts the focus from cataloging anomalies to understanding the generative dynamics that produce them.

4.2. The functional role of noise and the topology of preference

Classical decision theory often treats noise as an extraneous contaminant to be minimized. Within the dynamical systems framework, however, stochasticity assumes a constitutive and generative role. Intrinsic neural variability and attentional fluctuations prevent premature convergence, enabling the system to sample multiple attractor trajectories before commitment (Klatzmann et al., 2025). Mathematically, noise allows escape from shallow attractor basins, fostering exploration and adaptability. This challenges the deep-seated ideal of determinism in economic modeling, positioning uncertainty not as a flaw but as a fundamental property of cognition; an engine of creativity and cognitive resilience that safeguards against rigid, maladaptive preference architectures.

This leads to perhaps the most profound implication of the framework: a topological theory of preference. In classical theory, utility is a scalar; preference is a number. In the neurodynamic paradigm, preference corresponds to the structure of the system's state space; the arrangement, depth, and connectivity of its attractor basins (Ye & Li, 2021). A change in preference is therefore not a recalibration of a value, but a topological deformation of the cognitive manifold. Contextual cues, emotional states, and framing manipulations reshape this landscape, altering the relative stability of competing options. Preference reversals occur when these deformations cross a critical threshold, inducing a bifurcation; a phase transition from one cognitive equilibrium to another (Guo & Vetschera, 2022).

This topological view unifies findings across disciplines: it aligns with neuroscience evidence that value is encoded in distributed activation geometries, explains the co-occurrence of continuity and discontinuity in choice patterns, and transforms welfare economics from a static optimization problem into the study of a dynamic landscape of possible, context-dependent equilibria (Dennison et al., 2022).

4.3. From homo economicus to *Homo dynamicus*: The agent as a complex adaptive system

The conceptual shift outlined above necessitates a corresponding evolution in our model of the economic agent. The classical Homo economicus, a static optimizer of pre-existing utilities, gives way to *Homo dynamicus*: a decision-maker whose preferences are emergent, context-sensitive, and temporally extended states within a continuously evolving neural field (Ruesseler et al., 2023). Stability is not an axiomatic premise but a dynamical achievement; rationality arises not from possessing fixed goals but from the capacity to reach adaptive coherence under fluctuating internal and external conditions (Dennison et al., 2022). This vision reinstates the agent as an evolving organism, whose cognitive architecture mirrors the dynamical regularities of complex adaptive systems found throughout biology and physics (Morgan, Neal & Ballard, 2024). The transition is more than semantic; it represents a foundational reorientation from descriptive sufficiency to generative mechanism. Behavioral patterns once catalogued as "biases" are recast as lawful manifestations of the system's intrinsic dynamics, governed by identifiable parameters of competition, noise, and landscape topology rather than lists of cognitive errors (Scherbaum et al., 2023).

4.4. Implications for theory and policy: From static optimization to dynamic stabilization

By replacing the paradigm of static preferences with that of dynamic cognitive equilibria, the neurodynamic framework profoundly reshapes economic theory and the philosophy of policy intervention. If preferences are context-dependent attractor states rather than stable utility functions, then policy cannot be designed based on assumed fixed welfare landscapes. Instead, interventions; be they informational nudges, default options, or regulatory frameworks, operate as control parameters

that modulate the topology of collective decision spaces (Morgan, Neal & Ballard, 2024). Framing, for instance, acts not by changing a fixed value but by deforming the cognitive manifold, potentially inducing a bifurcation that shifts populations of agents from one equilibrium to another.

This insight creates a powerful bridge between micro-level cognition and macro-level economic phenomena. Financial volatility, shifts in consumer sentiment, and herd behavior can be reinterpreted as manifestations of systemic bifurcations; points where the aggregate cognitive equilibrium of a market or society undergoes a phase transition under the pressure of feedback, information cascades, or uncertainty (Scherbaum et al., 2023). Consequently, the aim of regulation and policy design evolves from the static optimization of individual utilities toward the dynamic stabilization of complex systems. The goal becomes to maintain the socio-economic system near a regime of adaptive criticality; sufficiently stable to avoid chaos and panic, yet sufficiently flexible to adapt and reorganize in response to shocks (Ruesseler et al., 2023). Policy effectiveness is thus evaluated by its capacity to foster cognitive and systemic resilience: the ability of the decision-making system (individual or collective) to absorb perturbations and re-equilibrate without becoming trapped in pathological attractors such as irrational exuberance, paralyzing indecision, or rigid dogma.

4.5. Philosophical dimensions: Agency, uncertainty, and the fluid self

The implications of neurodynamic rationality extend beyond economics into the philosophy of mind and agency. If cognition is a continuous trajectory within a high-dimensional neural state space, then agency itself is best understood as an emergent property of a system navigating its own stability landscape (Zhang, Yu, Diao & Qi, 2023). The classical dichotomy between determinism and freedom dissolves into a complementary relationship: the deterministic laws governing the flow of neural activity coexist with the genuine indeterminacy introduced by stochastic noise and sensitive dependence on initial conditions (bifurcation). The "self" that chooses is not a fixed, central executive but a dynamically stabilized pattern; a coherent configuration that persists through continuous micro-level reorganization (Hassannejad Nazir et al., 2024; Ruesseler et al., 2023).

In this light, uncertainty is not the enemy of rationality but its very condition of possibility. It is the noise that enables exploration and the shallow attractor landscapes that allow for flexibility. Economic choice, therefore, becomes a microcosm of the human condition: a perpetual negotiation between the need for momentary coherence (to act) and the inevitability of change (to adapt). The neurodynamic model provides a formal, mathematical language for this negotiation-a "mathematics of becoming" rather than of static being (Morgan, Neal & Ballard, 2024).

4.6. Toward an integrative science of mind and markets

The neurodynamic approach culminates in a powerful, integrative vision: it provides a rare and robust bridge between levels of explanation traditionally separated by disciplinary boundaries. By employing the universal language of nonlinear dynamical systems, it forges explicit links from micro-level neural dynamics (competition in attractor networks) to individual cognitive phenomena (preference construction and reversal), and finally to macro-level collective behavior in markets and societies (Scherbaum et al., 2023). This is not merely a metaphorical analogy but a structural isomorphism. Both brains and economies are open, nonequilibrium systems operating near critical points, sustained by feedback loops, adaptation, and stochasticity.

Market volatility, bubble formations, and opinion cascades can be understood as large-scale bifurcations, where the collective attractor landscape of interacting agents undergoes a phase transition; a direct scaling-up of the same principles that explain an individual’s preference reversal under framing (Zhang et al., 2023).

This synthesis demands and enables a new form of methodological collaboration. It acknowledges that the complexity of human behavior cannot be fully captured by any single equation or disciplinary lens. Yet, it insists that the mathematics of dynamical systems offers a formally rigorous and conceptually adequate language for this fluidity (Dennison et al., 2022). The challenge ahead is to articulate this language through empirically grounded, multi-scale models-a task that inherently invites deeper collaboration across neuroscience, psychology, computational modeling, and economics. Future research must focus on calibrating model parameters with neuroimaging and behavioral data, testing predictions about the conditions for bifurcation in real-world settings, and exploring how meso-level institutional structures shape the collective cognitive landscapes of groups and organizations.

In sum, the neurodynamic framework articulated here does more than propose a new model; it advocates for a new ontology of economic choice. Decision-making is reconceived as the self-organization of a complex adaptive system, rather than the execution of an algorithmic rule or the revelation of a pre-computed preference. Rationality is reframed as emergent metastability; the poised capacity for coherent action within a perpetually changing context. Preference is understood as topological and dynamic, a temporary valley in a shifting cognitive landscape, not a static scalar value.

This paradigm shift carries profound epistemic implications. It moves economics from a science focused on predicting equilibrium outcomes based on static assumptions, toward a science concerned with mapping the evolution of cognitive and economic trajectories in state space. It reunites economics with the broader family of complex systems sciences, embracing a worldview where order arises from process, stability from flux, and where the economic agent is finally understood not as a flawed calculator, but as a living, adaptive, and dynamically rational system-*Homo dynamicus*.

This vision does not invalidate the insights of classical or behavioral economics but subsumes them within a deeper, mechanistic, and temporally rich explanatory framework. The journey from Homo economicus to *Homo dynamicus* is, ultimately, a journey toward a more complete, biologically grounded, and philosophically coherent science of human decision-making.

5. Conclusion

The preceding analysis has sought to reframe the foundations of decision theory through the lens of dynamical systems, proposing that preference, rationality, and choice are not static entities but emergent properties of an evolving neurocognitive field.

This perspective transforms the act of decision-making from a problem of computation to one of self-organization, where stability and change coexist within a continuously shifting landscape of neural and contextual forces. In doing so, it bridges the conceptual divide between economics and neuroscience, offering not merely an interdisciplinary dialogue but a unifying formal language for the study of human behavior.

5.1. Summary of theoretical contributions

The central contribution of this work lies in advancing a neurodynamic theory of preference, grounded in the mathematics of nonlinear dynamical systems and supported by empirical evidence from cognitive neuroscience. By formalizing the decision process as a system of coupled differential equations, the model captures how competing neural populations evolve through recurrent interactions, noise, and feedback toward transient equilibria that manifest as behavioral choices. Analytically, the framework elucidates three core mechanisms:

(i) Stability, representing the emergence of coherent preferences through local attractor convergence;

(ii) Bifurcation, accounting for preference reversals as lawful topological shifts induced by contextual or parametric changes; and

(iii) Metastability, capturing the balance between flexibility and coherence that underpins adaptive rationality.

Conceptually, these mechanisms reconfigure the foundations of economic rationality. Rather than presuming pre-existing utilities or consistent choice functions, the model situates coherence as a dynamically achieved equilibrium. Behavioral "anomalies" thus emerge not as violations of logic but as expressions of lawful transitions within a complex cognitive topology.

5.2. Toward a dynamic epistemology of choice

The implications of this perspective extend beyond the mechanics of modeling. It invites a reorientation in the epistemology of economics-from description to generation, from statics to dynamics. To understand economic behavior, one must not only catalog outcomes but reconstruct the processes that give rise to them.

The neurodynamic framework accomplishes this by providing a mechanistic bridge between levels of explanation: the neural, the cognitive, and the economic.

In this dynamic epistemology, knowledge of choice is not a snapshot of preferences frozen in time but a mapping of trajectories in state space-a representation of how thought evolves, stabilizes, and reconfigures. This reconceptualization situates economic theory within the broader movement in the sciences of complexity, which views systems as evolving ensembles governed by feedback, nonlinearity, and emergent order.

By embracing this paradigm, economics moves closer to the physical and biological sciences in both method and spirit-concerned less with equilibrium as a condition and more with equilibrium as a process.

5.3. From neural dynamics to collective behavior

The neurodynamic framework not only illuminates individual choice but also offers a lens for understanding collective phenomena. Markets, institutions, and societies are cognitive systems writ large-networks of interacting agents whose behaviors generate emergent macro-patterns analogous to neural population dynamics.

Just as local competition and noise produce global coherence in the brain, the interplay of heterogeneous beliefs, expectations, and feedback loops produces collective equilibria in economic systems. This analogy suggests a continuity between micro-level neural processes and macro-level market behavior, both operating near the edge of criticality. The same dynamical principles that explain preference reversals at the individual level may account for bubbles, cascades, and volatility at the societal level. A neurodynamic economics, therefore, holds the promise of a unified formalism-one capable of spanning the entire hierarchy of decision-making, from synaptic interactions to market fluctuations.

5.4. The future of economic thought

The path forward, however, is not merely technical but philosophical. The neurodynamic approach challenges the static ontology that has long underpinned economic reasoning. It compels a recognition that the human mind is not a calculator but a self-organizing system; that rationality is not a rule but a rhythm; and that preference is not a number but a dynamic geometry continually reshaped by context, emotion, and uncertainty.

In this sense, the evolution of economic thought mirrors the evolution of the very phenomena it seeks to explain. The field is moving from the analysis of equilibrium states toward the study of evolving attractor landscapes-from the economics of being to the economics of becoming.

This transformation invites a new synthesis of disciplines: an economics that listens to neuroscience, learns from physics, and converses with philosophy.

Ultimately, to understand value is to understand dynamics-not only the dynamics of prices and markets but the deeper, hidden dynamics of thought itself. By embracing this vision, economics reclaims its original humanistic ambition: to comprehend the patterns through which minds, in their striving for coherence, collectively create the complex order we call economy.

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Conflict of Interest Disclosure: No potential conflict of interest was declared by the author.

Artificial Intelligence Statement: No artificial intelligence tools were used while writing this article.

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