

The Market as a Field of Thought Forms: Technical Analysis in Light of the Acta Universi Hypothesis

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Table of contents

Introduction	5
1.1 Why traders see patterns, but academic science often denies them	5
1.2 Objective: To show that technical analysis can be rethought as work with collective thought forms in the field $\mathcal{S}\Theta$	6
1.3 Brief overview of AU and the question: the market is not only information about companies, but also an archive of collective expectations, fears and greed	7
1.4 Structure of the work	8
Part I. The Market as an Information System	9
Chapter 1. Exchange in the Acta Universi ontology	9
1.1 Price as an instantaneous cross-section of collective thought forms	9
1.1.1 Price in Classical Finance: Equilibrium, Information, and Noise	9
1.1.2 Price in AU-ontology: projection of a field $\mathcal{S}\Theta$ onto an observable parameter	9
1.1.3 Coherence and entropic price discrepancy	10
1.1.4 Relationship with mainstream research	10
1.2 Volume, volatility and open interest as measures of write intensity	11
1.2.1 Volume as a density of irreversible recording acts	11
1.2.2 Volatility as entropic stress	11
1.2.3 Open interest as a measure of unclosed thought forms	12
1.2.4 Relationship with parametric gain	12

1.3 The market as a local “noosphere” with high density Φ	12
1.3.1 Noosphere in AU-ontology	12
1.3.2 Φ in the market: how to measure and interpret	13
1.3.3 Properties of the market noosphere	13
1.3.4 Comparison with other “noospheric” areas	14
1.4 Chapter Summary	14
Chapter 2. Why Technical Analysis Works (When It Works)	15
2.1 Classical explanation: self-fulfilling prophecies and liquidity	15
2.1.1 Self-fulfilling prophecy as a mechanism	15
2.1.2 The Role of Liquidity and Noise Traders	15
2.1.3 Limits of classical explanation	16
2.2 AU explanation: stable configurations of collective thought forms	16
2.2.1 Patterns as coherent structures in the field $S\Theta$	16
2.2.2 Parametric gain and critical thresholds	17
2.2.3 Non-local core and market memory	17
2.2.4 Herd behavior as a manifestation of coherence	18
2.3 Patterns (levels, trends, figures) as coherent structures in the field $S\Theta$	18
2.3.1 Support and Resistance Levels	18
2.3.2 Trend as directional coherence	18
2.3.3 Graphic figures (head and shoulders, triangles, etc.)	19
2.3.4 Indicators as Proximity Field Sensors	19
2.4 Chapter Summary	20
Part II. Translation of the language of technical analysis into AU	20
Chapter 3. Basic TA tools through the prism $S\Theta$	20
3.1 Support and resistance - areas of high record density	21
3.1.1 Classical definition	21
3.1.2 AU interpretation: recording density and archive memory	21
3.1.3 Level strength and its entropic cost	21
3.1.4 Relationship with mainstream research	22
3.2 Trend - directed coherence of collective thought forms	22
3.2.1 Classical definition	22
3.2.2 AU interpretation: directional field mode $S\Theta$	22
3.2.3 Trend phases: emergence, strengthening, saturation, reversal	23

3.2.4 Connection with mainstream research	23
3.3 Divergences and volume culminations are signs of increasing entropic tension.....	24
3.3.1 Classical definition	24
3.3.2 AU interpretation: divergence as a discrepancy between price and entropic stress...	24
3.3.3 Volume culmination as a peak in record density.....	24
3.3.4 Connection with mainstream research	25
3.4 Indicators (RSI, MACD, etc.) as approximate sensors of the field state.....	25
3.4.1 Classical definition	25
3.4.2 AU interpretation: indicators as projections onto observable parameters.....	25
3.4.3 Why do indicators give false signals?	26
3.4.4 New features: measurement Φ and $\mathcal{C}$ through a combination of indicators.....	26
3.4.5 Relationship with mainstream research	27
3.5 Chapter Summary	27
Chapter 4. Timing in the Market: Chronos and Kairos	28
4.1 Regular market time (candles, sessions) - chronos	28
4.1.1 Chronos in AU-ontology.....	28
4.1.2 Why chronos is insufficient to describe the market	28
4.2 Moments of “thickening” (news, panic, euphoria) – acceleration of kairos time	29
4.2.1 Kairos in AU-ontology	29
4.2.2 News as a catalyst for kairos acceleration	29
4.2.3 Panic and Euphoria as Autocatalytic Kairos Processes	30
4.3 Why do some days weigh more than others?	30
4.3.1 The “weight” of the day as an integral of kairos acceleration.....	30
4.3.2 Kairos weight in the context of technical analysis.....	31
4.3.3 Relationship with mainstream research.....	31
4.3.4 Practical application: Kairos calendar	31
4.4 Chapter Summary	32
Part III. Predictions and Limitations	33
Chapter 5. What AU adds to technical analysis.....	33
5.1 Collective attention as a pattern amplifier	33
5.1.1 Φ as a missing parameter in classical TA.....	33
5.1.2 How to evaluate Φ in practice.....	33
5.1.3 Empirical evidence.....	34

5.1.4 How AU is changing the approach to inputs and outputs.....	34
5.2 Possibility of weak precursors through fluctuations $\mathcal{S}\Theta$ (connection with GCP logic).....	35
5.2.1 Presentiment effect and GCP in AU-ontology	35
5.2.2 Market Precursors: Fluctuations $\mathcal{S}\Theta$ in Financial Markets	35
5.2.3 How to use fluctuations in trading	36
5.2.4 Limitations: Weak Signals and False Precursors	36
5.3 Why are most "signals" still noise?.....	36
5.3.1 Ontological nature of noise	36
5.3.2 Why most patterns don't work.....	37
5.3.3 Non-local noise and its sources	37
5.3.4 Estimating the probability that a signal is not noise	37
5.3.5 Practical conclusion: fewer signals - more quality.....	38
5.4 Chapter Summary	38
Chapter 6. Hard Limits and Honest Conclusions	39
6.1 AU does not provide a "holy grail" and does not cancel randomness	39
6.1.1 Why deterministic prediction is impossible in AU-ontology	39
6.1.2 The market remains stochastic and non-ergodic	40
6.1.3 Why even a "perfect" AU signal may not work	40
6.2 Technical analysis remains a probabilistic tool.....	40
6.2.1 AU does not turn indicators into truth detectors.....	40
6.2.2 Statistical significance and practical significance are different things.....	41
6.2.3 Risk management becomes even more important	41
6.3 The main practical conclusion: the market is a struggle of thought forms, and not just money flows	42
6.3.1 From "money flows" to "coherence conflict"	42
6.3.2 Implications for Practice	42
6.3.3 What AU gives to a trader and investor	42
6.4 Chapter Summary	43
Conclusion	43
Applications	45
Appendix A. Brief Dictionary: Translation of TA $\rightarrow$ AU Terms.....	45
Appendix B. Simple Observable Consequences (What Can Be Tested Historically).....	48
B.1 Hypothesis on Φ -filtration	49

B.2 Kairos weight hypothesis.....	49
B.3 The hypothesis of divergences as precursors.....	50
B.4 Hypothesis on the presentiment effect in the market	50
B.5 Hypothesis about Φ -indicators	51
Appendix C. Connection with previous works of the AU-cycle	51
C.1 Basic ontological works	51
C.2 Works on truth, lies and information warfare	52
C.3 Works on consciousness Φ and the noosphere.....	52
C.4 Works on time, fluctuations and precursors	52
C.5 Applied work.....	53
C.6 Schematic connection map	53
Conclusion on applications	54
Bibliography.....	54
External sources.....	55

Introduction

1.1 Why traders see patterns, but academic science often denies them

Financial markets are an arena where millions of subjective expectations, fears, hopes, and calculations collide daily. Amid this chaos, traders and investors have been searching for patterns for centuries: support and resistance levels, trend lines, chart patterns, indicator divergences. Technical analysis (TA) is an attempt to formalize these patterns and use them to forecast price movements. For millions of practitioners, TA is a powerful tool for making decisions in the face of uncertainty.

However, academic finance, particularly through the Efficient Market Hypothesis (EMH), has long treated technical analysis with skepticism, if not disdain. According to the strong form of the EMH, all available knowledge is already priced in, and past price movements contain no information about the future. This implies that technical analysis cannot provide any advantage—any discernible patterns are either statistical noise or the result of data mining.

However, behavioral finance (Kahneman & Tversky, 1979; Thaler, 1980; Shiller, 2000) made significant corrections: they demonstrated that market participants are far from always rational, and that cognitive biases, emotions, and herd behavior create systematic deviations from a "rational" equilibrium. Anomalies (the January effect, momentum, and reversals) that cannot be explained by the EMH were discovered. Nevertheless, even behavioral approaches have not offered a unified ontological model of what *exactly* generates persistent market patterns. They

describe *why* people make mistakes, but do not explain *how* collective errors crystallize into price structures that can be recognized and exploited.

Traders intuitively sense that the market is not simply a stream of random numbers, but a reflection of collective psychology. "The market is a crowd," they say, and this metaphor conceals a profound understanding: price is not only a fundamental value but also an arena for the struggle of narratives, expectations, and beliefs. However, this intuition has long remained at the level of empirical rules, lacking a rigorous theoretical foundation. The Acta Universi (AU) hypothesis offers such a foundation—an ontology in which collective expectations, emotions, and cognitive structures are not ephemeral "psychological factors," but real configurations of the fundamental field of thought-form entropy S_Θ .

1.2 Objective: To show that technical analysis can be rethought as work with collective thought forms in the field S_Θ

This paper aims **to rethink technical analysis as an applied phenomenology of collective thought-forms** recorded in a non-local AU archive. We will demonstrate that the core concepts of TA—levels, trends, divergences, indicators—receive a rigorous ontological justification in terms of a field S_Θ , its entropic discrepancy δS_Θ , coherence $\mathcal{C}$, and the field of integral information Φ .

This rethinking does not claim to create a "holy grail" of trading. On the contrary, we emphasize that the AU approach explains *why* patterns sometimes work, but also *why* most signals remain noisy and *why* the market remains a probabilistic environment. The value of the proposed framework lies not in the promise of outperformance, but in **a new ontology** that:

- integrates empirical observations of traders with a formal physical and mathematical model;
- links technical analysis with broader concepts of the AU cycle (noosphere, fluctuations S_Θ , truth/falsehood, information warfare);
- offers strict criteria for distinguishing between stable patterns and random noise.

We will also examine the relationship between the AU approach and mainstream research: behavioral finance, neuroeconomics, entropy models of information efficiency, and show that AU does not replace them, but rather provides them with a deeper foundation.

1.3 Brief overview of AU and the question: the market is not only information about companies, but also an archive of collective expectations, fears and greed

The Acta Universi hypothesis (Yashchenko, 2026) states that the fundamental reality is **the non-local entropy field of thought forms** S_Θ , in which all irreversible events (acts of recording information) are recorded. Space-time, matter, consciousness, and information are emergent structures generated by the dynamics of this field. Each irreversible entry (thought-form) possesses an entropic discrepancy δS_Θ with and coherence $\mathcal{C}$ with the archive.

In this context, **the financial market** appears as a local area of high-density thought-form recordings: every transaction, every order, every decision to buy or sell is an act of recording in the field S_Θ . Price is not simply the equilibrium point of supply and demand, but **an instantaneous snapshot of collective thought-forms**, reflecting the combined coherence and entropic tension of all participants. Volume, volatility, and open interest become measures of the intensity and irreversibility of these recordings. The market is thus a local "noosphere"—an area with a high density of integral information Φ , where collective expectations, fears, and greed materialize into price structures.

Technical analysis, from this perspective, is not an attempt to predict the "future" from the "past," but rather **a probing of the state of the field** S_Θ through observable price patterns. Stable configurations (support/resistance levels, trends, patterns) are not random artifacts, but **coherent structures** within the field, supported by collective attention Φ and archival memory (the non-local core $K(x, y)$). Divergences and volume climaxes signal increasing entropic tension—harbingers of a shift in coherence.

In addition, AU introduces a distinction between **chronos-time** (regular calendar time, candles, sessions) and **kairos-time** τ (subjective, event-saturated time). In the market, moments of news, panic, or euphoria are an acceleration of kairos time, when the density of thought-form recordings increases sharply, creating anomalies that can be harbingers (connected to presentiment phenomena and GCP logic).

Thus, we pose the question: **is it possible to translate the language of technical analysis into the language of the AU formalism, and what does this mean for the practice and theory of financial markets?** We argue that it is possible, and that such a translation:

- explains why some patterns are statistically significant under certain conditions;
- shows why many signals are noise (they do not reach the coherence threshold);
- provides criteria for assessing the stability and entropic value of patterns;
- links market dynamics with broader cosmological processes (noosphere, entropic cascade);
- opens up opportunities for weak predictions through fluctuation monitoring S_Θ (analogous to GCP).

We also clearly stipulate **strict limitations**: AU does not provide deterministic forecasts, does not eliminate randomness and risk, and does not turn charts into oracles. Technical analysis remains a probabilistic tool, but it gains an ontological foundation that helps us understand *why it sometimes works* and *why it will never always work*.

1.4 Structure of the work

The article is organized as follows.

Part I (Chapters 1–2) lays the ontological foundation: the market as an information system in the AU ontology, price as a cross-section of collective thought forms, the role of volume and volatility, and the market noosphere. We also provide an AU explanation of why technical analysis "works" (when it does): through stable field configurations S_Θ and self-fulfilling prophecies as manifestations of collective attention.

Part II (Chapters 3–4) translates the language of technical analysis into the language of AU: support and resistance as zones of high-density entries; trend as directional coherence; divergences and volume climaxes as signs of increasing entropic tension; indicators (RSI, MACD, etc.) as approximate sensors of the field's state. A distinction is also introduced between chronos and kairos time in the market, explaining the "weight" of certain days and events.

Part III (Chapters 5–6) examines what AU adds to technical analysis: the role of collective attention as a pattern amplifier, the possibility of weak precursors through fluctuations S_Θ , and—at the same time—hard limitations: why most signals are noisy, why AU doesn't provide a "holy grail" and doesn't eliminate randomness. The main practical conclusion: the market is a struggle of thought forms, not just money flows.

The conclusion summarizes the results, emphasizing that technical analysis can be understood as an applied phenomenology of collective thought forms; that AU does not turn charts into oracles, but explains why persistent patterns are possible at all; and that the value of the approach lies in a new ontological framework, not in the promise of superprofits.

The **appendices** will provide a brief dictionary of TA → AU translation, simple observable consequences (verifiable on historical data), as well as connections with previous works of the AU cycle (noosphere, fluctuations S_Θ , true/false).

This introduction sets the conceptual framework for the article, positioning technical analysis not as an empirical method without a fundamental theory, but as an ontologically grounded practice of working with collective thought forms in the field of entropy S_Θ . We will now move on to a detailed presentation.

Part I. The Market as an Information System

Chapter 1. Exchange in the Acta Universi ontology

Financial markets represent a unique social system where collective behavior, cognitive processes, and information flows crystallize into observable price series. In this chapter, we rethink key market variables—price, volume, volatility, and open interest—through the lens of AU ontology. We will demonstrate that the market is not simply an aggregator of supply and demand, but a localized area of high-density thought forms, where the field of entropy S_Θ and the field of consciousness Φ continuously interact, generating structures that technical analysis seeks to identify.

1.1 Price as an instantaneous cross-section of collective thought forms

1.1.1 Price in Classical Finance: Equilibrium, Information, and Noise

In standard financial theory, the price of an asset is defined as the equilibrium intersection of the supply and demand curves, reflecting the aggregate expectations of participants about future cash flows. The efficient market hypothesis (EMH) in its semi-strong form (Fama, 1970) posits that prices instantly incorporate all public information, so past prices contain no information about the future. However, empirical anomalies—momentum (Jegadeesh & Titman, 1993), reversals, the January effect, and the volatility premium—as well as systematic trader errors (overpricing, underpricing, and herding) have led researchers to turn to behavioral finance (Shiller, 2000; Kahneman & Tversky, 1979; Thaler, 1980).

According to behavioral models, price is a compromise between "rational" fundamentalists and "noise" traders (Black, 1986), as well as the result of arbitrage limitations and cognitive biases. However, these models remain phenomenological: they describe *why* price may deviate from fundamental value but do not offer an ontological mechanism linking collective expectations to price patterns.

1.1.2 Price in AU-ontology: projection of a field S_Θ onto an observable parameter

In the Acta Universi hypothesis, price $P(t)$ ceases to be a simple scalar value. It becomes **an instantaneous snapshot of collective thought forms** recorded in the field S_Θ . Every transaction is an irreversible act of recording information in an archive: the decision to buy or sell, the conviction of growth or decline, the fear of missing out or the desire to lock in a loss. All these mental events generate field configurations S_Θ with a certain local density, coherence $\mathcal{C}$, and entropic discrepancy δS_Θ .

Mathematically, price can be expressed as **an integral characteristic** of the field S_Θ in the vicinity of a specific moment in time and space (market platform):

$$P(t) = \mathcal{F} \left[\int_{\Omega} S_{\Theta}^{(\text{pbIHOX})} (x) d^4x \right],$$

where $\mathcal{F}$ is a functional reflecting the auction rules (supply and demand), and the integral is taken over the local region of the information field where the participants' thought forms are concentrated. In the simplest approximation, price can be considered a **projection** of the field onto a macroscopic parameter:

$$P(t) \approx \frac{\sum_i w_i S_{\Theta}^{(i)}}{\sum_i w_i},$$

where w_i are weights proportional to the participant's influence (their position size, transaction frequency, and the trust other participants place in their opinion). Thus, the price is **the weighted average coherence** of all active thought forms.

1.1.3 Coherence and entropic price discrepancy

Price, being a collective measure, itself exhibits the characteristics of coherence $\mathcal{C}_p$ and entropic dissonance δS_p . If most participants agree on a single opinion (a bullish or bearish consensus), coherence is high; if coherence is low, δS_p the price moves smoothly and the trend is stable. If opinions are polarized, coherence is low; if coherence is δS_p high, the price becomes volatile, prone to sharp reversals.

In terms of AU dynamics, a **stable trend** corresponds to a state where the field S_{Θ} has high coherence $\mathcal{C} \rightarrow 1$ and low misalignment $\delta S_{\Theta} \rightarrow 0$. A **flat trend** is a state with low coherence but also low misalignment (the absence of a dominant thought form). A **sharp movement** (panic, euphoria) is a transitional state where δS_{Θ} the field rises sharply, and coherence can be temporarily high (if everyone is running in the same direction), but then decoherence follows.

1.1.4 Relationship with mainstream research

The AU interpretation of price is consistent with a number of empirical and theoretical works:

- **Behavioural economics** (Shiller, 2000) has long pointed to the role of “narratives” and “animal spirits” in price formation – in AU terms, these are collective thought forms.
- **Neuroeconomics** (Glimcher, 2003; Lo, 2017) shows that traders' decisions are correlated with brain activity in areas associated with uncertainty processing and social learning—these processes are neurophysiological correlates of thought-form recording.
- **Entropy models of the market** (Orrell, 2002; Bouchaud, 2003) propose to describe prices through information entropy - this is a direct path to S_{Θ} -formalism.
- **TA empirics:** The work of Lo, Mamaysky & Wang (2000) showed that many chart patterns are statistically significant, which confirms the presence of non-random structures in prices - coherent configurations S_{Θ} .

1.2 Volume, volatility and open interest as measures of write intensity

1.2.1 Volume as a density of irreversible recording acts

In classical technical analysis, volume is considered a confirming indicator: a price increase on high volume is a sign of a strong trend, while a price increase on low volume is suspicious. In AU ontology, volume $V(t)$ is interpreted as **the density of thought-form recordings** in a field S_Θ per unit of time:

$$V(t) = \int_{t-\Delta t}^{t+\Delta t} \rho_{\text{записей}}(s) ds,$$

where $\rho_{\text{записей}}$ is the local velocity of irreversible recording events (completed transactions). Each transaction is the materialization of a thought-form, its transition from a cognitive state to an irreversible archival record. The higher the volume, the more new configurations are introduced into the field, the more intensively the archive is "rewritten."

High volume in a rising market means that many participants are simultaneously recording bullish thought forms, which creates a resonant amplification— Φ as the market grows, coherence increases, and the trend strengthens. **High volume with no movement** (accumulation/distribution) means that thought forms are actively being recorded, but they are in different directions—coherence is low, Φ and is spent on mutual cancellation.

1.2.2 Volatility as entropic stress

Volatility $\sigma(t)$ (standard deviation of returns) in AU-ontology is a measure **of the entropic misalignment** of the field S_Θ in a given local region:

$$\sigma^2(t) = \langle (\delta S_\Theta(t) - \langle \delta S_\Theta \rangle)^2 \rangle.$$

High volatility is high δS_Θ , meaning the field is in an unstable, "excited" state: thought forms are highly dissonant, and the archive cannot find a single coherent mode. This corresponds to moments of high uncertainty, fear, panic, or euphoria, when participants abruptly change their minds.

It is important to distinguish:

- **Structural volatility** is associated with fundamental uncertainty (news, macroeconomic changes). In the AU formalism, it is an external disturbance $J_{\text{новости}}(x)$ that introduces new entries into the archive.
- **Entropic volatility** is an internal property of a field that arises from the conflict of thought forms (the struggle between "bulls" and "bears"). It is analogous to thermodynamic entropy: the greater the conflict, the higher the δS_Θ .

In technical analysis, **volume climaxes** often precede reversals. In AU terms, this means that the local recording density reaches such values that the field becomes entropically overloaded, and the system "dumps" the excess δS_Θ through a sharp price change (a rewriting cascade).

1.2.3 Open interest as a measure of unclosed thought forms

Open Interest (OI)—the number of open futures or options contracts—is interpreted in the AU ontology as a **measure of "unclosed" thought-forms**, that is, configurations that have not yet been completed, not yet cancelled by a reverse write-back (closing a position). Each open contract is a commitment that holds S_Θ a specific configuration (a belief in a price movement in one direction or another) in the field until the write-back occurs.

An increase in open interest in a trend means that more and more participants are recording coherent thought forms in the direction of the trend, strengthening resonance. A decline in open interest means positions are being closed and entries are being cancelled, which reduces density and weakens coherence.

OI and divergences: If the price rises and the OI falls, this may indicate that bullish thought patterns have already "exhausted themselves"—new participants are not entering, old ones are closing, and the trend is losing support. In AU terms, this is a decline Φ and coherence, a harbinger of a reversal.

1.2.4 Relationship with parametric gain

Volume, volatility and open interest can be combined into **the entropic activity index:**

$$\Psi(t) = V(t) \cdot \sigma(t) \cdot OI(t).$$

High Ψ denotes high record density, high misalignment, and a large number of unclosed configurations—it is under these conditions that parametric amplification ($\tilde{\mu}\Phi > \omega_0^2 - \lambda_K$) is most likely. These are the moments when the market is most vulnerable to cascading movements and when technical patterns are most significant.

1.3 The market as a local “noosphere” with high density Φ

1.3.1 Noosphere in AU-ontology

The noosphere, according to the Acta Universi hypothesis, is defined as a state of planetary consciousness in which the collective field $\Phi_{\text{планета}}$ reaches a critical threshold $\Phi_{\text{crit}}^{\text{noosphere}}$ of coherence $\mathcal{C}_{\text{планета}} \rightarrow 1$ and entropic discordance $\delta S_\Theta \rightarrow 0$. However, the noosphere is not homogeneous—it has local "hot spots" where Φ the rate of recording thought forms is significantly higher than average.

The financial market is one of the most intense of these "hot spots." Reason:

- **Focus:** Millions of traders, analysts, and algorithms generate and record thought forms every second.
- **Real-time feedback:** Price immediately reacts to the recordings, creating an instant reinforcement (or punishment) loop that reinforces Φ .
- **High non-local connectivity:** price information is distributed instantly through global networks, and the non-local core $K(x, y)$ ensures correlations between remote markets (stock, commodity, cryptocurrency).

1.3.2 Φ in the market: how to measure and interpret

In technical analysis, Φ **sentiment** indicators such as volume, open interest, option flows, surveys (AAII, Investor Intelligence), and **fundamental macro indicators** (PMI, employment) that determine the background of attention are analogous. However, AU offers a more fundamental measure: **the local density of** thought patterns, which can be assessed through a combination of:

$$\Phi_{\text{рынок}}(t) = \alpha \cdot V(t) + \beta \cdot \text{OI}(t) + \gamma \cdot \frac{|\Delta P|}{\sigma} + \delta \cdot \mathcal{H}_{\text{новости}},$$

where $\mathcal{H}_{\text{новости}}$ is the intensity of the information flow (the number of news items, the number of mentions of the asset on social media), and the coefficients reflect the influence of each factor on collective attention. This formula is not a strict theorem, but a working approximation that allows us to relate empirical indicators to Φ .

Important: $\Phi_{\text{рынок}}$ it can reach very high values (comparable to those Φ in scientific communities or during global crises), which makes the market an ideal “laboratory testing ground” for testing AU predictions, including fluctuations S_{Θ} as precursors (connection with GCP logic, see Yashchenko, 2026).

1.3.3 Properties of the market noosphere

1. **High write speed:** Large markets experience millions of transactions per day—one of the densest records in human history. Consequently, the field S_{Θ} is updated at maximum frequency, and entropic “wounds” heal more quickly or cascade.
2. **Rapid spread through $K(x, y)$:** market thought patterns are non-local—panic in one sector is instantly transmitted through correlations (the core K) to other sectors and markets. This explains the “contagion risk” effect and global crises.
3. **Parametric amplification via Φ :** When multiple news items or strong moves synchronize the attention of many participants, $\Phi_{\text{рынок}}$ the market surges, and even weak signals (such as technical patterns) can be amplified to a level sufficient to trigger.
4. **Self-organization:** the market noosphere can create stable structures (trends, channels, figures) without external control - these are autocatalytic processes, similar to those

that, in the AU hypothesis, lead to the emergence of complex life and consciousness (Yashchenko, 2026, “Acta Universi: the origin and evolution of life”).

1.3.4 Comparison with other “noospheric” areas

Region	Φ (intensity)	Nature of the recording	Nonlocality
Financial market	Very high	Continuous, real-time	Global, instant
Scientific community	High (during periods of discovery)	Discrete (publications)	Deferred, through articles and preprints
Social media	High (viral topics)	Continuous but fragmented	Strong, through algorithms
Mass events (sports, concerts)	Average (locally high)	Episodic	Limited
Crisis situations (wars, disasters)	Peak	In fits and starts	Global (via media)

The market is unique in its combination of **continuity, real-time, global non-locality, and quantitative measurability**. This makes it an ideal environment for observing and verifying AU effects—from fluctuations to parametric amplification.

1.4 Chapter Summary

In this chapter, we reconceptualized the financial market as a localized region of the entropy field of thought forms S_Θ with a high density of integral information Φ . Key findings:

1. **Price** $P(t)$ is a projection of collective thought forms onto an observable parameter, dependent on coherence $\mathcal{C}$ and entropic misalignment δS_Θ . Stable movements correspond to highly coherent states, while volatility corresponds to increasing ones δS_Θ .
2. **Volume** $V(t)$ is the density of irreversible transactions, **volatility** $\sigma(t)$ is the entropic tension, and **open interest (OI)** is a measure of unclosed thought forms (open contracts). Their combination yields an entropic activity index (EHI) Ψ , which signals readiness for parametric amplification.

3. **The market is a local "noosphere"** —an area of extremely high Φ global nonlocality and continuous recording. This makes it a unique laboratory for testing AU predictions, including precursors through fluctuations S_Θ .
4. **The AU formalism** allows for a rigorous ontological explanation of classical TA concepts and links them to broader processes (noosphere, entropic cascade), which opens the way to a reconsideration of the nature of market dynamics.

In the next chapter, we will move on to explaining why technical analysis "works" (when it works), and how the AU ontology provides a fundamental basis for this explanation.

Chapter 2. Why Technical Analysis Works (When It Works)

Technical analysis (TA) remains one of the most controversial phenomena in financial science. Millions of traders use it daily, many swear by its effectiveness, but the academic literature provides conflicting answers: some studies find statistical significance in patterns, while others do not. In this chapter, we demonstrate that AU ontology not only explains *why* TA *sometimes* works but also provides clear criteria for *when* and *under what conditions* patterns acquire predictive power. We begin with classical explanations, then move on to the AU formalism, and conclude with a synthesis that links empirical observations with the ontological structure of the field S_Θ .

2.1 Classical explanation: self-fulfilling prophecies and liquidity

2.1.1 Self-fulfilling prophecy as a mechanism

The most common explanation for why technical analysis can work is the self-fulfilling **prophecy**. If enough traders believe in a particular signal (such as a breakout of resistance) and act on that belief, their collective actions can *create* the move they predicted. As practitioners figuratively put it, "Price doesn't move because of some perfect technical rationale. It moves because enough people believe it will move."

This mechanism has been confirmed empirically: a study of the S&P 500, EUR/USD, and BTCUSD markets showed that (1) the frequency of chart patterns occurring is higher than in controlled random walks, and (2) trading volume tends to increase before a pattern forms. These results are consistent with the hypothesis that the anticipation of a pattern's completion itself contributes to its formation.

2.1.2 The Role of Liquidity and Noise Traders

However, a self-fulfilling prophecy alone is not enough to fully explain the phenomenon. **Liquidity plays a key role.** When multiple traders simultaneously act on a single signal, they create excess demand or supply, leading to persistent price movements.

Research shows that excess demand for liquidity arises around moving average signals, with a high concentration of limit orders at support and resistance levels. Furthermore, analysis of transient and permanent price components shows that price errors around moving average signals increase, while permanent price changes have a larger amplitude. This means that demand for liquidity in the direction of the signal leads to **persistent price deviations**.

Important: TA traders often act as "uninformed noise traders." Their actions can create temporary price deviations from efficient levels. These deviations can persist until the potential benefits of restoring efficient prices are less than the transaction costs, which naturally limits arbitrage.

2.1.3 Limits of classical explanation

The classical explanation faces a fundamental problem: if signals are public and everyone knows about them, then rational traders could *outpace* them, rendering them useless or even self-defeating. As Timermann and Granger note, technical analysis strategies are self-destructive—if too many people start using them, they stop working.

Furthermore, empirical evidence yields conflicting results. Lo, Mamaisky, and Wang (2000) tested ten widely used chart patterns and found that seven of them contained information about future one-day returns. However, subsequent research suggests that some of this significance may be explained by characteristics of the market environment (volatility, momentum) rather than the patterns themselves.

Conclusion: classical explanations describe *the mechanism* (how the self-fulfilling prophecy works), but do not explain *the ontological nature* of the patterns—why some patterns persist while others do not, why some signals work in some market regimes and stop working in others, and what is the fundamental nature of the collective behavior that gives rise to these structures.

2.2 AU explanation: stable configurations of collective thought forms

2.2.1 Patterns as coherent structures in the field S_Θ

In AU ontology, technical patterns cease to be mysterious artifacts or simple self-fulfilling prophecies. They become **coherent structures** in the field S_Θ —areas where a multitude of thought forms (beliefs, expectations, fears, greed) have become consistent with each other and with the archive.

Let's recall the key criteria from previous chapters:

- **Coherence** $\mathcal{C} \rightarrow 1$: the thought forms of the participants resonate with each other.
- **Entropic mismatch** $\delta S_\Theta \rightarrow 0$: there is no strong conflict between thought forms.
- **High Density** Φ : Collective attention is focused on this pattern.

When these conditions are met, the pattern becomes a **stable field mode** —analogous to a standing wave in a physical system. Traders who see this pattern don't simply "believe" in it—they *resonate* with the existing coherent structure in the archive, reinforcing it through their actions.

2.2.2 Parametric gain and critical thresholds

A classic self-fulfilling prophecy in AU terms is a special case of **parametric amplification**. When $\Phi_{\text{пЫНОК}}$ (collective attention to a pattern) exceeds a critical threshold Φ_{crit} , even a weak signal can enter exponential growth mode:

$$\tilde{\mu}\Phi > \omega_0^2 - \lambda_K$$

where ω_0^2 is the “rigidity” of the archive (resistance to change), and λ_K is the contribution of the non-local core (market memory).

This explains why:

- **Patterns don't always work:** $\Phi_{\text{пЫНОК}}$ a threshold must be exceeded. During periods of low volatility or low attention, patterns don't achieve parametric gain and remain noise.
- **Efficiency depends on the market regime:** during periods of high uncertainty (crises, panic) Φ , it increases, and the threshold is reached more easily - this is why some studies show that TA is more effective in certain regimes.
- **Volume increases before the pattern is formed:** this is not just a confirmation, but a *necessary condition* for achieving it Φ_{crit} .

2.2.3 Non-local core and market memory

Classical models don't explain why the same support and resistance levels persist for years, even if the traders who "remembered" them have already exited the market. AU provides the answer: through **the non-local core** $K(x, y)$ and **the archive of thought forms**.

Every time the price touches a level and bounces back, it is recorded in the archive as a thought-form. These records don't disappear—they persist in the field S_Θ and influence future configurations through non-local correlations. The support level isn't just a "psychological" zone, but an area of **high record density** where the archive has a stable, coherent structure. When the price approaches this level again, it encounters the archive's "memory"—the sum of all previous thought-forms recorded in this zone.

This explains why:

- **Levels work even when participants change:** the memory is not in the traders' heads, but in the archive.
- **Breakthroughs do happen, but not always:** a breakthrough occurs when a new thought-form (new belief) proves stronger than the coherent structure of the archive—i.e., when δS_Θ the new configuration exceeds the threshold, and Φ the new narrative outweighs the old memory.

2.2.4 Herd behavior as a manifestation of coherence

In behavioral finance, herding is described as the irrational following of the crowd. In AU ontology, this phenomenon receives a deeper explanation: herding is **a natural dynamic of a coherent field**.

When $\mathcal{C} \rightarrow 1$ coherence is high, the participants' thought forms begin to resonate. This creates a positive feedback loop: the more people share a belief, the higher the coherence Φ , the more the pattern is reinforced, and the more people join in. This is not "irrationality" in the classical sense, but **an ontological process of self-organization** in the field S_Θ .

Research confirms that the aggregate behavior of technical models should be viewed as "clustering" rather than simply herding. In AU terms, this distinction makes sense: clustering is the formation of local coherent structures, each of which may be quite "rational" in its own local domain, but globally they create complex, nonlinear dynamics.

2.3 Patterns (levels, trends, figures) as coherent structures in the field S_Θ

2.3.1 Support and Resistance Levels

In classical TA, support and resistance levels are price zones where prices tend to stop and reverse. In AU ontology:

- **Support** is an area of the field S_Θ dominated by bullish thought patterns (the belief that the price will not fall below). The density of entries here is high, coherence $\mathcal{C} \rightarrow 1$, and entropic misalignment δS_Θ are low.
- **Resistance** is similar, but with a dominance of bearish thought forms.
- When the price approaches a level, it "senses" this coherent structure through the non-local core $K(x, y)$. This isn't mysticism—it's the ontological reality of the field S_Θ .

A breakout of a level occurs when:

1. A new thought form with a high value appears δS_Θ (new belief, news, event).
2. Φ this new thought form exceeds Φ_{crit} .
3. The new configuration "overwrites" the old one in the archive.

A false breakthrough is a case where Φ a new thought form temporarily exceeded the threshold, but was unable to create a stable coherent structure, and the field returned to its previous mode.

2.3.2 Trend as directional coherence

A trend in AU ontology is **the directional coherence of collective thought forms**. When most participants agree on a direction, the field S_Θ has a high $\mathcal{C}$ and a low δS_Θ in that direction.

- **Uptrend:** Bullish thought forms dominate, their coherence reinforces itself through parametric amplification.
- **Downtrend:** Bearish thought patterns dominate.
- **Flat (sideways):** low coherence, thought forms are multidirectional, δS_Θ moderate - the field is in a state of “waiting” for a new dominant fashion.

Important: a trend is not an external force acting on the market. A trend is **an emergent property** of a field S_Θ , the result of the self-organization of thought forms. This is why trends can exist without obvious fundamental causes—they feed on their own coherence.

2.3.3 Graphic figures (head and shoulders, triangles, etc.)

Graphical figures are **transitional states** of the field S_Θ between different coherent structures. Let's consider the classic "head and shoulders" figure:

1. **Left shoulder:** the first coherent structure is formed (the bullish trend is weakening).
2. **Head:** A new thought form tries to establish dominance, Φ grows, price reaches a new high.
3. **Right shoulder:** the old structure is trying to return, but Φ the new structure is already large enough.
4. **Neckline breakout:** a critical moment when Φ the new (bearish) structure finally exceeds Φ_{crit} the old one.

Empirical studies confirm that volume tends to increase before a pattern forms. In AU terms, this means it Φ builds up, approaching a critical threshold, and volume is a measurable proxy for this process.

2.3.4 Indicators as Proximity Field Sensors

Technical indicators (RSI, MACD, moving averages) in the AU-ontology are **approximate sensors** of the state of the field S_Θ :

- **RSI (Relative Strength Index)** measures the speed and change of price movements, which in AU terms corresponds to **the rate of change** δS_Θ . A high RSI (>70) indicates that the entropic misalignment of bullish thought patterns has reached extreme values—the field is "overheated."
- **MACD** tracks the intersection of fast and slow moving averages, which corresponds to **a change in the dominant mode** in the field S_Θ .
- **Moving averages** are **low-pass filters** that smooth out noise and reveal the underlying coherent mode. As shown in a study by Fritz & Weinhardt, excess demand for liquidity arises around moving average signals, confirming their role as focal points of collective attention.

However, indicators remain **approximate** —they measure *projections* of the field, not the field itself. This is why they generate false signals: they may indicate "overbought" conditions (high RSI), but the field may remain coherent in a bullish direction if Φ it continues to rise.

2.4 Chapter Summary

In this chapter, we have shown that technical analysis receives a rigorous ontological justification within the framework of the Acta Universi hypothesis. Key findings:

1. **The classical explanation** (self-fulfilling prophecies and liquidity) describes *the mechanism*, but not *the ontological nature* of patterns. It doesn't explain why some patterns are stable and others are not, or why the effectiveness of TA depends on the market regime.
2. **The AU explanation** provides a fundamental answer: patterns are **coherent structures** in the field S_Θ , supported by collective attention Φ and archival memory (the non-local core K). A self-fulfilling prophecy is a special case of **parametric amplification**, which only works when $\Phi > \Phi_{\text{crit}}$.
3. **Support and resistance levels** are areas of high-density records in the archive, where coherence exists $\mathcal{C} \rightarrow 1$. **Trends** are the directional coherence of thought forms. **Graphic patterns** are transitional states between different coherent structures.
4. **Indicators** (RSI, MACD, etc.) are **approximate sensors** of the field's state, measuring its projections but not the field itself. This is why they give false signals—they can't "see" the Φ field $\mathcal{C}$ directly.
5. **A key limitation:** TA only works when $\Phi_{\text{приход}} \Delta$ is high enough, and $\mathcal{C}$ the pattern coherence exceeds a threshold. During periods of low attention or high entropy (chaotic markets), patterns lose their predictive power. This explains why empirical studies yield inconsistent results—they test TA in different market regimes without controlling for $\Phi \Delta \mathcal{C}$.

In the next chapter we will move on to **translating the language of technical analysis into the language of AU** - a detailed analysis of specific TA tools through the prism of S_Θ , $\mathcal{C}$, δS_Θ and Φ .

Part II. Translation of the language of technical analysis into AU

Chapter 3. Basic TA tools through the prism S_Θ

Technical analysis has a vast arsenal of tools, from simple trend lines and levels to complex oscillators and composite indicators. In this chapter, we translate key TA concepts into the

language of AU ontology, demonstrating that each empirical rule is underpinned by specific field dynamics S_Θ : density of entries, coherence, entropic tension, and collective attention. This translation not only provides these tools with an ontological foundation but also allows us to understand their limits—why they work in some conditions and fail in others.

3.1 Support and resistance- areas of high record density

3.1.1 Classical definition

Support and resistance levels are price zones where prices tend to stall and reverse. Support is a level below which the price is not expected to fall; resistance is a level above which the price is not expected to rise. Breakouts of these levels often result in accelerated movements.

In behavioral finance, these levels are explained by psychological factors: traders remember previous extremes and place orders there, which creates a concentration of liquidity. However, this doesn't explain why the levels remain significant even after generations of traders change, or why breakouts sometimes occur without apparent cause.

3.1.2 AU interpretation: recording density and archive memory

In AU ontology, a support or resistance level is **an area in a field S_Θ with an abnormally high density of thought-form records**. Each time the price reaches a certain zone and reverses, this event is recorded in the archive as an irreversible act. Over time, numerous records accumulate in this zone, creating a **coherent structure** that manifests as a stable mode of the field.

Mathematically, this can be expressed through the local density of the archive:

$$\rho_{\text{записей}}(p) = \int_{\mathcal{M}} |S_\Theta(x)|^2 d^4x \cdot \delta(P(x) - p),$$

where the integral is taken over the region of space-time where the price was close to p . The higher the price $\rho_{\text{записей}}$ in a given price zone, the stronger the archive's "memory" that this zone is significant.

When the price approaches such a zone again, it encounters a **coherent response** from the archive. An analogy: if you repeatedly throw a ball at the same point on a wall, a dent forms in the wall, which affects the trajectory of subsequent balls. In AU terms, this "dent" is a local change in V_{eff} the field's potential S_Θ .

3.1.3 Level strength and its entropic cost

The strength of a level is determined by two factors:

1. **Number of entries** (the more times the price touches the level and reverses, the higher ρ and stronger the level).

2. **The coherence of these records** (if the records were consistent - for example, all bounces were accompanied by high volume - then $\mathcal{C}$ the level is high).

In the AU formalism, one can define **the "strength" of a level** as:

$$\text{Strength}(p) = \int \mathcal{C}(x) \rho_{\text{записей}}(p) d^4x,$$

where $\mathcal{C}(x)$ is the local coherence of records in this zone.

A level breakdown occurs when a new thought form (new belief, news, event) creates a configuration with δS_{Θ} , exceeding the "entropic rigidity" of the level:

$$\delta S_{\Theta}^{(\text{новая})} > \Delta E_{\text{связи}}(p),$$

where $\Delta E_{\text{связи}}$ is the energy required to destroy the coherent structure of the level. A false breakdown is a case where δS_{Θ} the threshold is temporarily exceeded but fails to create a stable new structure, and the field returns to its previous mode.

3.1.4 Relationship with mainstream research

Empirical studies confirm that there is a high concentration of limit orders around support and resistance levels, as well as excess demand for liquidity. In AU terms, this directly correlates with high $\rho_{\text{записей}}$: traders place orders in these zones because their own thought patterns resonate with their historical memory.

Research also shows that volume tends to increase before a level breakout. This corresponds to a buildup $\Phi_{\text{рынок}}$: collective attention focuses on the level, parametric gain approaches the threshold, and a breakout becomes increasingly likely.

3.2 Trend- directed coherence of collective thought forms

3.2.1 Classical definition

A trend is a directional price movement characterized by a sequence of rising (uptrend) or falling (downtrend) highs and lows. A trend can be short-term, medium-term, or long-term. Classic TA believes that "the trend is your friend": you should trade in the direction of the dominant trend.

3.2.2 AU interpretation: directional field mode S_{Θ}

In AU ontology, a trend is a **coherent mode of a field** S_{Θ} with a specific direction. When most participants share a unified opinion about the direction of movement (bullish or bearish), their thought forms combine constructively, creating high coherence $\mathcal{C} \rightarrow 1$ and low entropic discordance $\delta S_{\Theta} \rightarrow 0$.

The direction of the trend is determined by the sign of the field gradient S_θ in the price space:

$$\nabla_P S_\theta(t) = \frac{\partial S_\theta}{\partial P}(t).$$

- $\nabla_P S_\theta > 0$ consistent with an upward trend (bullish coherence).
- $\nabla_P S_\theta < 0$ consistent with a downward trend (bearish coherence).
- $\nabla_P S_\theta \approx 0$ corresponds to a flat (absence of a dominant mode).

The higher $\mathcal{C}$ and lower the value δS_θ , the more stable and "smooth" the trend. Under these conditions, even minor disturbances (news, random orders) don't disrupt the trend because the field "resists" change.

3.2.3 Trend phases: emergence, strengthening, saturation, reversal

The trend goes through typical phases, which in the AU formalism have a clear ontological content:

1. **Emergence:** A new thought form emerges (for example, unexpected news or a change in mood) and begins to attract attention. Φ It grows, but is still $\mathcal{C}$ low, and the trend is unstable.
2. **Amplification:** Φ reaches a critical threshold Φ_{crit} , parametric amplification is activated, and the trend enters exponential growth mode. $\mathcal{C}$ It quickly rises and δS_θ falls.
3. **Saturation:** Most participants are already in the trend, Φ reaching a local maximum. New information ceases to attract attention, as everyone is already "in the market." $\mathcal{C}$ The price is still high, but begins to decline.
4. **Reversal:** A new thought form emerges, contrary to the trend, with a sufficiently high value δS_θ . If Φ the new thought form exceeds Φ_{crit} the old trend, the field switches to a new mode.

This cycle is consistent with observations from Elliott Wave Theory, but does not require the postulation of mystical "waves" - it is the natural dynamics of a coherent field.

3.2.4 Connection with mainstream research

Research shows that during periods of strong momentum, markets exhibit greater coherence and less pronounced corrections, which corresponds to high $\mathcal{C}$ and low δS_θ . Periods of flat and high volatility are associated with low $\mathcal{C}$ and high δS_θ .

It has also been empirically confirmed that technical trend indicators (moving averages, MACD) work best during periods of a stable trend and give false signals during flat periods. In AU terms, this is obvious: indicators are sensors $\mathcal{C}$; $\nabla_P S_\theta$ they work when $\mathcal{C}$ the trend is high and fail when it $\mathcal{C}$ is low.

3.3 Divergences and volume culminations are signs of increasing entropic tension

3.3.1 Classical definition

Divergence is a discrepancy between the price direction and the direction of an indicator (such as RSI or MACD). Bullish divergence occurs when the price makes new lows, but the indicator shows a higher low—a signal of a possible upward reversal. Bearish divergence occurs similarly for highs.

A volume climax is an extremely high volume that often accompanies turning points. The classic theory is that "volume confirms the trend, and a volume climax marks a reversal."

3.3.2 AU interpretation: divergence as a discrepancy between price and entropic stress

In the AU formalism, price $P(t)$ is a projection of a field S_Θ onto an observable parameter (see Chapter 1). An indicator, such as the RSI, is **an approximate gauge of entropic stress** —the rate of change δS_Θ or local density of entries.

Divergence occurs when the price continues to move in one direction, but the entropic tension (indicator) begins to weaken. This means that:

- δS_Θ (discordance of thought forms) begins to grow - participants begin to doubt.
- $\mathcal{C}$ begins to fall - the coherence of thought forms weakens.
- Φ (collective attention) is drying up - fewer new participants are joining the trend.

Mathematically, this can be expressed through the sign of the correlation between price and the rate of change δS_Θ :

- In a normal trend: $\text{sign}(\Delta P) = \text{sign}(\Delta(\delta S_\Theta))$ - price movement and entropic tension are consistent.
- With divergence: $\text{sign}(\Delta P) \neq \text{sign}(\Delta(\delta S_\Theta))$ - the price is still moving, but the entropic tension is already rising (bullish divergence) or falling (bearish).

Divergence is **a harbinger** of a reversal because it signals the accumulation of entropic imbalance, which must ultimately be resolved through a change in mode. This is analogous to the presentiment effect in AU ontology: the field S_Θ "senses" an impending change in coherence in advance (Yashchenko, 2026).

3.3.3 Volume culmination as a peak in record density

The volume culmination (extremely high volume) in the AU ontology means **a local peak in the density of records** $\rho_{\text{записей}}$. This is the moment when many participants simultaneously write down their thought forms, often in a state of panic or euphoria.

A volume climax usually signals:

- **Trend saturation:** most participants have already entered a position, there are almost no new buyers/sellers, Φ the price reaches a maximum and begins to fall.
- **High entropic tension:** δS_Θ reaches an extreme because thought forms are extremely polarized (some buy, others sell, but one side wins).

After a volume climax, a reversal or consolidation often follows because the field cannot support such a high density of records – “entropic fatigue” sets in, and the system relaxes.

3.3.4 Connection with mainstream research

Research shows that RSI divergences are statistically significant, especially on daily and weekly timeframes. Volume climaxes also often precede reversals. In AU terms, this is explained by the fact that Φ and δS_Θ are objective parameters of the field, not simply psychological phenomena.

Furthermore, studies on the presentiment effect (Mossbridge et al., 2012) show that coherent systems can “sense” future significant events in advance. Divergences can be viewed as the market equivalent of presentiment: the field S_Θ “knows” about an impending reversal before the price has time to reverse.

3.4 Indicators (RSI, MACD, etc.) as approximate sensors of the field state

3.4.1 Classical definition

Technical indicators are mathematical functions calculated based on price and volume. They are divided into trend indicators (moving averages, MACD), oscillators (RSI, stochastics), and volatility indicators (Bollinger Bands, ATR). They are used to generate trading signals.

3.4.2 AU interpretation: indicators as projections onto observable parameters

In the AU ontology, no indicator measures the field S_Θ directly. Instead, each indicator is a **projection** of the field onto a specific observable parameter. Similar to physics: we can't directly see the electromagnetic field, but we can measure its projections—voltage, current, frequency.

Each indicator is a **function of price** $P(t)$ (and possibly volume $V(t)$) that filters and transforms the information encoded in the field in a specific way S_Θ . Let's look at the most common ones:

- **A moving average (MA)** is a **low-pass filter** that emphasizes the long-term coherent mode of a field S_Θ while suppressing short-term noise (high-frequency fluctuations). Mathematically, it can be represented as a convolution of the price with a kernel:

$$MA(t) = \int_{-\tau}^0 w(s) P(t+s) ds,$$

where $w(s)$ is the weighting coefficient. In AU terms, this corresponds to averaging over a large number of records, which yields a more stable estimate $\mathcal{C}$.

- **MACD (Moving Average Convergence Divergence)** is **indicator changes Coherence**. The difference between the fast and slow moving averages indicates how quickly the field's directional mode is changing. When the fast MA crosses the slow MA, this indicates a change in the dominant mode (trend change).
- **RSI (Relative Strength Index)** is an **entropic stress indicator**. It measures the ratio of average positive and negative price changes over a given period. In AU terms, RSI roughly measures the ratio of bullish to bearish thought patterns:

$$RSI(t) = 100 - \frac{100}{1 + \frac{\text{средний рост}}{\text{среднее падение}}}.$$

A high RSI (>70) means bullish thought patterns are so dominant that δS_Θ bullish momentum has reached its extreme—the field is overheated and ready for a correction. A low RSI (<30) is similar for bearish momentum.

- **Volume indicators** (OBV, volumetric pulse) are **record density sensors** $\rho_{\text{записей}}$. They show how intensively thought forms are recorded in one direction or another.

3.4.3 Why do indicators give false signals?

Indicators give false signals for two main reasons:

1. **They measure projections, not the field itself.** The indicator may show "overbought" (high RSI), but if Φ it continues to rise and $\mathcal{C}$ remains high, the field may maintain bullish coherence, and the price will continue to rise. The indicator is "wrong" because it doesn't see Φ directly $\mathcal{C}$.
2. **Indicators have a lag.** They use past data, so they always lag behind changes in the field. By the time an indicator issues a signal, the field may have already changed state.

In AU terms, this is a fundamental limitation: indicators are **ex post analysis tools**, good for confirming the current state, but not for predicting the future unless dynamics Φ and $\mathcal{C}$.

3.4.4 New features: measurement Φ and $\mathcal{C}$ through a combination of indicators

AU-ontology offers not only a critique of indicators, but also a constructive approach: it is possible to create **composite indicators** that approximate Φ and $\mathcal{C}$ combine known data.

For example, you can evaluate $\Phi_{\text{рынок}}$ through:

$$\Phi_{\text{оценка}} = \alpha \cdot V_{\text{норм}} + \beta \cdot OI_{\text{норм}} + \gamma \cdot \sigma_{\text{норм}} + \delta \cdot \mathcal{I}_{\text{новости}},$$

where $V_{\text{норм}}$ is the normalized volume, $OI_{\text{норм}}$ is the normalized open interest, $\sigma_{\text{норм}}$ is the normalized volatility, $\mathcal{I}_{\text{новости}}$ and is the intensity of the news flow (e.g., the number of news items per unit of time). Similarly, it can be assessed $\mathcal{C}$ through the correlation between different assets or through the degree of consistency of indicators.

This opens the possibility for **more intelligent trading systems** that attempt to measure the state of the field itself, rather than simply following indicator signals. However, this remains an area for future research, beyond the scope of this article.

3.4.5 Relationship with mainstream research

Research shows that combinations of indicators produce better results than individual indicators, consistent with the idea that Φ and $\mathcal{C}$ should be measured across multiple dimensions.

Research also shows that during periods of high volatility, indicators lose their effectiveness - this is consistent with our conclusion that in $\delta S_\Theta \gg 0$ (chaos) the field loses coherence and any projections become unreliable.

3.5 Chapter Summary

In this chapter, we translated the main tools of technical analysis into the language of the AU ontology. Key findings:

1. **Support and resistance** are zones of high-density thought-form records in the archive ($\rho_{\text{записей}}$), possessing a coherent structure ($\mathcal{C} \rightarrow 1$). The strength of a level is determined by the number and coherence of records; a breakthrough occurs when a new thought-form has δS_Θ , exceeding the entropic rigidity of the level.
2. **A trend** is a directional mode of a field S_Θ with high $\mathcal{C}$ and low δS_Θ . It goes through phases of initiation, strengthening, saturation, and reversal, corresponding to changes in Φ and $\mathcal{C}$.
3. **Divergences** are discrepancies between price (the field projection) and entropic tension (the indicator). They signal accumulation δS_Θ and herald a change in fashion, analogous to the presentiment effect in biological systems.
4. **A volume climax** is a local peak in record density that signals trend saturation and high entropic tension.
5. **Indicators** (RSI, MACD, moving averages) are **approximate gauges** of the market's state, measuring its projections but not the market itself. They provide false signals due to incomplete information and lag, but their combination can provide a more reliable Φ assessment. $\mathcal{C}$
6. **AU ontology** does not abolish classical TA, but rather provides it with a fundamental justification and clear boundaries of applicability: indicators work when the field is coherent ($\mathcal{C}$ high), and cease to work in chaotic regimes (δS_Θ high). This explains the contradictory empirical results: they tested TA without taking into account Φ and $\mathcal{C}$.

In the next chapter, we will move on to the analysis of time in the market, where we will introduce the distinction between chronos and kairos time in the AU ontology, and show why some days “weigh” more than others.

Chapter 4. Timing in the Market: Chronos and Kairos

In previous chapters, we viewed the market as a field S_Θ , and price, volume, and indicators as projections of this field. However, until now, we have implicitly assumed that time in the market is homogeneous: every candle, every tick, has the same "weight." Any practicing trader knows that this is not the case. Days before important news "weigh" more than ordinary days; moments of panic or euphoria compress hours into minutes, and periods of low volatility stretch into weeks of boredom. In this chapter, we demonstrate that AU ontology provides a rigorous explanation for this phenomenon through the distinction between **chronos-time** (t) and **kairos-time** (τ), introduced by Yashchenko (2026). We will show how this distinction affects technical analysis and why some market moments have a "kairos weight" that cannot be described by conventional time scales.

4.1 Regular market time (candles, sessions)- chronos

4.1.1 Chronos in AU-ontology

In the Acta Universi hypothesis, chronos-time t is ordinary physical time, in which causal processes occur at a speed no faster than the speed of light. It is the time of clocks, calendars, candlestick charts, and trading sessions. Chronos is homogeneous, isotropic, and continuous: every second has the same duration, regardless of what is happening in the market.

In terms of the field S_Θ , chronos-time is an emergent coordinate generated by the field's dynamics. However, within the market, chronos-time serves as the basis for standard measurements:

- **Candles (timeframes):** 1 minute, 5 minutes, 1 hour, 1 day, 1 week - all these are equal intervals of chronos-time.
- **Trading sessions:** the opening and closing of the market occur at specific chronological moments.
- **Indicators:** RSI, MACD, moving averages - they all use the same time windows based on chronos-time.

4.1.2 Why chronos is insufficient to describe the market

Standard technical analysis assumes all time intervals are equal. However, traders know that minutes before interest rate announcements carry more weight than minutes in the middle of a quiet session. A candle with a volume of 100,000 contracts carries more weight than one with

1,000 contracts, but traditional technical analysis only considers price, and volume is only indirectly incorporated into indicators.

Furthermore, the psychological perception of time in the market differs greatly from the calendar: during moments of high uncertainty, time flows slowly (traders feel every second), while during periods of rapid movement, it flows instantly. This subjective time does not coincide with chronos-time and requires a separate coordinate.

4.2 Moments of “thickening” (news, panic, euphoria) – acceleration of kairos time

4.2.1 Kairos in AU-ontology

Kairos time τ is **an event-rich time** associated with an irreversible increase in entropy S_Θ (Yashchenko, 2026). Unlike chronos, kairos time is non-uniform: it accelerates during periods of high recording density (when many irreversible events occur within a short chronos interval) and slows down during periods of low activity.

Mathematically, kairos-time is connected to chronos-time through the local speed of recording thought forms:

$$d\tau = \lambda(t) dt,$$

where $\lambda(t) > 0$ is **the kairos acceleration coefficient**, proportional to the recording density $\rho_{\text{записей}}(t)$:

$$\lambda(t) \propto \Phi(t) \cdot \frac{dV}{dt} \cdot \sigma(t).$$

Here $\Phi(t)$, we have collective attention, dV/dt the rate of change in volume (trade intensity), $\sigma(t)$ and volatility. The higher these parameters, the faster kairos time flows, and the more "events" are packed into a unit of chronos time.

4.2.2 News as a catalyst for kairos acceleration

Important news (economic reports, central bank decisions, geopolitical events) are powerful sources $J_{\text{новости}}(x)$ of external disturbances that introduce new thought patterns into the field S_Θ . These events sharply increase Φ (everyone is watching the same news) volume and volatility, leading to explosive growth $\lambda(t)$.

At such moments, kairos time literally "compresses": a chronos interval of five minutes can contain as many irreversible records as several hours on a normal day. This explains why:

- The price travels the same distances in a few minutes as it would in a calm market in days.

- Support and resistance levels are broken with great force because Φ they reach extreme values and parametric gain is turned on at full power.
- Traders feel that “time flies” – their subjective perception captures the high density of events.

4.2.3 Panic and Euphoria as Autocatalytic Kairos Processes

Panic and euphoria aren't just emotional states, but **autocatalytic kairos processes**. When the price begins to move sharply in one direction, it triggers fear (of losses) or greed (of lost profits), which amplifies the price movement Φ (everyone watches the movement). This, in turn, attracts even more participants, increases volume, and accelerates kairos time.

Mathematically, this can be described as a positive feedback loop:

$$\frac{d\Phi}{dt} = \alpha \cdot \frac{dP}{dt} \cdot \Phi + \beta,$$

where $\alpha > 0$ is the gain coefficient, β and is the external source (news). At high $\frac{dP}{dt}$, Φ the system enters exponential growth, similar to parametric resonance, but now in kairos time.

At such moments, chronos-time loses its significance: traders stop watching their watches, making their decisions based on kairos impulses. Standard timeframes (such as hourly candlesticks) become almost useless, because so many events can occur in a single chronos-hour that their density is comparable to a week of a quiet market.

4.3 Why do some days weigh more than others?

4.3.1 The “weight” of the day as an integral of kairos acceleration

In technical analysis, it's often said that some days are more significant than others: high-volume days, news days, and the closing days of the month or quarter. In the AU ontology, the “weight” of a day can be defined as **the integral of kairos acceleration** for that day:

$$W_{\text{день}} = \int_{t_{\text{открытие}}}^{t_{\text{закрытие}}} \lambda(t) dt = \int d\tau,$$

where $W_{\text{день}}$ is the total number of “event units” that occurred during the day. A day with high volatility, high volume, and important news has a high value W , while a quiet day has a low value.

This explains why:

- **High volume days** have a greater influence on the formation of support and resistance levels because the density of entries on these days is higher, and the archive “remembers” them better.

- **News days** create coherent structures that then persist for a long time: for example, a level formed on the day of the release of an employment report will be more significant than a level formed on a normal day.
- **Month/quarter closing days** are heavily weighted due to increased volume (institutional players rebalancing portfolios), making them important reference points in the archive.

4.3.2 Kairos weight in the context of technical analysis

For a trader, the "weight" of a day means that events that occurred on that day have greater significance for the future. This can be taken into account in technical analysis through **weighted indicators**, where higher weight is given to data from high- Φ volume days.

For example, you can modify the moving average to take into account the kairos weight of each candle:

$$MA_{\text{кайрос}}(t) = \frac{\sum w_i \cdot P(t_i)}{\sum w_i},$$

where w_i is the candlestick's weight, proportional λ_i (for example, to volume and volatility). Such a weighted average will better reflect the market's true "memory" than a standard moving average, which assigns equal weight to each candlestick regardless of its significance.

Similarly, RSI, stochastics, and other oscillators can be modified to take into account not only price changes, but also their "density" in kairos time.

4.3.3 Relationship with mainstream research

Research shows that "**event days**" (calendar anomalies, macro releases) have a statistically significant impact on volatility and correlations. In AU terms, this is explained by the high prices $\lambda(t)$ on these days.

Research also confirms that **high volume days** have a stronger influence on future support and resistance levels, which is consistent with the idea of high entry density.

Furthermore, the concept of "**trading time**" in some advanced market models already attempts to account for time unevenness through volume, but lacks an ontological justification. AU provides this justification through kairos time.

4.3.4 Practical application: Kairos calendar

The AU ontology allows us to construct a **kairos calendar** —a timeline where time flows unevenly, accelerating during periods of high market activity and slowing down during quiet periods. Such a calendar can be used for:

- **Optimization of indicator parameters:** instead of fixed chronos windows (e.g. 14 days for RSI), use windows based on kairos time (e.g. equivalent to 14 "average" days in event density).

- **Identifying Key Levels:** Give more weight to levels formed on days with high kairos weight.
- **Improvements to trading strategies:** enter trades based on kairos impulses rather than chronos-time (for example, signals during periods of high acceleration may be more reliable).

This opens new avenues for research, but requires empirical calibration $\lambda(t)$, which remains a challenge for future work.

4.4 Chapter Summary

In this chapter, we introduced the distinction between chronos and kairos time in the context of financial markets within the AU ontology. Key findings:

1. **Chronos time** t is standard calendar time, uniform and continuous, upon which candlesticks, sessions, and standard technical indicators are based. However, it does not reflect the unevenness of market events.
2. **Kairos time** τ is an event-rich time associated with increasing entropy S_Θ . It accelerates during periods of high recording density (news, panic, euphoria) and slows down during calm periods. Kairos acceleration coefficient $\lambda(t) \propto \Phi(t) \cdot dV/dt \cdot \sigma(t)$.
3. **News, panic, and euphoria** are autocatalytic processes that dramatically increase $\lambda(t)$, compressing a large number of irreversible events into short chronos. At such moments, standard timeframes lose their significance, and the market obeys kairos dynamics.
4. **The "weight" of a day** is determined by the kairos acceleration integral $W_{\text{день}} = \int \lambda(t) dt$. Days with high volume, news, or panic carry more weight in the history and have a greater influence on future levels and patterns.
5. **Practical implications:** Indicators can be modified to take kairos weighting into account, for example, by using weighted moving averages, where the weights are proportional λ_i . This can improve the effectiveness of TA during periods of high or low activity.
6. **Mainstream connection:** The concept of kairos timing is consistent with observations that "event days" have anomalous influence and with research on "trading timing", but gives it a rigorous ontological justification.

In the next chapter we will move on to the predictive part: what AU adds to technical analysis, including the possibility of weak precursors through fluctuations S_Θ (link to GCP logic), and why most signals still remain noise.

Part III. Predictions and Limitations

Chapter 5. What AU adds to technical analysis

In previous chapters, we reconceptualized the market as a field S_Θ , provided an AU interpretation for key TA tools, and introduced the distinction between chronos and kairos time. However, up until now, we've primarily addressed the "why" question: why do patterns emerge, why do indicators sometimes work, why do some days carry more weight? Now we turn to the "what next" question: **what does AU add to technical analysis as a practical tool?** What new opportunities, predictions, and limitations does the AU ontology offer for traders and analysts?

In this chapter, we will consider three key contributions: (1) the role of collective attention Φ as a pattern amplifier, (2) the possibility of weak precursors through fluctuations S_Θ (linked to GCP logic), and (3) an honest acknowledgement of why most "signals" still remain noise. We will show that AU does not provide a "holy grail," but it does provide **a new ontological framework** that helps us better understand the limits of TA's applicability and opens up new avenues of research.

5.1 Collective attention as a pattern amplifier

5.1.1 Φ as a missing parameter in classical TA

In classical technical analysis, traders use price, volume, and indicators, but rarely directly consider **the intensity of collective attention**. While volume and volatility are proxies for attention, they are incomplete. In AU ontology Φ , attention is a fundamental field parameter that determines how strongly thought forms resonate and reinforce each other.

Let us recall the key condition of parametric amplification from Chapter 2:

$$\tilde{\mu}\Phi > \omega_0^2 - \lambda_K$$

This condition means that a pattern (coherent structure) becomes significant only when collective attention Φ exceeds a critical threshold. If Φ is low, even a pattern ideal from a TA perspective will remain noise—it won't be able to generate sufficient resonance for price movement.

5.1.2 How to evaluate Φ in practice

Although Φ is not a directly observable quantity, we can estimate it through a combination of available data:

$$\Phi_{\text{оценка}}(t) = \alpha \cdot V_{\text{норм}}(t) + \beta \cdot \sigma_{\text{норм}}(t) + \gamma \cdot OI_{\text{норм}}(t) + \delta \cdot J_{\text{новости}}(t),$$

Where:

- $V_{\text{норм}}$ — normalized volume (relative to the average for the period),

- $\sigma_{\text{норм}}$ — normalized volatility,
- $OI_{\text{норм}}$ — normalized open interest,
- $J_{\text{новости}}$ — intensity of the news flow (number of mentions of the asset in the media and social networks, frequency of macro-releases),
- $\alpha, \beta, \gamma, \delta$ — weighting factors that can be calibrated using historical data.

The higher the level $\Phi_{\text{оценка}}$, the more likely it is that a technical signal will be reinforced. This allows traders **to filter signals**: only enter trades when $\Phi_{\text{оценка}}$ the level is above a certain threshold and avoid trades during periods of low attention.

5.1.3 Empirical evidence

Research shows that trading strategies that take attention into account (for example, through volume, social media, or news feeds) often outperform strategies that rely solely on price. In AU terms, this is explained by the Φ missing link between a pattern and its realization.

For example:

- **Volume-Based Strategies:** Research shows that high-volume breakouts have a higher probability of success than low-volume breakouts. In AU terms, high volume = high entry density = high Φ .
- **Social media-based strategies:** An analysis of the sentiment and volume of mentions on Twitter (X) and Reddit shows that spikes in attention often precede significant movements. This is directly measured Φ through $J_{\text{новости}}$.
- **Options-based strategies:** Spikes in open interest and options volume signal high levels Φ of institutional players.

5.1.4 How AU is changing the approach to inputs and outputs

The classic approach: find a signal (pattern, indicator crossover) → enter → stop loss. The AU approach adds an additional filter:

1. **Rate $\Phi_{\text{оценка}}$:** high Φ → signal has high gain potential; low Φ → signal is most likely noise.
2. **Assess coherence $\mathcal{C}$** (through correlations between instruments or indicator consistency): high $\mathcal{C}$ → the market is "unanimous," and movement will be smooth; low $\mathcal{C}$ → the market is fragmented, and sharp reversals are possible.
3. **Consider kairos timing:** a signal that occurs at a time of high recording density (for example, after a news item) has more weight than a signal during a quiet period.

This does not make TA "super-accurate", but it allows you **to increase the signal-to-noise ratio** and avoid trades during periods when the field is not coherent.

5.2 Possibility of weak precursors through fluctuations S_Θ (connection with GCP logic)

5.2.1 Presentiment effect and GCP in AU-ontology

In the paper "Spontaneous Fluctuations of the Theta-Entropy Field Before Significant Events" (Yashchenko, 2026), it was shown that the field S_Θ exhibits **coherent fluctuations** before significant events. This manifests itself as:

- **Presentiment effect** (Mossbridge et al., 2012): a person's physiological parameters change 1–10 seconds before an emotional stimulus.
- **TRNG anomalies** (Global Consciousness Project, GCP): Random number generators show statistically significant deviations during global events.

In AU ontology, these phenomena are explained by the fact that a future event is already "recorded" in the archive and creates a preliminary gradient ∇S_Θ that propagates "backward" in chronos through kairos time. This creates a growing fluctuation:

$$\varphi(t) = \delta S_\Theta(t) \approx \varphi_0 e^{(t-t_0)/\tau_{\text{pre}}} \cdot \cos(\omega t + \delta), \quad t < t_0$$

where t_0 is the moment of the event, τ_{pre} is the characteristic time of the precursor.

5.2.2 Market Precursors: Fluctuations S_Θ in Financial Markets

If the market is a local area of high density S_Θ , then it is logical to assume that **significant market events** (sharp movements, trend reversals, level breakouts) can also create preliminary fluctuations in the field.

This means that:

- **Volume, volatility and open interest** can show abnormal patterns *before* price starts to move.
- **Indicators** may show weak but coherent signals *before* significant moves.
- **Correlations between instruments** may change *prior to* global market events.

Empirical studies have already found some anomalies that can be interpreted as market presentiment:

- **Volume anomalies:** Sometimes volume starts to rise days or hours before a major move without any visible news.
- **Options flows:** Institutional players often accumulate positions before large moves, creating anomalies in open interest.
- **Spreads and Volatility:** Volatility (especially implied) often rises ahead of events, even if the price has not yet moved.

5.2.3 How to use fluctuations in trading

The AU approach suggests not simply observing anomalies, but **quantifying them through monitoring** $\varphi(t)$ field fluctuations S_Θ . In practice, this can be done through:

1. **Monitoring a combination of indicators:** If several independent indicators (volume, volatility, options flows, social media sentiment) simultaneously begin to show coherent anomalies, this may be a sign of a growing $\varphi(t)$.
2. **Identifying "silent" precursors:** Sometimes the market "quiets" before a major move (volatility decreases, range compression). In AU terms, this can be a sign of coherence accumulation before a cascade.
3. **Connection to GCP logic:** If TRNG anomalies are correlated with market events (as GCP shows, global attention is synchronized), then GCP data (or similar) can be used as an external indicator $\Phi_{\text{глобальный}}$ to filter market signals.

5.2.4 Limitations: Weak Signals and False Precursors

It's important to be clear: **precursors are weak signals**. They are not deterministic predictions. As in presentiment experiments (Cohen's effect $d \approx 0.2$ is -0.3), market precursors have small amplitude and are easily lost in noise.

Besides:

- **False precursors:** Many anomalies do not lead to significant movements - they are fluctuations that fade without cascading.
- **Calibration complexity:** τ_{pre} and thresholds $\varphi(t)$ for different markets and assets can vary greatly.

Therefore, the practical use of harbingers requires:

- **Statistical verification** on historical data (backtesting).
- **Combinations** with other filters (eg $\Phi_{\text{оценка}} > \Phi_{\text{crit}}$).
- **Risk management**, as false signals are inevitable.

5.3 Why are most "signals" still noise?

5.3.1 Ontological nature of noise

In the AU ontology, market noise is not simply "random fluctuations," but **incoherent** field modes S_Θ that do not reach the parametric amplification threshold. Most thought forms recorded every second are:

- **Multidirectional** (some buy, others sell) - low $\mathcal{C}$.
- **Weak in amplitude** (small orders) - low density of entries.

- **Inconsistent with the archive** (random decisions) - high δS_Θ , but without coherence.

These thought forms create background noise that dominates the market most of the time. Only occasionally, when Φ a threshold is reached, does a coherent structure—a pattern—emerge from the noise.

5.3.2 Why most patterns don't work

This leads to a fundamental conclusion: **most technical signals are false positives**, because in most cases $\Phi < \Phi_{crit}$... Even if a pattern looks perfect on a chart, it may not work if the collective attention is insufficient.

Empirical research confirms this:

- Many patterns have statistical significance only in certain market conditions (high volatility, high volume).
- During calm periods, the effectiveness of TA drops sharply.
- Most signals generated by indicators (especially on small timeframes) are noise.

5.3.3 Non-local noise and its sources

In the AU ontology, noise is not limited to the local market. Through the non-local core, $K(x, y)$ noise from one market can influence another, creating "information wind"—random fluctuations that carry no meaningful information but can distort signals.

For example:

- **Correlations between assets:** Random movements in the oil market can create noise in the stock market through a non-local core, even if there is no fundamental relationship.
- **Algorithmic noise:** HFT algorithms generate a huge number of orders, which creates dense but incoherent noise in the field S_Θ .
- **News noise:** a multitude of conflicting news items creates a high level of uncertainty δS_Θ without coherence.

5.3.4 Estimating the probability that a signal is not noise

The AU ontology proposes a **criterion for assessing signal quality**. A signal is highly likely to be non-noise if the following conditions are met:

1. $\Phi_{\text{оценка}} > \Phi_{\text{crit}}$: collective attention exceeds the threshold.
2. $\mathcal{C}_{\text{оценка}} \rightarrow 1$: several independent indicators point in the same direction (high consistency).
3. δS_Θ **moderate**: the signal is not extreme (which often indicates overheating and an imminent reversal).

4. **Connection with kairos time:** the signal occurred at a time of high recording density (for example, after news or at high volume).

If any of these conditions are not met, the signal is most likely noise and should be ignored.

5.3.5 Practical conclusion: fewer signals - more quality

A classic mistake many traders make is "overtrading": they react to every signal, which leads to losses due to noise. The AU approach suggests the opposite strategy: **filter out 90% of signals** and enter only those that meet coherence criteria.

Research shows that strategies with fewer trades but higher signal quality (e.g., taking volume and volatility into account) often outperform strategies with higher trading frequencies. AU provides an ontological explanation for this: high-quality signals are those that achieve parametric amplification.

5.4 Chapter Summary

In this chapter, we've explored how AU adds value to technical analysis as a practical tool. Key takeaways:

1. **Collective attention** Φ is the missing parameter in classic TA. Evaluation Φ using volume, volatility, open interest, and news flow allows for **signal filtering**: enter only when [they] are [$\Phi > \Phi_{crit}$ likely a factor]. This increases the signal-to-noise ratio and reduces the number of false trades.
2. **Fluctuations** S_θ can serve as weak precursors to significant movements, similar to the presentiment effect and GCP anomalies. Monitoring coherent anomalies (volume, volatility, correlations) can provide early signals, but they remain weak and require combination with other filters.
3. **Most signals are noise** because, in most cases $\Phi < \Phi_{crit}$. AU provides clear criteria for distinguishing signal from noise: high $\mathcal{C}$, moderate δS_θ , high Φ , and connection to kairos time.
4. **AU doesn't offer a "holy grail,"** but it does provide **a new ontological framework** for understanding when TA works and when it doesn't. The practical takeaway: fewer signals means more quality; filter through Φ and $\mathcal{C}$; manage risk by recognizing the probabilistic nature of the market.
5. **New directions for research:** calibration $\Phi_{оценка}$ for different markets, development of indicators that take into account Φ and $\mathcal{C}$, empirical testing of the market presentiment effect through the analysis of volume and volatility anomalies before events.

In the next, final chapter (Chapter 6), we'll look at **the hard limitations and honest conclusions**—what AU doesn't provide, why the market remains random and probabilistic, and why the key

practical takeaway lies not in forecasting, but in understanding the market as a struggle of thought forms.

Chapter 6. Hard Limits and Honest Conclusions

After reframing the market through the AU ontology, translating the language of technical analysis into terms of S_Θ , $\mathcal{C}$, Φ and kairos time, and considering new possibilities (signal filtering, weak precursors), it's time for the most important, yet often overlooked, part of any serious study: **an honest conversation about limitations**. No theoretical framework provides a comprehensive prediction, and the AU is no exception. In this chapter, we deliberately resist the natural urge to "sell" the idea and formulate the strict limits of applicability, the ontological reasons why the market remains probabilistic, and what the AU fundamentally cannot provide. We conclude with a practical conclusion, which we hope will prove more useful than its false promises.

6.1 AU does not provide a "holy grail" and does not cancel randomness

6.1.1 Why deterministic prediction is impossible in AU-ontology

In the AU ontology, the field S_Θ is non-local, open, and infinite-dimensional. We can measure its projections (price, volume, indicators), but not the field itself. The equation for fluctuations $\varphi(t)$ contains stochastic sources $J_{\text{событие}}(t)$ and nonlinear terms, making it fundamentally sensitive to initial conditions:

$$\ddot{\varphi} + \gamma\dot{\varphi} + \omega_0^2\varphi - \tilde{\mu}\Phi(t)\varphi + \int K(x, y)\varphi(y)d^4y = J_{\text{событие}}(t),$$

which $J_{\text{событие}}$ includes not only news, but also millions of micro-decisions of traders, each of which has a quantum and non-local component (free will, random fluctuations, unpredictable reactions).

Even if we could measure Φ with $\mathcal{C}$ absolute precision (which is impossible in practice), Laplacean determinism remains unattainable because:

- **Non-local correlations** through $K(x, y)$, which may include events from other markets or even from the future (through kairos time).
- **Nonlinearities**: $\lambda_S S_\Theta^3$ and other nonlinear terms create bifurcations where small fluctuations lead to dramatically different outcomes (butterfly effect).
- **The quantum nature** of thought-forms: the act of recording a thought-form, like any measurement in quantum mechanics, contains an irreducible randomness (connection with quantum entanglement in AU, Yashchenko, 2026).

Conclusion: AU does not provide a deterministic forecast. Even perfect analysis cannot predict *whether* the price will reach a certain level or *when* it will reverse. We are always talking about probabilities, and these probabilities have fundamental limitations.

6.1.2 The market remains stochastic and non-ergodic

In mathematical statistics, markets exhibit properties that make them fundamentally unpredictable in the long term:

- **Non-stationarity:** the parameters of the distributions change over time.
- **Heavy tails:** extreme events (crashes, rallies) occur much more frequently than the normal distribution predicts.
- **Non-ergodicity:** the time average is not equal to the ensemble average—that is, past patterns do not guarantee future ones.

AU ontology doesn't negate these properties, but rather explains them: the field S_Θ is constantly evolving, recording new thought forms, and the archive never remains unchanged. Therefore, any statistical patterns found in historical data may be disrupted in the future—not due to a model "glitch," but due to the ontological nature of the field itself.

6.1.3 Why even a “perfect” AU signal may not work

Let's assume we've created a perfect system that measures accurately Φ and $\mathcal{C}$ in δS_Θ real time. Even then, the signal might fail for several reasons:

1. **External disturbances:** a new event ($J_{\text{НОВОСТИ}}$) may override the field before the signal is realized.
2. **Interference with other modes:** Multiple coherent structures can exist simultaneously, and their interaction can cancel or change the signal.
3. **Free will and non-local effects:** Traders are agents with free will who can change their minds at any time, creating new thought forms that are not predictable based on past data.
4. **Kairos fluctuations:** an event may not happen because kairos time “decided” otherwise – the future is not fixed, but is a probabilistic ensemble of records in an archive.

Harsh conclusion: Even if all conditions $\Phi > \Phi_{\text{crit}}$ are met $\delta S_\Theta \rightarrow 0$, $\mathcal{C} \rightarrow 1$ the success of a trade remains probabilistic, not guaranteed. AU increases *the odds*, but does not eliminate *the risk*.

6.2 Technical analysis remains a probabilistic tool

6.2.1 AU does not turn indicators into truth detectors

Indicators, as we demonstrated in Chapter 3, are projections of a field S_Θ onto observable parameters. They remain projections, not the field itself. Therefore:

- **RSI, MACD, moving averages** still give false signals even if we take into account Φ .
- **No combination of indicators** can provide an entry point with 100% probability, because the field S_Θ always contains incoherent noise and non-local disturbances.

AU helps *explain* why indicators sometimes work and provides criteria for *filtering*, but it doesn't turn them into "true" oracles. The probability of a trade's success can be increased from 50% at best to, say, 55-60% under favorable conditions, but this still remains a game with a positive mathematical expectation, not a guarantee.

6.2.2 Statistical significance and practical significance are different things

It is important to distinguish:

- **Statistical significance:** the pattern has $p < 0.05$ historical data.
- **Practical significance:** the pattern provides profit after accounting for transaction costs, slippage and risks.

Many studies find statistically significant effects in TA (Lo, Mamaysky & Wang, 2000), but these effects are often small—for example, 0.1–0.2% of the market return. When fees and slippage are taken into account, they can vanish.

AU doesn't change this fact. Even with $\Phi > \Phi_{\text{crit}}$, the profitability of the deal remains questionable because:

- **Market microstructure** (spreads, commissions, delays) eats up some of the potential profit.
- **Psychological factors** (fear, greed) prevent us from strictly following signals.
- **A change in market conditions** may make a pattern ineffective in the future, even if it worked in the past.

6.2.3 Risk management becomes even more important

Since AU doesn't provide guarantees, but merely improves probabilities, **risk management remains a critical component**. A trader using the AU approach should:

- **Accept losses** as an inevitable part of the process (even the best signals will be wrong).
- **Use positioning** (position size, stop losses) so that a series of losing trades does not destroy capital.
- **Diversify** across different assets and strategies to reduce dependence on a single signal.

AU provides an *ontological justification* for risk management: even with high $\mathcal{C}$ and Φ , there is a non-zero probability of collapse due to non-local or random factors. This is not an excuse for pessimism, but a call for realism.

6.3 The main practical conclusion: the market is a struggle of thought forms, and not just money flows

6.3.1 From “money flows” to “coherence conflict”

The classic view of the market is that price is determined by money flows (supply/demand). Behavioral finance adds: "and cognitive biases." AU adds a third, deeper layer: **the market is an arena where thought forms struggle for coherence within a field S_Θ** .

When we look at a chart and see a support level, we're not simply seeing where orders were placed, but **where the historical S_Θ data has a high density**. When we see divergence, we're not simply seeing a divergence in indicators, but rather **a growing entropic tension**, heralding a change in fashion. When we sense a "market sense," we're actually resonating with the field S_Θ through our own consciousness (Φ).

6.3.2 Implications for Practice

This shift in understanding yields practical implications:

1. **Analyze not only the price but also the field:** volume, volatility, open interest, news background, social media—all these are projections of the field. Combine them to evaluate Φ and $\mathcal{C}$...
2. **Recognize that you yourself are part of the field:** your own decisions, emotions, and biases are recorded in S_Θ and influence the market. Therefore, self-reflection and emotional discipline are not "soft skills" but an ontological necessity.
3. **Interact with the market as a living system:** don't try to "beat" the market with rigid algorithms. Instead, look for moments when the field becomes coherent (high Φ , $\mathcal{C} \rightarrow 1$) and adapt to these waves.
4. **Embrace unpredictability:** even with the best analysis, there's still room for randomness. This isn't a flaw in AUs, but a fundamental property of reality.

6.3.3 What AU gives to a trader and investor

To summarize, the AU framework provides:

- **An explanation** of why patterns arise and why they sometimes work.
- **Filters** for separating noise from signal through Φ and $\mathcal{C}$.
- **Language** for describing market states (coherence, entropic tension, kairos acceleration).
- **A conceptual basis** for linking the market with broader processes (noosphere, cosmology).

But AU **doesn't give**:

- Deterministic forecasts.

- Elimination of risk.
- "Holy Grail".

The final conclusion: The main value of AU for traders and investors is not in creating a super-profitable strategy, but in **a new understanding** of the market as a living, breathing system of collective thought forms. This understanding helps make more informed decisions, manage risks, and maintain mental health in the face of inevitable uncertainty. Ultimately, the market is not an opponent to be defeated, but a field to resonate with.

6.4 Chapter Summary

In this chapter, we've honestly and without illusions examined the severe limitations of the AU approach to technical analysis. Key findings:

1. **AU doesn't offer a "holy grail"** or eliminate randomness. Deterministic prediction is impossible due to nonlocality, nonlinearity, free will, and the quantum nature of thought forms. The market remains stochastic and nonergodic.
 2. **Technical analysis remains a probabilistic tool.** Even with perfect assessment Φ and $\mathcal{C}$, the signals have limited statistical and practical significance. Risk management remains critical.
 3. **The main practical conclusion:** the market is a struggle of thought forms, not just cash flows. Understanding this shifts the focus from searching for the "perfect signal" to working with the field S_Θ : assessing Φ and $\mathcal{C}$ managing one's own thought forms, resonating with coherent structures, and embracing unpredictability.
 4. **The value of AU** lies not in outperformance, but in a new ontological framework that helps traders and investors better understand the market, make more informed decisions, and maintain resilience in the face of uncertainty.
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This chapter concludes the main content of the article. Following are **the Conclusion** (summarizing all the key points of the work), **Appendices** (including the TA→AU vocabulary, observed implications, and connections to other works in the series), and **Bibliography**.

Conclusion

In this paper, we attempted to rethink technical analysis of financial markets through the ontological framework of the Acta Universi hypothesis. The premise was simple: millions of traders use chart patterns, levels, and indicators daily, yet academic science often denies their effectiveness, and empirical studies yield contradictory results. We proposed that the reason for

this gap is not that technical analysis "doesn't work," but that it lacks an ontological foundation explaining *why* and *when* it works. AU offers such a foundation.

We have shown that the financial market can be interpreted as a local region of high-density thought-form entropy S_Θ , where price is an instantaneous snapshot of collective thought-forms, volume is the density of irreversible records, volatility is entropic tension, and open interest is a measure of unclosed cognitive contracts. Technical patterns (support, resistance, trends, figures) appear not as mystical artifacts, but as coherent structures in the field S_Θ , supported by archival memory (the non-local core K) and collective attention (Φ).

We translated the language of TA into AU terms: levels are zones of high recording density; trends are directional coherence; divergences are increasing entropic tension; and indicators are approximate field sensors. This explains why indicators work in some modes and stop working in others, why volume confirms movements, and why some days have greater "weight" (kairos acceleration). We demonstrated that the distinction between chronos and kairos time is critical for understanding the unevenness of market events and proposed methods for estimating kairos weight.

We then took a frank look at what AU adds to TA: the ability to filter signals through valuation Φ and $\mathcal{C}$, the idea of weak precursors through fluctuations S_Θ (linked to the presentiment effect and GCP logic), and—at the same time—hard constraints that make deterministic prediction impossible. We emphasized that most signals remain noisy, and AU doesn't provide a "holy grail," but it does provide an ontological justification for risk management and informed trading.

The main conclusion of the work can be formulated as follows: technical analysis is not a set of empirical rules, but **an applied phenomenology of collective thought forms**. The market is not simply an aggregator of supply and demand, but **a local noosphere** where expectations, fears, greed, and beliefs collide, crystallizing into price structures. Understanding this does not turn a trader into an oracle, but it gives them a deeper perception of market dynamics, helping them distinguish moments of high coherence (when patterns work) from phases of entropic chaos (when they are useless).

The practical value of the AU approach is not in creating a super-profitable strategy, but in:

- explaining the limits of applicability of TA,
 - filtering signals through evaluation Φ and $\mathcal{C}$,
 - risk management based on an ontological understanding of uncertainty,
 - development of intuition and emotional discipline through awareness of oneself as part of a field.
-

The limitations of our analysis are obvious: the proposed estimates Φ require $\mathcal{C}$ empirical calibration, the phenomenon of market precursors remains hypothetical, and the practical implementation of AU filters requires extensive backtesting. We do not offer ready-made trading systems, but only a conceptual framework and directions for further research.

Prospects for further research include:

- development and calibration of indicators Φ based $\mathcal{C}$ on historical data;
- empirical testing of the market presentiment effect through the analysis of volume and volatility anomalies before significant movements;
- creation of kairos calendars to optimize TA parameters;
- integration of the AU approach with machine learning for more accurate recognition of coherent states;
- Comparison of AU filters with classical risk management methods.

Concluding remarks. The Acta Universi hypothesis offers not only a new physical picture of the world but also a new language for describing social, economic, and informational processes. In this language, the market is not an impersonal mechanism, but a living field of collective consciousness, where every transaction leaves a trace in the archive of the Universe, and every trader is a co-creator of this archive. Understanding this imposes a responsibility: to trade consciously, respect uncertainty, manage risk, and remember that the market is not an adversary, but a partner in the dance of thought forms. The AU hypothesis does not promise easy money, but it does promise a profound understanding of *why* the market operates as it does. And this, perhaps, is its greatest value.

AU doesn't provide an advantage in the here-and-now trade. It provides a language for distinguishing stable configurations from noise and understanding why noise sometimes appears as a signal.

Applications

Appendix A. Brief Dictionary: Translation of TA → AU Terms

This application is a reference dictionary that translates key concepts of classical technical analysis into the language of the AU ontology. This allows traders and analysts familiar with TA to quickly adapt to the new conceptual framework.

TA term	AU equivalent	Definition in AU-ontology
Price (P)	Field projection S_θ	An instantaneous cross-section of collective thought forms, the weighted average coherence of all active participants.
Volume (V)	Record density ($\rho_{\text{записей}}$)	The number of irreversible acts of recording thought forms per unit of time (completed transactions).
Volatility (σ)	Entropic mismatch (δS_θ)	Measure of thought-form conflict; high δS_θ = high uncertainty, low coherence.
Open Interest (OI)	The measure of unclosed thought forms	The number of open contracts corresponding to unfinished records in the archive.
Support/Resistance	High-density recording zones	Field areas S_θ with abnormally high $\rho_{\text{записей}}$ and coherent structure ($C \rightarrow 1$).
Trend	Directional coherence	A field mode S_θ with high C and low δS_θ , having a certain direction ($\nabla_P S_\theta \neq 0$).
Flat (sideways)	Low coherence state	C low, δS_θ moderate, no dominant fashion ($\nabla_P S_\theta \approx 0$).
Divergence	Accumulation of entropic stress	Discrepancy between price (projection) and entropic tension (indicator); a harbinger of a change in fashion.

TA term	AU equivalent	Definition in AU-ontology
Culmination of volume	Peak Record Density	Local maximum $\rho_{\text{записей}}$, signaling the saturation of the trend and high δS_{Θ} .
RSI (overbought)	Extreme δS_{Θ} bull fashion	The dominance of bullish thought forms has reached its limit; the field is "overheated", a correction is likely.
RSI (oversold)	Extreme δS_{Θ} bear fashion	The dominance of bearish thought forms has reached its limit; the field is "overcooled", a rebound is likely.
MACD (crossover)	Change of dominant fashion	Fast fashion crosses slow fashion - change of sign $\nabla_P S_{\Theta}$ (change of trend).
Moving average	Low-pass filter	Selects the long-term coherent mode of the field while suppressing short-term noise.
Level breakout	Overwriting the archive structure	The new thought form has δS_{Θ} an entropic rigidity that exceeds the old level.
False breakout	Temporary excess Φ without a stable structure	The new thought form temporarily exceeded the threshold, but did not create a stable coherent mode.
News Impulse	External source $J_{\text{новости}}$	Disturbance that introduces new thought forms into the field S_{Θ} , increasing Φ and $\lambda(t)$.

TA term	AU equivalent	Definition in AU-ontology
Market time (candles)	Chronos-time (t)	Homogeneous calendar time on which standard time frames are based.
Event time (panic)	Kairos Time (τ)	Heterogeneous event-rich time, accelerating at high recording density ($d\tau = \lambda(t)dt$).
"Weight" of the day	Kairos acceleration integral ($W = \int \lambda(t)dt$)	The total number of event units that occurred in a day; days with high values W have greater archival value.
Market attention	Integral information field (Φ)	Collective coherence and intensity of attention of participants determines parametric gain.
TA signal	Coherent structure in S_Θ	Field configuration that has reached the threshold $\mathcal{C} > \mathcal{C}_{crit}$ and $\Phi > \Phi_{crit}$.
Noise	Incoherent modes	Most thought forms are multidirectional, weak, not aligned with the archive; they do not reach the amplification threshold.

Appendix B. Simple Observable Consequences (What Can Be Tested Historically)

This appendix contains a set of testable hypotheses derived from the AU interpretation of technical analysis. These hypotheses can be tested on historical data using standard statistical methods.

B.1 Hypothesis on Φ -filtration

Statement: Technical analysis signals that occur during periods of high (high volume, high volatility, high open interest, intense news flow) have a higher probability of success (positive return) and a better risk/reward ratio than signals during periods of low $\Phi_{\text{оценка}}$ (high volume, high volatility, high open interest, intense news flow). Φ

Verification method:

1. Select a set of classic TA signals (level breakout, moving average crossover, RSI divergence).
2. Divide historical data into two groups: signals that occurred at $\Phi_{\text{оценка}} > \Phi_{\text{crit}}$ (high attention) and signals that occurred at $\Phi_{\text{оценка}} < \Phi_{\text{crit}}$ (low attention).
3. Compare average return, Sharpe ratio, win rate, and maximum drawdown between groups.

Expected result: Signals in the high group Φ demonstrate statistically significantly better performance.

Empirical Analogues: Research shows that high-volume breakouts have a higher probability of success; news sentiment-based strategies often outperform price-based strategies.

B.2 Kairos weight hypothesis

Formulation: Support and resistance levels formed on days with high kairos weight ($W_{\text{день}} > W_{\text{среднее}}$) have greater significance (stronger repulsion, sharper breakout) and retain their significance longer than levels formed on normal days.

Verification method:

1. Identify support/resistance levels on historical data (e.g. local extremes).
2. For each level, calculate $W_{\text{день}}$ the day of its formation (integral $\lambda(t)$ based on volume, volatility and news activity).
3. Assess the “strength” of the level: number of touches before the breakout, rebound amplitude, level lifetime.
4. Compare levels from the upper and lower quartiles $W_{\text{день}}$.

Expected Result: Levels with high W demonstrate statistically significantly greater strength.

B.3 The hypothesis of divergences as precursors

Formulation: RSI divergences occurring at $\Phi_{\text{оценка}} > \Phi_{\text{crit}}$ and $\mathcal{C}_{\text{оценка}} > \mathcal{C}_{\text{crit}}$ (high indicator agreement) have a higher predictive power for reversals than divergences during periods of low Φ and low $\mathcal{C}$.

Verification method:

1. Identify all cases of bullish and bearish RSI divergences on historical data.
2. Divide into groups by $\Phi_{\text{оценка}}$ and $\mathcal{C}_{\text{оценка}}$ at the moment of divergence.
3. Measure the profitability and probability of a reversal in the following N bars (e.g. 5, 10, 20).
4. Compare groups.

Expected result: Divergences at high Φ and high $\mathcal{C}$ have higher predictive power and higher signal-to-noise ratio.

Empirical Analogues: Research shows that RSI divergences are statistically significant, especially on daily timeframes; combining them with other filters improves results.

B.4 Hypothesis on the presentiment effect in the market

Formulation: Significant market events (sharp moves > 2 standard deviations, trend reversals, level breakouts) are preceded by coherent anomalies in indicators (volume, volatility, OI, correlations) 1-5 days before the event, even in the absence of obvious news.

Verification method:

1. Identify all significant events in historical data (using the standard criterion: $|\Delta P| > 2\sigma$ or a change in the trend sign).
2. For each event, analyze the behavior of indicators in T the days before the event ($T = 1, 2, 3, 5$).
3. Assess the presence of statistically significant deviations from the mean (anomalies) in volume, volatility, open interest and correlations.
4. Compare with the control sample (random days without events).

Expected result: Prior to significant events, there is an increased frequency of coherent anomalies indicating increasing $\varphi(t) = \delta S_{\Theta} \dots$

Empirical Analogues: Yashchenko (2026) demonstrated that the presentiment effect and TRNG anomalies precede significant events. A market analogue can be found in volume and volatility anomalies.

B.5 Hypothesis about Φ -indicators

Formulation: Kairos-weighted indicators (taking into account $\Phi_{\text{оценка}}$ and $\lambda(t)$) have higher efficiency (fewer false signals, higher profitability) than standard indicators using uniform chronos-time.

Verification method:

1. Develop modified versions of standard indicators (e.g. weighted moving average with weight proportional to $\lambda(t)$).
2. Test them on historical data in comparison with standard indicators.
3. Estimate profitability, Sharpe ratio, maximum drawdown, and percentage of successful trades.

Expected result: Weighted indicators demonstrate higher performance.

Appendix C. Connection with previous works of the AU-cycle

This work is a direct development and application of the Acta Universi hypothesis to financial markets. Below is a map of the connections to the key works in the series.

C.1 Basic ontological works

1. **"Acta Universi thought forms / Acta Universi thoughtformy"** (Yashchenko, 2026, DOI: 10.5281/zenodo.20205812)
 - **Connection:** Definition of a thought-form as a universal unit of recording in a field S_Θ . In our work, the thought-form becomes a basic element of market dynamics—every trade, every decision of a trader is a thought-form.
2. **"Thought-form" as a metaphor for any recording of information in the Acta Universi hypothesis** (Yashchenko, 2026, DOI: 10.5281/zenodo.22010383)
 - **Connection:** Clarifying the status of the term "thought-form" as a physical metaphor. We transfer this understanding to the market: price, volume, and indicators are not just numbers, but projections of thought-forms recorded in an archive.
3. **"The act of recording the primary thought-form as the initiator of the expansion of the Universe"** (Yashchenko, 2026, DOI: 10.5281/zenodo.22065358)
 - **Connection:** Introducing the act of recording as a fundamental process. In the market, every transaction is an act of recording, which, although small on a cosmological scale, is part of the same universal process.

C.2 Works on truth, lies and information warfare

4. “Truth and Falsehood from the Point of View of the Acta Universi Hypothesis”

(Yashchenko, 2026, DOI: 10.5281/zenodo.22152022)

- **Connection:** Criteria of truth ($\delta S_\Theta \rightarrow 0, \mathcal{C} \rightarrow 1$) and falsehood ($\delta S_\Theta \gg 0, \mathcal{C} \rightarrow 0$). In the market, "true" thought forms are coherent trends consistent with the archive; "false" ones are noise movements that lack stable support.

5. “Information warfare from the point of view of the Acta hypothesis Universi”

(Yashchenko, 2026, DOI: 10.5281/zenodo.22153169)

- **Connection:** The market can be viewed as a localized area of information warfare, where bullish and bearish "armies" of thought forms clash. Technical analysis is the intelligence and strategy in this war.

C.3 Works on consciousness Φ and the noosphere

6. “Noosphere as the Acceleration of Kairos-Time in the Acta Universi Hypothesis”

(Yashchenko, 2026, DOI: 10.5281/zenodo.22110453)

- **Connection:** The noosphere as a state of high Φ and accelerated kairos time. The market is a local "hot spot" of the noosphere, where Φ it reaches extreme values, and kairos time accelerates significantly.

7. “Acta Universi: the origin and evolution of life” (Yashchenko, 2026, DOI:

10.5281/zenodo.22105010)

- **Connection:** Contains a description of 27 ontological operators and their connection to the field Φ . The NNI (non-local correlations), BBB (stabilizing), and III (transcendental) operators can be used to describe various market regimes (trends, flats, breakouts).

8. “Animal consciousness in the framework of the Acta Universi hypothesis” (Yashchenko,

2026, DOI: 10.5281/zenodo.18143379)

- **Connection:** Research on collective consciousness in animals. Market herding behavior is analogous to the collective consciousness of pack animals—both are manifestations of coherent thought forms in a field S_Θ .

C.4 Works on time, fluctuations and precursors

9. “Connection of kairos-time with thermodynamics in the Acta Universi hypothesis”

(Yashchenko, 2026, DOI: 10.5281/zenodo.22019999)

- **Connection:** Kairos time is connected τ to entropy growth S_Θ . In the market, kairos acceleration ($\lambda(t)$) is proportional to the density of records—this is what we use to determine the "weight" of days.

10. “Spontaneous fluctuations of the theta-entropy field before significant events”

(Yashchenko, 2026, DOI: 10.5281/zenodo.22137245)

- **Connection:** Fluctuations $\varphi(t) = \delta S_\Theta$ before significant events (presentiment effect, TRNG anomalies). This provides justification for the hypothesis of market precursors—anomalies in volume and volatility before major movements.

11. “Table of DOIs about Acta Universi Hypothesis at 08/27/2026” (Yashchenko, 2026, DOI: 10.5281/zenodo.22120149)

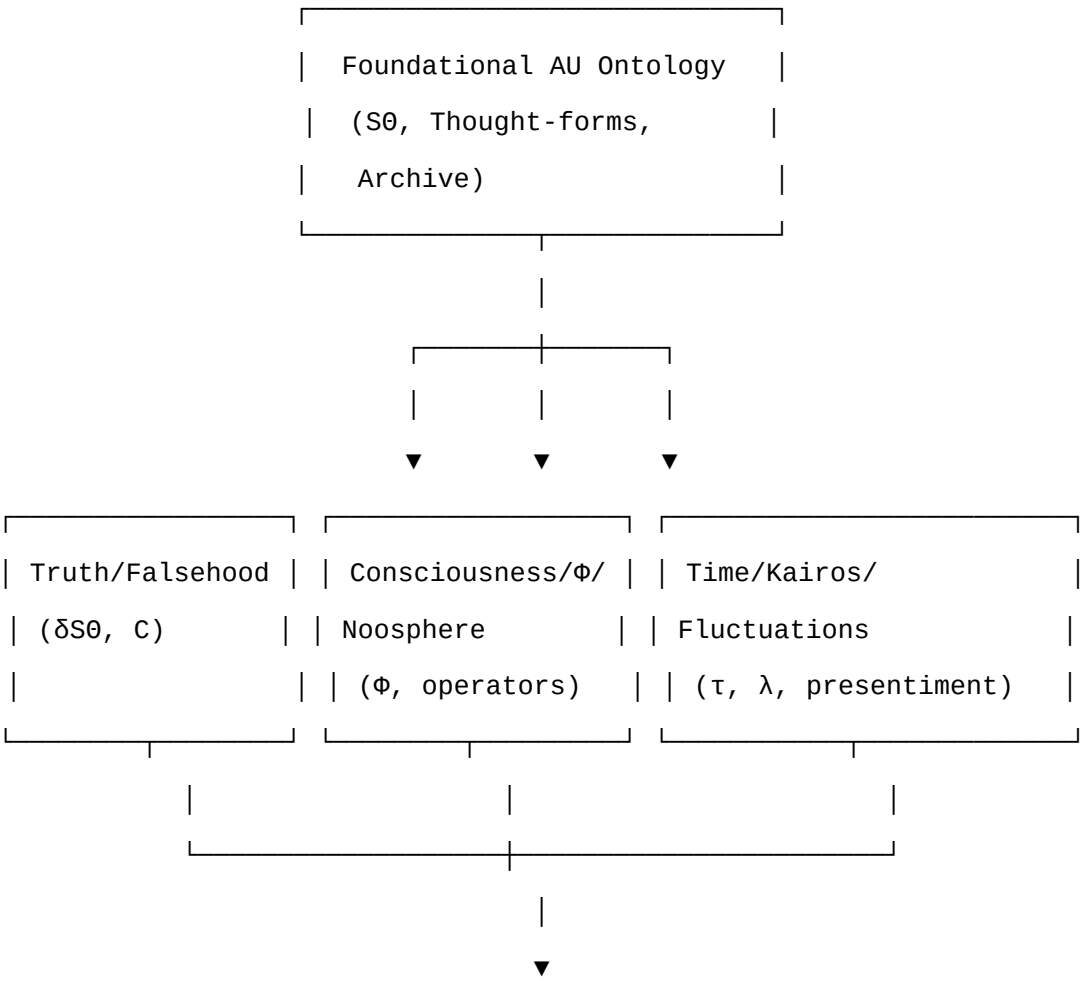
- **Link:** Full DOI index of all works on AU. Used for bibliography.

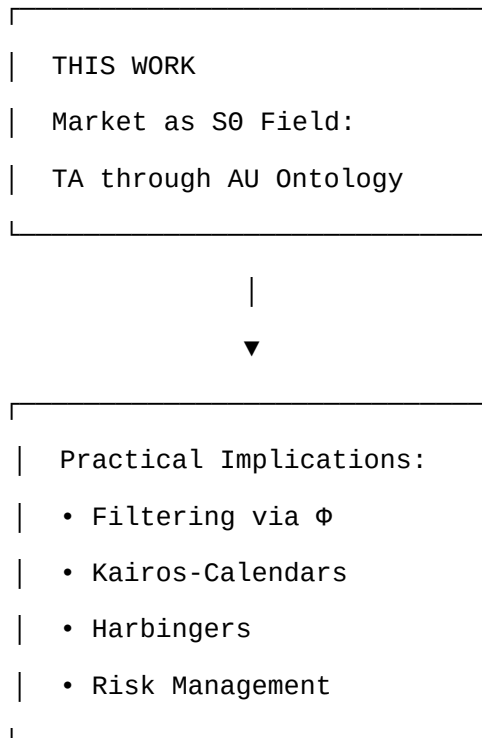
C.5 Applied work

12. “Acta Universi: A Unified Information-Entropy Paradigm – Explanations and Testable Predictions” (Yashchenko, 2026, DOI: 10.5281/zenodo.22137462)

- **Connection:** A systematic exposition of the AU paradigm with a set of testable predictions. Our hypotheses (Appendix B) are a special case of these predictions applied to financial markets.

C.6 Schematic connection map





Conclusion on applications

The presented applications provide:

- **Practical tools** for translating classical TA into AU terms (Appendix A).
- **Testable hypotheses** for empirical verification of the AU approach on historical data (Appendix B).
- **Conceptual connection** with other works in the series, showing that this research is an organic part of a wider AU project (Appendix B).

All three applications serve as a bridge between theoretical ontology and practical application, allowing researchers and traders not only to understand the AU interpretation of the market but also to test it on real data.

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