

$$\mathbb{E}[X] \geq \mu$$

$$\sigma = \sqrt{\frac{1}{n} \sum_n (x_i - \mu)^2}$$



ALGORITHMIC SKEPTICISM

How to Trade Based on
Mathematics, Not Emotions

Julius Vega

Julius Vega
Algorithmic Skepticism:
How to Trade Based on
Mathematics, Not Emotions

<https://litres.ru/74549397>

SelfPub; 2026

Аннотация

Every morning, billions of orders and executions form a continuous stream — impossible to grasp, yet measurable and understandable. Markets are no longer guesswork but a realm of numbers, where every move has concrete causes. This book stems from the belief that behind the chaotic dance of quotes lies a rigorous logic, accessible to those who work with data, not insight.

Содержание

Introduction	4
Chapter 1: The Philosophy of Algorithmic Skepticism	12
Chapter 2: Cognitive Traps of the Retail Trader	22
Chapter 4: Metrics and Filters for Market Analysis	45
Chapter 5: Risk and Position Management	58
Конец ознакомительного фрагмента.	69

Julius Vega

Algorithmic Skepticism:

How to Trade Based on

Mathematics, Not Emotions

Introduction

Every morning, as the trading session opens, billions of transactions, orders, cancellations, and executions coalesce into a continuous stream of information that no observer can take in at a glance, yet that can be measured, broken down into its components, and, ultimately, understood. Financial markets are no longer an arena for intuitive guesswork and lucky hunches—they have become a realm of numbers, in which every price move is the consequence of concrete causes that lend themselves to analysis. This book grew out of the conviction that behind the seemingly chaotic dance of quotes lies a rigorous internal logic, one accessible to anyone prepared to work with data rather than rely on flashes of insight.

Data as the Only Objective Reality

It is tempting to see the market as something mystical—a system governed by invisible forces, crowd sentiment, rumor, and premonition. Yet on closer inspection, it becomes clear that every price movement is driven by perfectly concrete mechanics: the balance of supply and demand, the distribution of liquidity across price levels, the speed at which orders are executed, the volume traded at specific moments in time. All of these parameters are measurable. They do not require faith—they require observation and analysis.

The philosophy on which this book rests is at once simple and radical: data is the only source of objective truth about the state of the market. Everything else—interpretations, emotions, expectations—is secondary, derived from the information that can be extracted, processed, and structured. A trader who bases decisions on subjective impressions is playing a game of incomplete information against opponents who work with the complete dataset. This is not a matter of morality, or of discipline in the narrow sense. It is a matter of epistemology, that is, of how we can know anything at all about a complex system of which we ourselves are a part.

This approach does not deny the role of human judgment. On the contrary, it demands a higher level of critical reflection from the trader: the ability to tell signal from noise, a meaningful

pattern from a random coincidence, a stable structure from a transient anomaly. Data does not speak for itself—one must know how to question it. The ability to pose the right questions of market data is what separates the systematic trader from the casual gambler.

The Digital Evolution of Markets

Financial markets have come a long way from the trading floors where deals were struck by voice and hand signal to fully electronic systems in which orders are executed in microseconds. This evolution has transformed not only the speed of trading but its very nature. Where market information was once fragmented and hard to come by, today it is available in abundance—quotes, volumes, order book depth, and trade history are accessible in near-real time to anyone who wants them.

Yet this abundance has created a new problem—the problem of filtering. When there is too much data, it becomes tempting to drown in it, to overload one's analysis with dozens of indicators and metrics, and to miss the forest for the trees. The digital evolution of markets has not simply given us more information—it has compelled us to develop a new discipline for working with it. The ability to discard the superfluous, to retain only what is meaningful, and to build compact, testable models has become no less important a skill than access to the data itself.

As the volume of information grew, the composition of

market participants changed as well. Where several decades ago prices were set predominantly by people making decisions on the basis of analysis and intuition, today a substantial share of trading volume passes through automated systems that respond to changing market conditions within fractions of a second. This fundamentally changes the rules of the game for those who continue to rely exclusively on visual observation of the chart. The market has become an ecosystem in which algorithms interact with one another, giving rise to new patterns of behavior that cannot be explained by human psychology alone.

The Place of Algorithmic Trading in Modern Trading

Algorithmic trading is not, as is often assumed, the preserve of large funds and institutional players. It is, first and foremost, a way of thinking in which a trading decision is formalized into a set of clear, verifiable rules. An algorithm need not mean a fully automated system running without human involvement—it can simply be a disciplined approach in which every decision to enter or exit a position is governed by predetermined logic rather than by the impression of the moment.

The value of the algorithmic approach lies not in any guarantee of profit—no such guarantee can ever exist—but in its removal from decision-making of the random component introduced by shifting emotional states. An algorithm feels no

rush of excitement after a string of winning trades, nor does it panic after a drawdown. It follows its rules until those rules are revised on the basis of an objective analysis of their performance.

The algorithmic approach, however, is a tool, not an end in itself. The complexity of a model is no measure of its quality. The most robust and reliable systems are frequently built on relatively simple principles, yet rest on a deep understanding of how market mechanics work at the micro level. Overcomplicating an algorithm by piling on redundant parameters and filters more often creates an illusion of precision than a genuine edge.

Technical Analysis as a Language for Describing Market Processes

In this book, technical analysis is treated not as a collection of mystical shapes and lines that foretell future price movement, but as a language for describing the current state of the balance between buyers and sellers. A candle on a chart is not merely a visual element but a compressed reflection of the struggle that played out over a given interval of time. A support level is not a magic line but a zone where buying interest has historically concentrated.

We will not treat technical analysis as a set of ready-made recipes whose mechanical application guarantees success. Instead, we will examine it as a system for interpreting data on liquidity, volume, and volatility—a system that demands

constant adaptation to changing market conditions. What worked yesterday in a calm trend may prove useless today amid heightened turbulence. That is why our approach centers not on memorizing patterns but on understanding why those patterns sometimes work and sometimes do not.

The book will pay particular attention to those aspects of technical analysis that popular literature rarely covers: the mechanics of the order book, the distribution of volume across price levels, and the relationship between liquidity and volatility. It is these elements that form the foundation on which any meaningful trading system is built, whether it is fully automated or operated by a human.

Aims of the Book and Its Audience

This book does not promise quick riches, nor does it contain secret formulas that guarantee success. Such promises would be not only dishonest but also at odds with the very philosophy on which our approach rests: the market does not yield to simplistic solutions, and anyone who claims otherwise is either deceiving themselves or deliberately deceiving others.

Our aim is to equip the reader with a fundamental body of knowledge that will allow them to analyze market data independently, to formulate and test their own hypotheses, and to understand the limitations of the tools they use. What we seek to cultivate is not a set of ready-made strategies but a way of

thinking, one applicable to any market and any time horizon—from intraday trading to long-term investing.

The book is addressed both to those who are just setting out in the world of financial markets and are looking for a solid theoretical foundation on which to build, and to those who already have trading experience but feel the need to systematize their knowledge and move from an intuitive approach to a more rigorous, data-driven one. We assume that the reader is prepared to invest time and effort in a deep understanding of the subject rather than to look for shortcuts.

Structure and Logic of the Exposition

The material in this book is arranged so that each chapter builds on concepts introduced in the ones before it. We begin by cultivating a critical, skeptical view of market data: the ability to question seemingly obvious patterns and test their statistical significance before trusting them with capital. From there we turn to trading discipline, understood not as abstract willpower but as a systematic approach to controlling how decisions are executed.

Particular attention is given to the practical side of studying the market, from available educational resources to concrete case studies of individual assets that illustrate the specific character of today's digital economy. A substantial portion of the book is devoted to the methodology of testing trading hypotheses on

historical data—a process without which any strategy remains merely a theoretical construct, unproven in practice. The book closes with chapters on visualizing market structure and on the practical skill of reading charts as a multilayered source of information about the balance of power in the market.

Trading as a Path of Continuous Learning

In closing, one point needs emphasis: working with financial markets is not a one-time act of acquiring knowledge, after which profits can simply be harvested without obstacle. It is a continuous process of observing, forming hypotheses, testing them, and revising one's own understanding of how the market works. The market changes, evolving alongside technology, the regulatory environment, and the makeup of its participants, and any model, however flawless it may seem today, will sooner or later need to be revisited.

That is why this book is not a collection of final truths but an invitation to systematic inquiry. We offer the reader not ready-made answers but a toolkit and a methodology for finding those answers independently as conditions keep shifting. The path from a novice who relies on intuition to a trader who makes decisions on the basis of rigorous data analysis is long and difficult, but it is this path that leads to durable, reproducible results. Let us begin it with the most important step—cultivating a healthy skepticism toward our own beliefs about how the market works.

Chapter 1: The Philosophy of Algorithmic Skepticism

The Market as a System, Not an Oracle

Before we turn to specific analytical tools, we must first agree on how we look at the subject itself. A financial market is neither a text that can be deciphered once and for all nor a mechanism with constant parameters, like a clock whose pendulum keeps a fixed beat. It is a dynamic system made up of millions of independent decisions, each of which alters the very environment in which the next decision is made. This is exactly why the approach we call algorithmic skepticism begins not with the question "which indicator is more accurate," but with the question "on what grounds do I claim to know anything at all about future price movement."

Skepticism here is neither a pose of intellectual pessimism nor a refusal to act. It is a working method, one that requires every claim about the market to be operationalized: translated into a measurable quantity, tested for robustness, and furnished with the conditions under which it ceases to hold. Algorithmic skepticism is a refusal to take the chart at its word. A line on the screen is a compressed, coarse-grained representation of a far

richer process: the flow of orders, their cancellation, partial fills, and the competition for price-time priority. A candle on a daily chart is the product of thousands of micro-decisions squeezed into four numbers: open, high, low, and close. To work with this compression directly, bypassing any understanding of what lies beneath it, is to build a forecast on the shadow of an object rather than on the object itself.

The first principle follows from this: every trading decision must rest not on a visual pattern as such, but on an understanding of the mechanics that produced it. A head-and-shoulders or a double top is not a cause of price movement but a consequence of a particular distribution of liquidity and participant activity at a specific moment. The skeptic does not reject these patterns outright, but demands that the visual form be backed by confirmation in volume, order imbalance, and volatility dynamics. Form without substance is market folklore, handed down from book to book without critical scrutiny.

Liquidity as the Primary Substance of the Market

If we were to look for the "matter" of which market dynamics are made, it would turn out to be liquidity—the market's capacity to absorb trades without a significant change in price. Liquidity is not an abstraction or a metaphor but an eminently measurable quantity: the depth of the order book at different price levels, the speed at which orders are replenished after being filled, the width

of the spread between the best bid and the best ask. It is liquidity that determines what any theoretically elegant strategy becomes once it collides with real-world execution: a source of income, or a chain of slippage that eats away the entire projected profit.

Algorithmic skepticism demands that we treat liquidity not as a constant but as a variable that shifts with the time of day, the trading session, upcoming news events, and the overall state of the market. A deep order book with substantial volume at key levels acts as a shock absorber: it dampens sharp moves, absorbing aggressive orders without any significant shift in price. A thin order book, by contrast, amplifies volatility—here even a relatively small order can produce a price dislocation, a gap, a cascade of triggered stop orders. Understanding these mechanics changes the very framing of the problem: the question is not "Where will the price go?" but "What liquidity structure lies behind the current move, and what will happen if that structure is exhausted?"

This leads to a practical conclusion that matters for the architecture of any trading system: position size and execution aggressiveness must be inversely proportional to the instrument's current liquidity. A system that ignores this principle behaves as if the market were an infinitely elastic medium, ready to absorb any order without consequence. Such an assumption holds only in theoretical models, not in reality, where every large trade leaves a footprint and shifts the balance of forces, if only briefly.

The Order Book as a Mirror of Intentions

If liquidity is the substance of the market, then the order book is its instantaneous snapshot—a reflection of how participants' intentions are distributed at any given moment. Each line in the order book is not merely a number but a concrete commitment: someone stands ready to buy or sell a specific volume at a specific price. Unlike a candlestick chart, which shows what has already happened, the order book shows what is possible—what may occur if the market reaches those levels.

Algorithmic skepticism requires that we treat the order book as a source of hypotheses rather than ready-made conclusions. A cluster of large buy orders at a particular level may signal genuine demand from an institutional player, but it may just as easily prove to be a transient illusion—an order that will be canceled a second before price touches it. This phenomenon, which market participants know by various names, calls not for blind faith in visible volume but for an analysis of its persistence over time: how long the order stays in the book, whether it is replenished after partial fills, and whether its appearance correlates with genuine aggressive activity on the opposite side.

Here we introduce an important concept—volume delta, the difference between aggressive buying and aggressive selling within a given price range. On its own, delta is not a signal to act. It becomes informative only in conjunction with price

dynamics: if delta shifts in favor of buyers but price fails to rise, this points to hidden resistance—someone is absorbing demand and keeping price from moving. If delta tilts toward sellers while price holds or rises, this signals hidden accumulation. Such divergences between visible imbalance and actual price behavior are far more valuable information than the mere fact of an imbalance.

Crucially, the order book is never analyzed in isolation. A volume imbalance taken out of context is noise that is easily mistaken for signal. Only by setting the order book against trade flow, execution speed, and changes in volatility do scattered observations resolve into a coherent picture. This demand for comprehensive analysis is not an optional recommendation but a precondition without which any conclusions about market mechanics remain unreliable.

Volatility as a Language of Uncertainty

The third fundamental element of market architecture is volatility—a measure of how strongly and how rapidly price deviates from its average over a given period. In everyday usage, volatility is often equated with risk as such, but this equation is imprecise. Volatility is better understood as the temperature of the market, a gauge of the intensity of the processes at work within it. A high temperature does not automatically signal danger—it signals that the range of possible outcomes has

widened, and any system trading the instrument must account for that widening.

Algorithmic skepticism requires us to treat volatility not as a static property of an instrument but as a process with its own dynamics: periods of calm give way to bouts of sharp fluctuation, and the transition between these regimes is often nonlinear. A market can remain in a low-volatility state for weeks, building up potential energy, and then discharge that accumulation in a sharp, short-lived impulse. This clustering of volatility is an empirically observed property of financial time series, and ignoring it renders any risk model unsound from the outset.

Hence the principle of adaptivity: the volatility-dependent parameters of a trading system—position size, the width of protective stops, the spacing between trades—cannot be held constant. They must be recalculated according to the prevailing market regime. A system designed for calm conditions is bound to run into serious trouble the moment the range of price movement abruptly widens; conversely, an overly cautious configuration calibrated for turbulence will prove ineffective in quiet periods, forgoing a significant share of the market's potential movement.

Volatility and liquidity are interdependent: they do not exist independently of one another—a decline in liquidity is almost always accompanied by a rise in volatility, since it takes less pressure to move price through a thin order book. Understanding this interdependence allows the algorithmic skeptic to see a sharp

rise in volatility not as random noise but as a logical consequence of a changed market structure, and to respond to that change systematically rather than emotionally.

The Architecture of Analysis: From Disparate Data to an Integrated System

The three elements we have described—liquidity, the order book, and volatility—do not operate independently of one another. Together they form a unified architecture of analysis in which each component performs a strictly defined role while also serving as the context for interpreting the others. This is the principle that underlies modularity as a working method: the complex task of understanding the market is broken down into self-contained yet interconnected blocks, each of which can be tested, improved, and replaced on its own without bringing down the system as a whole.

The liquidity analysis module is responsible for assessing how safely and efficiently a trade of a given size can be executed under current conditions. The order book analysis module tracks the balance of participants' intentions and identifies discrepancies between the visible distribution of orders and actual price behavior. The volatility analysis module determines the current market regime and sets the adaptation parameters for the other modules. Crucially, these blocks do not work in isolation: a signal from one module can, and should, modify the behavior of

another. For instance, detecting shallow order book depth should automatically reduce the permissible position size, however attractive the signal may appear from the standpoint of the price pattern.

This architecture offers an important advantage: it is robust to changes in individual components. If one of the modules exhibits systematic errors under particular market conditions, it can be corrected or replaced without rebuilding the entire system. Monolithic strategies, in which all the rules are interwoven into a single, indivisible logic, lack this flexibility—any change to a single parameter risks affecting the behavior of the system as a whole in unpredictable ways.

The Principle of Feedback as a Condition for System Survival

Modularity alone does not guarantee sound analysis. An architecture, once built and fixed in place, inevitably becomes outdated as the structure of the market, the composition of its participants, and the nature of their interactions change. That is why the second cornerstone principle of algorithmic skepticism is feedback—the continual testing of how well the decisions taken correspond to the processes actually unfolding.

Feedback operates on two levels. The first is the testing of individual hypotheses: if an order book analysis module systematically interprets a particular imbalance pattern as a sign

of reversal, while the statistics show that in most cases the move continues, the hypothesis must be revised rather than defended after the fact with convenient explanations. The second level is the testing of the architecture as a whole: whether the modules work together coherently, whether their signals contradict one another, and whether the combination of rules creates a false sense of confidence where no objective grounds for it exist.

Feedback is what distinguishes algorithmic skepticism from dogmatic adherence to a methodology chosen once and for all. Skeptics are not in love with their models—they treat each one as a working hypothesis, valid exactly as long as practice confirms it and to be corrected immediately once it begins to diverge systematically from reality. This demands a certain intellectual discipline: the ability to admit that one's own constructs have failed, without emotional attachment to the effort invested in them.

Skepticism as a Method, Not a Denial

Algorithmic skepticism is neither nihilism nor a refusal to build trading systems on the pretext that they are inherently unreliable. On the contrary, it is a demand that systems be built more deliberately, with a clear awareness of the limits of their applicability. The skeptic does not claim that the market is unknowable—the claim is rather that knowing the market requires constant verification, not a single act of faith in a pattern

once discovered.

This approach changes the very ethics of working with market data. Instead of searching for the "perfect formula" that will explain price behavior once and for all, the skeptic structures a continuous dialogue with the market: formulating hypotheses, testing them against objective metrics of liquidity, the order book, and volatility, building in feedback mechanisms, and remaining ready to revisit even fundamental assumptions whenever practice shows them to be untenable. The essence of the philosophy that will underpin every subsequent chapter of this book lies not in denying that analysis is possible at all, but in this constant readiness to revise.

Chapter 2: Cognitive Traps of the Retail Trader

The Brain as Adversary: Why Intuition Misleads Us in the Market

The human mind was not shaped for trading futures, nor for reading volume delta. It was honed over millennia in an environment where speed of reaction mattered more than statistical accuracy, and where the ability to spot a predator in the undergrowth in an instant was prized above the capacity to assess probability distributions. This evolutionary baggage, invaluable for survival on the savanna, becomes a systemic handicap the moment that same brain sits down in front of a price chart.

The financial market is an environment fundamentally hostile to our innate cognitive machinery. Here there is no predator to be spotted in a fraction of a second—there is noise, which our brain stubbornly tries to turn into signal. Here there is none of the linear causality we are accustomed to in everyday life—instead, nonlinear dynamics prevail, in which small causes produce disproportionately large effects and apparent regularities fall apart as soon as the sample of observations is enlarged. The retail trader who sits down at the terminal brings this entire

evolutionary burden along, never suspecting how systematically it will fail them.

The problem is not a lack of intelligence or a shortage of knowledge. The problem is that certain errors of reasoning are built in and automatic. They operate at a level beyond the reach of mere willpower. Knowing that a trap exists by no means always protects us from falling into it—this is one of the most unpleasant truths confronting anyone who attempts to move from emotional to systematic trading. In this chapter we will examine six fundamental mechanisms that methodically turn the capital of retail market participants into statistical noise, from which more disciplined players extract their profits.

Belief in Patterns: How the Brain Finds Order Where None Exists

The deepest and most destructive of all the traps is the pathological tendency of the human mind to find patterns even in purely random data. This mechanism is so fundamental that no conscious effort can fully switch it off. Evolution has tuned the brain to err on the side of seeing a pattern that is not there rather than missing one that is: better to mistake the rustling of leaves for a threat a hundred times than to overlook a real one once. This asymmetry of risk made sense when survival was at stake, but in financial markets it becomes a source of persistent losses.

When a trader looks at a five-minute chart and sees a

technical-analysis formation taking shape, something important happens: the brain actively seeks visual confirmation of a hypothesis it already holds, while entirely disregarding the context in which that formation is emerging. It does not ask about the depth of the order book at that moment, about the actual volume behind the move, or about whether current liquidity is sufficient for the formation to carry any predictive value at all. It simply sees a familiar shape and reacts to it as though it were a signal.

What makes this trap especially dangerous is that the overwhelming majority of visual patterns a trader observes on lower timeframes under conditions of insufficient liquidity are not an expression of the collective psychology of market participants, but a byproduct of market maker activity, algorithmic systems, and the random noise of market microstructure. A formation that looks convincing on a chart is often an artifact—the result of a collision between several large orders, bearing no relation whatsoever to any stable regularity in crowd behavior.

Philosophically, this trap is rooted in the profound discomfort the human mind experiences in the face of randomness. We are constitutionally incapable of accepting that a significant share of price movement is the product of pure stochasticity superimposed on structural liquidity constraints. To acknowledge randomness is to acknowledge our own powerlessness to predict the future, and this runs counter to the

psyche's basic need for control and certainty. And so the brain readily constructs a narrative to explain any price movement, even when, objectively, no such explanation exists.

Confirmation Bias: The Trader's Selective Memory

The second pillar of the retail market participant's self-destruction is the tendency to remember selectively the information that confirms a belief already formed, and to forget, just as selectively, everything that contradicts it. This mechanism operates so imperceptibly that the trader remains genuinely unaware of how badly their own statistics are distorted.

Consider a typical situation: a trader uses a particular indicator to enter positions. Over the course of a month, the indicator generates twenty signals, six of which turn out to be profitable and fourteen losing. Yet what lingers in the trader's subjective memory is chiefly those same six successes—they carry a stronger emotional charge, they trigger a dopamine response tied to the sensation of triumph and of being right. The losing trades, by contrast, are pushed out of mind as something uncomfortable, something at odds with their self-image as a competent market participant.

The consequences of this selective remembering are catastrophic: the trader keeps using a statistically unprofitable strategy, sincerely believing in its effectiveness, because their subjective internal ledger of trades diverges radically from

the objective transaction log. This is not merely an error of perception—it is a fundamental rupture between reality and its mental representation, one that cannot be repaired without the rigorous, impartial, mechanical recording of every single trade, without exception.

Confirmation bias manifests itself not only in the after-the-fact assessment of results but also in the very process of deciding to enter a position. A trader who has already formed a hypothesis about an asset's direction begins, unconsciously, to search the chart and the news flow only for those signals that support it. A bearish divergence on an oscillator, plainly contradicting a long position, simply fails to register in their conscious mind—it is filtered out as irrelevant information. This creates a vicious circle: the more convinced the trader is that they are right, the less receptive they become to objective data pointing to the contrary.

The Anchoring Effect: The Prison of the Entry Price

The third trap concerns the distorting influence that an arbitrarily chosen reference point exerts on every subsequent assessment of the situation. The price at which a position was opened becomes, psychologically, an absolute and sacred benchmark around which all of the trader's further analysis begins to revolve, even though, objectively, this price carries no informational value for the market—the market is utterly indifferent to the price at which any particular participant entered

a trade.

The anchoring mechanism shows itself in the habit of holding on to losing positions, justified by a formula familiar to anyone who has ever traded: "As soon as the price gets back to my entry, I'll close out at breakeven." This phrase is the very quintessence of the cognitive trap—the trader ignores the entire body of objective data that may have changed since the position was opened: a growing imbalance in the order book, declining volatility that signals the exhaustion of the move, a divergence between momentum and price. Instead of analyzing the current market reality, they keep mentally appealing to an outdated, subjective reference point.

This trap is tantamount to a fundamental methodological error—fitting the facts to a desired, predetermined outcome. Rather than asking the honest question "What do the current data tell me about the likely direction of the move?" the trader asks an entirely different one: "How do I hold out until the moment when I can justify my original decision?" This turns the very logic of analysis on its head, transforming the analytical process into an act of psychological self-defense.

Anchoring takes other forms as well: an all-time high becomes the "fair level" to which the asset is bound to return; a round psychological number is perceived as an insurmountable barrier; a recent local extremum hardens into a rigid benchmark for future moves. In every one of these cases, an arbitrary reference point supplants objective analysis of the liquidity balance and the

structure of the market profile.

The Availability Heuristic: The Illusion of Competence After a Winning Streak

The fourth mechanism of self-destruction comes into play when traders begin to judge their own predictive ability solely on the basis of recent events that are readily available in memory, while entirely ignoring the broader and more representative statistical context. After several profitable trades in a row, a dangerous illusion takes hold: good fortune begins to look like the product of acquired skill rather than a favorable confluence of market circumstances.

This trap is especially insidious during periods of sustained directional movement, when practically any trend-following strategy yields a positive result simply by virtue of the overall direction of prices. A trader who went long during such a period comes to sincerely believe in their own analytical gift, without recognizing that an entirely random set of entries, synchronized with the prevailing move, would have produced an almost identical result. People systematically mistake the tailwind of a favorable trend for competence.

The problem with the availability heuristic is that human memory is structured not as an impartial database but as an associative network, in which recent and emotionally vivid events receive weight out of all proportion to their actual statistical

relevance. Five winning trades in a row feel like compelling evidence of a working system, even though, from the standpoint of mathematical statistics, this is a vanishingly small sample that supports no well-founded conclusions about the effectiveness of the approach. A genuine evaluation of a strategy demands analysis of results over a far longer time horizon, taking into account drawdown metrics, the distribution of losing streaks, and robustness across different market regimes—in other words, it demands precisely the cold statistical thinking that the availability heuristic methodically supplants with an emotionally charged impression of recent experience.

Underestimating Nonlinearity: Linear Thinking in a Nonlinear World

The fifth fundamental error stems from the fact that human thinking is innately predisposed toward linear models of cause and effect: if factor A changes slightly, then outcome B should change proportionally and predictably. The financial market categorically refuses to submit to this intuitively comfortable logic. It is a complex adaptive system, one in which small changes in conditions can produce disproportionately large consequences, and in which familiar patterns abruptly break down under the pressure of threshold effects.

The retail trader, schooled on simplified heuristics such as "if the indicator is below a certain level, a rise must be

coming soon," sees this model painfully refuted by reality time and again. When liquidity collapses abruptly, classic support levels that have served for years as reliable reference points can suddenly become zones of accelerated, cascading decline—because the sheer accumulation of limit orders resting at those levels, once taken out, amplifies the downward momentum rather than halting it. An "oversold" condition, which under a linear model ought to resolve quickly into a rebound, can persist for weeks and sometimes even months, in complete disregard of the expectations of those who think in terms of simple proportionality.

The market's nonlinearity also manifests in the phenomenon of volatility clustering: periods of calm tend to give way to periods of turbulence not gradually but abruptly, and the timing of that transition is fundamentally unpredictable within the framework of simplified linear models. The trader accustomed to extrapolating the recent past onto the near future is systematically caught off guard at the very moments of structural shifts in market regime—that is, exactly when the cost of error is greatest.

The Myth of Control and the Illusion of Simplicity: The Final Trap

The sixth and final trap combines several interrelated misconceptions that together produce the most dangerous

distortion of all—an overestimation of one's own ability to control the uncontrollable. The retail trader, armed with a mobile app and a dozen indicator-laden charts, continues to believe that they can "outplay" a market whose price formation has long been dominated by algorithmic systems that process information at speeds and on scales beyond the reach of human perception. This situation contains a paradox: the greater a trader's subjective confidence in their own superiority over the market, the faster their capital flows to those participants who have delegated decision-making to a strict mathematical discipline free of emotional fluctuation.

The illusion of control is closely intertwined with another widespread misconception—the belief that making one's analysis more complex automatically increases the probability of success. Charts cluttered with dozens of overlapping indicators create no more than the appearance of a deep understanding of what is happening, and that appearance has nothing to do with genuine predictive power. The market does not reward the complexity of the analysis itself—it rewards the statistical significance of the decisions taken, discipline in position management, and the ability to filter out noise, separating it from the rare signals that are genuinely informative.

The participants who survive in this market over the long run are not those who sincerely believe they possess some secret knowledge or unique instinct denied to everyone else, but those who have accepted a basic and psychologically uncomfortable

fact: the market is not an adversary to be outwitted by force of intellect or intuition, but a continuous stream of data in which the only truly hard currency is cold, impartial statistical regularity. Acknowledging one's own cognitive vulnerability is not a sign of weakness but the first and absolutely indispensable step toward a disciplined, systematic engagement with a market that ruthlessly punishes every illusion of control and rewards only sober, empirically validated calculation.

Chapter 3: Vulnerabilities of Algorithmic Systems

An algorithm does not tire, does not panic, and does not succumb to the temptation to recoup losses after a series of drawdowns. This dispassion breeds a dangerous illusion of invulnerability—as though, having shed human psychology, a trading system also sheds the risk of error. In practice, the opposite occurs: weaknesses simply change form. Where a human errs out of fear, an algorithm errs out of rigidity of construction. Where a trader panics at the sight of a red candle, the machine continues methodically executing commands that have already lost touch with market reality. The vulnerabilities of algorithmic trading are no less dangerous than human ones: they are simply buried deeper, in the very architecture of the system, and they do not surface immediately but at the moment when the market changes the rules of the game without warning.

Overfitting: The Trap of Perfect History

The first and, perhaps, most insidious vulnerability is overfitting—a state in which an algorithm ceases to search for patterns and begins instead to memorize specific historical episodes. The difference between learning and memorization seems abstract until you run into it with real capital at stake. A model optimized over a sufficiently long historical series with enough free parameters is capable of reproducing virtually any return on that very series. The difficulty is that such precision is not a sign of understanding the market, but a sign of fitting to noise.

The mechanism of overfitting can be compared to a portrait painter handed a single photograph and asked to produce an exact copy—a task that can be executed to perfection. But if the same painter is asked to draw a person from memory, relying on general facial features, the result will be far less precise, though considerably more universal. Algorithms overloaded with filters, additional conditions, and pinpoint exceptions "for that particular situation in March of such-and-such year" turn into portrait painters of the first type. They render the past beautifully and stand utterly helpless before the future, which will inevitably turn out to be a different person.

Multilayered optimization is particularly dangerous: a developer dissatisfied with the results begins tacking on

conditions one after another until the historical return curve becomes perfectly smooth. Each such condition is, in essence, a bargain struck with the past rather than with the future. The system starts responding not to structural market patterns but to random coincidences that are statistically inevitable in any sufficiently long data series. The more degrees of freedom a model has, the higher the probability that it will stumble on a false pattern and mistake it for a true one. This is a fundamental problem rooted in the very nature of statistics: given enough attempts, randomness begins to look like system.

Telling overfitting apart from a genuine pattern is extraordinarily difficult specifically because the two are outwardly indistinguishable—until the market supplies a new data sample on which the illusory pattern falls apart. The robustness of a strategy is tested not by the beauty of its historical equity curve, but by whether it remains functional when parameters are shifted, when the instrument is changed, when it is transposed onto a neighboring time period. If the slightest change in conditions collapses the entire logic of the system, that is a sure sign that what we are looking at is not a trading strategy at all, but a skillfully painted portrait of the past.

Dependence on Liquidity as a Hidden Foundation

The second fundamental vulnerability lies deeper than the logic of the algorithm itself—it is concealed in an assumption

that is rarely stated explicitly, yet underlies nearly every model: the market possesses sufficient liquidity to execute the algorithm's decision at the calculated price. This assumption holds in ninety percent of cases and fails catastrophically at the very moment when the cost of that failure is highest.

Liquidity is not a static parameter but a living substance that appears and disappears depending on the time of day, the macroeconomic backdrop, the actions of major market participants, and even technical failures at exchanges. An algorithm calibrated to average trading-session volumes perceives order book depth as a given, never questioning it until it suddenly evaporates. At that moment, a model calculating position size from historical slippage volatility discovers that actual slippage exceeds the built-in assumptions by orders of magnitude.

This vulnerability manifests with particular drama when liquidity collapses simultaneously across several correlated instruments. An algorithm conceived as a diversified portfolio of independent positions suddenly confronts the fact that correlation between assets shoots toward unity precisely when diversification is needed most. The reason is straightforward: in moments of panic, market makers withdraw capital from all risky instruments at once, leaving behind not a market with two sides but a vacuum in which price moves in jumps rather than along a smooth gradient.

A subtler form of this vulnerability also exists: dependence

on liquidity artificially created by the algorithms themselves. A significant share of the visible order book depth in today's markets is supplied by high-frequency market makers whose quotes exist for mere fractions of a second and vanish at the slightest sign of an information shock. A strategy backtested on data that includes this phantom liquidity will systematically overestimate its ability to execute trades at calculated prices. In reality, the moment an algorithm attempts to unwind a large position during a stress event, all that visible liquidity dissolves instantly, leaving the order to collide with an empty book.

Temporal Lags as a Built-In Delay from Reality

The third vulnerability is rooted in the very physics of information: any data on which an algorithm relies is already the past by the moment a decision is made. The difference between the actual market and the market as the system perceives it is measured in temporal lags—from microsecond delays in quote transmission to far more serious lags in the calculation of derivative indicators.

Oscillators and most classical indicators are calculated on the basis of completed periods—a candle must close before the indicator updates. This means that the signal generated by the indicator is by its nature a lagging reflection of movement that has already occurred, not a foresight of the future. Under conditions of a smooth trend with moderate volatility, this lag is

not critical—the tendency persists long enough that the delayed signal still proves useful. But at moments of sharp structural shifts, when price has no continuation and reverses almost instantaneously, the temporal lag becomes a direct source of losses: the algorithm receives a signal to act at the very moment when the movement that generated it has already run its course.

An even more dangerous form of temporal lag is connected to infrastructure delays: the time it takes for data to travel between the exchange, the broker, and the trading terminal. On highly liquid traditional markets, these delays are measured in milliseconds and rarely become critical for strategies operating on medium and long timeframes. But on markets with variable transaction processing speeds—for instance, where confirmation of an operation depends on network load—the delay can stretch to seconds or even minutes. In such moments, the algorithm acts blind, guided by a quote that has long since gone stale, while execution occurs at a completely different price. A cascading trigger of protective orders in such a situation can create a domino effect, in which one delayed signal provokes a series of subsequent ones, amplifying the original movement many times over.

Temporal lags cannot be eliminated entirely—only minimized. Even a theoretically ideal system capable of processing data instantaneously still faces the physical time required for signal transmission. The only reasonable response to this vulnerability is not to fight the lag but to acknowledge it

and build it into the very architecture of risk management: the system must reserve a buffer for the possible divergence between the calculated and the actual execution price, especially during periods of elevated volatility, when price is capable of traveling a significant distance in precisely the time it takes the signal to reach the point of execution.

Emergent Behavior: When Multiple Algorithms Create a New Reality

The fourth vulnerability is fundamentally different in character—it arises not from the properties of any single system, but from the collective interaction of many independently operating algorithms. Each developer, in building their model, proceeds from the assumption that the market is an external environment upon which their algorithm exerts negligible influence. This assumption holds true for a solitary participant with modest capital, but becomes false at scale, when hundreds and thousands of algorithms trained on similar data and employing similar logic begin responding to the same triggers in near-simultaneous fashion.

Emergent behavior in this context is the appearance of qualitatively new system behavior that cannot be directly derived from the properties of its individual components. A single algorithm responding to a breakout of a key level with a buy order behaves entirely rationally within its own logic. But when

thousands of such algorithms respond to that same breakout simultaneously, their collective action creates a positive feedback loop: purchases by one set of systems push the price upward, which triggers the exact same signals in neighboring systems, which pushes the price higher still, drawing the attention of ever more algorithms. The result is a price movement devoid of fundamental cause, generated entirely by structural resonance among homogeneous trading logics.

What is most troubling about this phenomenon is its self-reinforcing nature exactly where algorithms are most technically sophisticated. The more precisely models adhere to the same widely accepted principles of technical analysis, the more standardized their thresholds and trigger levels, the stronger the resonance effect becomes. Paradoxically, reducing the individual error of each separate model increases systemic risk across the entire ecosystem, because it unifies participant behavior. Diversity of approaches, which appears to be a shortcoming from the perspective of an individual developer striving for the perfect model, turns out to be a protective mechanism for the system as a whole—it distributes reactions across time and reduces the probability of synchronized triggering.

Emergent behavior manifests in more subtle forms as well—for instance, when cross-instrument and cross-exchange arbitrage algorithms begin transmitting a localized price shock into a global one, spreading the imbalance across the entire interconnected network of markets within fractions of a second.

What begins as a minor anomaly on a single venue turns into a systemic event encompassing dozens of correlated assets before human consciousness has time to comprehend what is happening.

Inadequate Volatility Assessment

The fifth vulnerability concerns a fundamental assumption underlying most risk models: that volatility obeys predictable statistical laws, and that its historical distribution provides a sufficient basis for assessing future risk. This assumption holds up reasonably well during calm periods and breaks down catastrophically at moments of structural shift.

Classical parametric models relying on the normal distribution of price increments systematically underestimate the probability of extreme deviations—the so-called fat tails of the distribution. In reality, sharp movements occur far more frequently than theoretical models predict, and their amplitude can exceed expectations several times over. An algorithm that sizes its positions based on the standard deviation of the preceding weeks or months turns out to be fundamentally unprepared for an event that, statistically, should occur once a decade but in practice occurs far more often—largely because real market distributions do not conform to simplified theoretical models.

There is also a reverse side to this problem—volatility clustering, a phenomenon whereby periods of calm and periods of turbulence tend to cluster in time rather than distribute evenly.

A model trained on a prolonged calm period comes to treat low volatility as the norm and calibrates its risk parameters accordingly low. When the market enters a turbulent phase, this understated calibration produces a systematic underestimation of risk precisely at the moment when the cost of error is greatest. Indicators built on historical variance respond to a regime change with a lag, since by their very construction they average information over some period rather than instantly recognizing a structural break.

Particularly dangerous is the situation in which low liquidity and understated volatility estimates compound one another. An algorithm sees a calm market with tight spreads and infers low risk, not realizing that this calm is illusory and holds only until an order large enough to appear reveals the true fragility of the liquidity beneath it. At that moment, the model that underestimated volatility finds itself doubly vulnerable—not only is it unprepared for a sharp price move, but it is also unprepared for that move to be amplified by the absence of opposing orders in the book.

Cognitive Biases of Developers as a Hidden Source of Systemic Risk

The sixth, and in some sense the most fundamental vulnerability, is rooted not in mathematics or market mechanics, but in the mind of the person who creates the algorithm.

Machine learning is conventionally considered objective simply because it operates with numbers rather than emotions. Yet every number, every training dataset, every chosen hyperparameter passes through a human decision, and thus bears the imprint of the very same cognitive biases from which algorithmic trading is meant to liberate the trader.

The first and most widespread bias of the developer is confirmation bias in the selection of training data. A strategy creator, initially convinced of the existence of a particular pattern, tends unconsciously to select the historical period and set of instruments in such a way that the hypothesis is confirmed. This is not always a conscious falsification. More often it is the result of dozens of minor decisions, each of which seems neutral, but which in aggregate steer the sample toward the desired result. The choice of this time window rather than an adjacent one, this evaluation metric rather than an alternative, this method of handling outliers rather than another—all of these are points where subjectivity seeps into what is supposedly an objective system.

The second bias is excessive faith in complexity as a marker of quality. A developer who has spent months building a multilayered model with dozens of parameters is psychologically inclined to regard its superiority over simple rules as self-evident, simply by virtue of the effort invested. This is the classic trap of justifying sunk costs: the more time spent creating a system, the harder it becomes to acknowledge that a simpler approach might

work no worse—and at times even better—in large part because it is less susceptible to overfitting.

The third bias is the illusion of objectivity in metrics. A developer choosing the objective function for model optimization brings to that choice their own beliefs about what matters and what is secondary. Optimization exclusively for total returns without accounting for the depth and duration of drawdowns reflects a hidden assumption about the psychological resilience of the future user of the system, an assumption that is rarely tested explicitly. A metric that appears strictly mathematical in fact embodies the creator's subjective choice of priorities.

Finally, the fourth and perhaps most insidious bias is the endowment effect applied to one's own creation. A developer who has invested intellectual effort and time into a particular architecture tends to interpret ambiguous testing results in favor of their model, to delay acknowledging its failure, and to seek justifications for individual losing trade sequences instead of honestly reassessing fundamental assumptions. This bias explains why numerous demonstrably unviable strategies continue to be exploited far longer than cold statistical analysis would permit: their creators are psychologically unprepared to admit the defeat of their own intellectual construct.

The aggregate of these six vulnerabilities forms not a list of isolated risks, but an interconnected system of weak points, where an error in one dimension amplifies vulnerability in another. An overfitted model is especially dangerous under

conditions of low liquidity, since it cannot recognize a regime shift in time due to time lags in indicator calculation. Inadequate volatility assessment becomes fatal at the very moment of emergent resonance among multiple algorithms. And underlying all of this stands the human being, whose own cognitive biases are invisibly embedded in code that is conventionally deemed impartial. Understanding this architecture of vulnerabilities is not a reason to abandon algorithmic trading, but rather a necessary condition for building systems capable of surviving not in the ideal laboratory conditions of a historical backtest, but in the real, unpredictable, and constantly changing market.

Chapter 4: Metrics and Filters for Market Analysis

Three Pillars of Filtration: Volatility, Liquidity, Momentum

Any attempt to analyze the market without a clear system of coordinates is doomed to become an endless wandering among candlesticks, lines, and multicolored indicators. To avoid drowning in this visual noise, we must isolate the foundation—three parameters around which the entire subsequent architecture of signal filtration is built: volatility, liquidity, and momentum. Each addresses its own task, and only their joint application creates a robust system of decision-making.

Volatility answers the question "how strongly can price change over a chosen time interval." It is not an abstract quantity, but an applied tool for calculating risk. A trader who ignores volatility is condemned either to stops so tight they get knocked out by market noise, or so wide that they turn capital management into a lottery. Volatility is dynamic: it contracts during periods of consolidation and expands sharply at moments of news releases or structural shifts. Understanding the current phase of volatility is the first filter that determines whether it is worth considering

entry into a position at all.

Liquidity is responsible for the executability of an idea. One can construct a strategy that is impeccable from the standpoint of logic, but if the market at the moment of intended entry lacks sufficient depth, any trade will become a struggle against slippage and widened spreads. Liquidity is not a constant, but a variable that changes depending on the time of day, day of the week, and the approach of macroeconomic events. Filtering by liquidity means that the trader consciously refuses entries during periods when the market is structurally unprepared to accept their order without losses.

Momentum is the third element, responsible for the strength and direction of the current movement. It shows how convincingly the market is moving in the chosen direction, and allows us to distinguish a full-fledged impulse from a sluggish price drift. Momentum does not exist in isolation from volatility and liquidity: strong movement under low liquidity often proves artificial and quickly retraces, whereas the same movement under high volume and sufficient order book depth testifies to a genuine redistribution of forces between buyers and sellers.

The synthesis of these three metrics creates a complete filter. Volatility determines the size of risk, liquidity determines the very possibility of safe execution, and momentum determines whether there is any sense in considering the movement as significant at all. The absence of even one element from this triad transforms analysis into an incomplete picture, where decisions

are made blindly with respect to one of the key aspects of market mechanics.

Volatility as a Risk Calculation Tool, Not Merely an Indicator

A widespread error lies in treating volatility as a secondary technical indicator, useful only for adjusting the appearance of a chart. In reality, volatility is the foundation upon which an entire capital management system is built. The Average True Range, reflecting the typical amplitude of price movement over a chosen period, should not be used in isolation, but rather in direct conjunction with position size and stop-loss level.

The logic is straightforward: if the typical daily range of an asset is two and a half percent, yet the stop-loss is placed at one percent, the trader is playing against the statistics of their own instrument. The market will, with high probability, hit such a stop before the movement has time to develop in the anticipated direction. The correct approach presupposes an inverse relationship: the higher the current volatility of the instrument, the smaller the volume of the position being opened should be, and the wider the stop-loss should be relative to the entry point.

One should recognize that volatility is not static over time. There exist periods of compression, when the range of movements contracts and the market seems to pause before a

decision, and periods of expansion, when amplitude suddenly increases. The transition from compression to expansion is one of the most informative signals, since it often precedes strong directional movement. The analyst's task is to track not only the absolute value of volatility, but also its historical dynamics, comparing current readings against multi-year average values. A sharp deviation from the norm is a signal that market conditions have changed and require a reassessment of customary risk parameters.

Volatility and liquidity are closely intertwined. The market becomes most dangerous for mechanical adherence to familiar rules exactly when liquidity suddenly falls while volatility simultaneously rises. Such a combination often precedes gaps, breaks, and cascading movements, where standard risk calculation models cease to function correctly. Understanding this interrelationship compels us to treat volatility not as a static figure in the corner of a chart, but as a living, constantly changing indicator of market state.

Liquidity as the Foundation of Idea Execution

Liquidity is often underestimated by beginning market participants, who focus exclusively on price direction while forgetting how realistic it actually is to enter and exit a position without substantial costs. Yet liquidity is what determines whether a theoretically sound idea will turn into a profitable trade

or drown in slippage and a widened spread.

The key error lies in assessing liquidity solely through the lens of total trading volume over a period. The absolute magnitude of turnover tells us little without understanding how it is distributed across time and price levels. Far more informative is the analysis of trade clustering—how volume is distributed around specific price points. If large volume concentrates within a narrow range, this signals the formation of a significant zone of interest among market participants, whereas volume spread thinly across a wide range points rather to an absence of consensus.

Liquidity also possesses a pronounced temporal structure. Different trading sessions exhibit fundamentally different market depth: periods of overlap between major sessions are traditionally characterized by elevated activity, while nighttime hours or pre-holiday periods are accompanied by a thinning of the order book. In such moments, even an order that would be modest by the standards of an ordinary day can trigger a move disproportionate to the real fundamental interest in the asset. Filtering signals by time of day is a necessary element of discipline, especially for instruments traded around the clock.

A practical filter worth incorporating into any analytical system is comparing current volume against the median value for the preceding period. If volume at the moment a signal forms is substantially below the typical level, it is reasonable to disregard that signal regardless of how visually attractive it appears on the chart. A breakout of a key level against a backdrop of depleted

liquidity will, with high probability, prove false, since the move is not backed by enough real participants willing to hold the new price.

The imbalance between buy and sell volume near significant price levels needs close examination. If price repeatedly tests a certain level, yet the volume of aggressive buying consistently declines, this signals weakening interest even though the level has not formally been broken. Such a divergence between price and volume is one of the most reliable indicators of an approaching shift in the balance of power.

Momentum and Its True Nature

Momentum is often confused with simple price direction, although it is in fact a fundamentally different category—it measures the speed and force of change, not the fact of a rise or fall itself. An asset may be rising, yet doing so ever more slowly, losing the inner energy of its move long before the price formally reverses. This is where the diagnostic value of momentum comes in: it allows us to see trend exhaustion before it becomes obvious from price itself.

Working with momentum requires understanding its relative, rather than absolute, nature. A strong move in a low-liquidity asset with a thin order book may look impressive on a chart yet carry no predictive value whatsoever, since it is not confirmed by real participation from major players. Conversely, a move

moderate in amplitude, accompanied by steady volume growth and narrowing spreads, may signal the formation of a sustainable trend.

A substantial error when working with momentum is examining it in isolation from the broader market context. A signal of accelerating movement carries fundamentally different weight depending on whether it occurs at the beginning of a trend, in its middle, or on the approach to a historical resistance level. The same numerical momentum reading can mean trend continuation in one context and a sign of exhaustion in another. That is why momentum should never be used as a standalone, isolated trigger for decision-making: it acquires meaning only in combination with the assessment of volatility and liquidity described above.

Timeframe Selection as an Architectural Decision

The choice of temporal scale for analysis is not a secondary technical detail, but a fundamental architectural decision that determines the entire subsequent logic of the system. Different timeframes answer fundamentally different questions, and any attempt to use the same horizon for all tasks inevitably leads to distorted conclusions.

Short-term trading with position holding spanning minutes or hours requires working with lower intervals—from minute to hourly candles. At these scales, market microstructure

dominates: local liquidity imbalances, brief spikes of aggressive orders, reactions to technical levels within the current session. Yet the finer the chosen interval, the more pronounced the market noise becomes—noise bearing no relation to sustainable patterns. Patterns that appear distinct on a minute chart often dissolve when the sample size increases, revealing themselves as statistical artifacts rather than reproducible models of market behavior.

Medium-term analysis, oriented toward holding positions from several days to several weeks, is reasonably constructed on a pairing of four-hour and daily charts. The four-hour interval allows us to capture local reversals and entry points with acceptable precision, while the daily chart establishes the broader context and confirms or refutes the direction suggested by the lower timeframe. This nesting of timeframes within one another is not a formality, but a method to filter out a substantial portion of false signals: movement that lacks confirmation on the higher interval will, with high probability, prove to be short-term noise.

For long-term positions, weekly and monthly charts become the primary source of information, where the overall picture emerges from the aggregate of numerous daily fluctuations, and random variations are virtually eliminated by the length of the observation period. Here, what matters is not tactical signals but macrostructural levels and the persistence of the dominant trend across many cycles.

The cardinal principle of multi-timeframe analysis is that a

signal obtained on a lower interval must receive confirmation on a higher interval before it becomes grounds for action. Divergence between timeframes is not a reason to disregard the analysis, but rather an independent source of information pointing to a transitional, indeterminate state of the market—one in which it is more prudent to refrain from active moves than to attempt to guess the direction in which this conflict will resolve.

Signal Filtering by Volume

Trading volume deserves separate, in-depth consideration, since it is most often the decisive factor separating a genuine signal from a market artifact. Price change alone is insufficient grounds for a decision: a move unconfirmed by volume will very likely prove to be a temporary fluctuation lacking any durable foundation.

A practical approach to filtering involves comparing current volume against its rolling median over the preceding period. If a breakout of a significant level is accompanied by volume that substantially exceeds typical values, this confirms the participation of major players and raises the probability that the move will continue. If, conversely, the breakout occurs against a backdrop of average or below-average volume, it is prudent to treat such a signal with considerable skepticism.

Of particular value is the analysis of the difference between the volume of aggressive buying and the volume of aggressive

selling near key price zones. A persistent skew toward buying, combined with a simultaneous absence of upward price movement, may indicate hidden accumulation by major participants who deliberately avoid a sharp shift in price so as not to trigger a premature reaction from other players. The inverse situation—price rising while the volume of confirming purchases declines—is a classic sign of a weakening trend, even if the price is formally continuing to set new local highs.

Volume clustering at specific price levels, not merely its distribution over time, adds yet another layer of analysis. Zones where the largest trading volumes have historically concentrated often go on to serve as significant support or resistance levels, since that is where the greatest mass of open positions accumulates among participants for whom that price carries psychological and financial significance.

Oscillators in the Context of Trend

The application of oscillators—indicators of overbought and oversold conditions that remain among the most widely used, yet simultaneously among the most frequently misinterpreted, tools of technical analysis—calls for careful examination. The fundamental error lies in treating the oscillator as an independent reversal signal, when in reality it merely reflects the degree of exhaustion in the current move relative to recent price history.

Oscillator readings must be interpreted strictly within the

context of the broader trend, never in isolation from it. A high oscillator reading signaling overbought conditions within an uptrend by no means always foreshadows an impending reversal—far more often it simply indicates the probability of a short-term correction within a continuing upward move. Attempting to open a short position on the strength of overbought territory alone, amid a strong uptrend, is one of the most common sources of losses among novice market participants, since a trend can hold an oscillator in an extreme zone considerably longer than intuition would suggest.

The productive approach is to use the oscillator not as an independent trigger but as an additional filter layered onto an already-established trend direction. If the higher timeframe confirms an upward move and price is trading above the long-term moving average, then an oversold reading on the lower interval may be treated as an area in which to look for trend-following entries, whereas an overbought reading in that same context serves as a signal for caution rather than a trigger for opening a position against the trend.

An additional layer of filtering comes from comparing oscillator readings against the position of price relative to moving averages of different periods. If price holds above the long-term average while the oscillator reaches extreme values characteristic of overbought conditions, the statistically more probable scenario is not a full-fledged trend reversal but a correction toward the intermediate-term moving average, followed by a resumption

of the primary move. Understanding this pattern spares traders from premature, loss-making attempts to trade against the dominant force in the market.

The Synthesis of Metrics as the Foundation of a Robust System

None of the metrics we have examined operates in isolation, nor should any be perceived as a self-sufficient source of trading decisions. Volatility without regard for liquidity becomes an abstract figure that fails to illuminate the real executability of an idea. Momentum without volume confirmation risks proving to be an illusion of strength where no genuine participant interest exists. An oscillator viewed outside the context of the dominant trend systematically misleads us about the probability of a reversal.

A robust signal-filtering system is built as a multilayered process, in which each successive filter strips away a portion of the noise left over from the one before it. First, the overall trend is determined on a higher timeframe; then the current level of volatility is assessed to calibrate risk; next, liquidity is checked for sufficiency to ensure safe execution; after that, volume is analyzed to confirm the significance of the move; and only at the very last stage are oscillators brought in—not as grounds for entry, but as a tool for refining timing and gauging the degree of exhaustion in the current impulse. Such a sequence transforms

a collection of disparate indicators into a coherent, logically integrated architecture of analysis, in which every decision rests on a constellation of mutually confirming data rather than on a single, isolated signal.

Chapter 5: Risk and Position Management

The market does not punish an incorrect forecast. It punishes an incorrectly calculated position size. This statement sounds paradoxical to a novice convinced that the main task of trading is guessing the direction of price movement. But anyone who has spent enough time in the market knows the bitter truth: even a strategy with forecast accuracy above fifty percent can drive an account to zero if the size of each bet is not reconciled with the mathematics of capital. And conversely, a mediocre system with only a modest edge can deliver steady returns for years, provided risk management is built as an engineering discipline rather than as an intuitive sense of "how much I can afford to lose."

Risk management is not a protective add-on to a trading strategy, but its load-bearing frame. Without it, any system of analysis, however sophisticated, turns into a lottery with a delayed explosion. In this chapter we will examine how position size is calculated, how volatility should determine the level of a stop-loss, how market liquidity intrudes on these calculations, and why correlation between open positions can imperceptibly transform a diversified portfolio into one enormous concentrated bet.

The Mathematics of Position Size: From Intuition to Formula

The first and most common mistake of a retail trader is determining position size "by eye," based on whatever sum feels psychologically comfortable to risk. This approach ignores a fundamental principle: position size must be a derivative of three variables—the size of the capital, the allowable risk per trade, and the distance from the entry point to the stop-loss. These three parameters form a rigid formula that leaves no room for emotional adjustments.

Allowable risk per trade is the percentage of capital a trader is willing to lose if the stop-loss is triggered. Standard practice limits this figure to one or two percent of the deposit. The number is not arbitrary: it is derived from the statistics of losing-trade sequences. Even a strategy with acceptable mathematical expectation is capable of generating five, seven, or sometimes ten losing trades in a row—this is not an anomaly but a normal manifestation of randomness within a limited sample. If risk per trade is two percent, a series of ten consecutive losses will reduce capital by roughly eighteen percent—painful, but not fatal. If risk per trade is ten percent, however, the same series will wipe out the deposit almost entirely, and recovery becomes mathematically all but impossible, since the percentage gain required to compensate for a deep drawdown grows nonlinearly

relative to the drawdown itself.

The central lesson is this: a fifty percent loss requires a hundred percent gain to return to the starting point. This is not abstract arithmetic but the reason why excessive risk per trade amounts to slow suicide for capital even under a formally profitable strategy.

The calculation of position size proceeds in reverse—from risk to volume. First, the trader determines the sum they are willing to risk in absolute terms—a percentage of capital. Then the distance from the entry point to the stop-loss is determined in price units. Dividing the allowable risk by this distance gives us the quantity of the asset that can be purchased without exceeding the risk limit. This mechanism automatically adjusts position volume according to how wide the stop-loss must be: the farther the stop sits from the entry price, the smaller the position volume, and vice versa. This inverse relationship is not a technical detail but a fundamental principle that protects capital from the emotional urge to "take more" at moments when the chart looks especially convincing.

This calculation must be performed anew for each trade, not used as a fixed number of lots. The market is constantly reshaping its internal geometry, and what yesterday required a fifty-point stop may today require a stop of one hundred fifty points because of increased volatility. Ignoring this recalculation is one of the most common reasons formally disciplined traders still lose capital: they observe the rule of "no more than two

percent risk" but forget that position size must adapt to the shifting price context.

Volatility as the Foundation for Stop-Loss Calculation

A stop-loss established without regard to the current volatility of the instrument is a stop-loss set blind. A fixed number of points, identical for a calm market and a market in a state of turbulence, is doomed either to trigger too frequently on normal price fluctuations or to leave excessive risk during moments of anomalous calm.

The Average True Range is a fundamental tool for calibrating the stop-loss to current market conditions. It shows the typical amplitude of price fluctuations over a given period, including gaps and breaks between sessions. The logic is simple and mathematically sound: a stop-loss set at a distance smaller than the average range will be systematically knocked out by ordinary market noise that has nothing to do with a trend reversal. A trader using such a tight stop will lose not because their hypothesis about the direction of movement is wrong, but because the very construction of the stop ignores the physics of market fluctuations.

The practical rule is to tie the stop-loss to a multiplier of the Average True Range—for example, one and a half or two ranges from the entry point. If an asset's range is fifty points, a stop-loss

set at a distance of seventy-five points accounts for the natural amplitude of noise, leaving room for random fluctuations that do not invalidate the trading idea. But here it is important to return to the previous section: the wider the stop, the smaller the position size must be so that the risk per trade remains within the established percentage of capital. Volatility and position size are not two separate parameters but two sides of the same formula, which must be calculated in tandem.

The dynamic nature of volatility needs examination on its own terms. It is not static—periods of calm are replaced by periods of high turbulence, and an algorithm or trader using an outdated value of the average range risks applying yesterday's market parameters to today's conditions. Volatility has a tendency to cluster: a period of high amplitude is often followed by a continuation of elevated activity, not an instantaneous return to calm. This means that the range calculation must be updated on a rolling basis, not taken as a constant over an extended period.

A separate trap is the use of a percentage stop-loss without any tie to volatility at all. A fixed percentage—for example, a one percent stop from the entry price—seems like a universal solution, but in reality ignores the fact that the same percentage can be either too tight or excessively wide depending on how prone the asset is to fluctuations in the first place. An instrument with historically low volatility, trading in a narrow range, requires a tighter stop in absolute terms than an instrument prone to sharp moves. Mixing these approaches is a frequent reason why

formally "sound" risk management still leads to uneven results across different assets in a portfolio.

Adaptation to Changing Liquidity

The calculation of position size and stop-loss rests on the assumption that the market will execute orders at the expected price. This assumption holds true only under conditions of sufficient liquidity. When market depth becomes depleted, all the risk mathematics built on theoretical calculations begins to diverge from the reality of order execution.

Slippage is the difference between the price a trader anticipated and the price at which an order actually executed. When the order book is deep, this difference is minimal and predictable. But in moments of liquidity depletion—during low-volume sessions, before the release of important economic data, during holiday trading, or during off-hours on cryptocurrency exchanges—that same order can execute at a price significantly worse than expected. A stop-loss set at a certain distance from the entry price may, in a thin order book, trigger at a price substantially different from the set level, turning a planned two-percent risk into an actual risk of five or seven percent.

This means that position sizing cannot be limited to price volatility alone—it must also account for the volatility of liquidity itself. The practical approach consists of monitoring order book depth and trading volume across different times of day and

market sessions. If current trading volume is substantially below the median value for the preceding period, this signals a need to reduce position size or to widen the planned stop-loss to account for expected slippage. This adjustment is not excessive caution—it is a direct consequence of the fact that order execution costs are part of the overall trade risk, not a separate, secondary quantity.

This problem is especially acute in assets with uneven liquidity distribution throughout the day. The Asian session in the foreign exchange market, off-hours on cryptocurrency exchanges, the period between the close of one national session and the opening of another—all these are moments when even a relatively modest market order can move the price by an amount that would be statistically insignificant during peak activity hours. An algorithm or trader ignoring this unevenness and applying identical risk parameters at any time of day will sooner or later encounter a situation where a formally correct position calculation proves practically impossible to execute at the expected price.

The liquidity problem also has an inverse side: the size of one's own position relative to the average trading volume of the instrument. If the volume of a planned trade constitutes a notable share of the asset's average daily turnover, the very opening or closing of the position can move the price against the trader, creating costs that were not factored into the initial risk calculation. This is especially relevant when working with assets of medium and low capitalization, where a position large

relative to the market transforms the trader from an observer of market dynamics into a direct participant influencing their own execution outcome.

Correlation of Risk and Capital Allocation

Calculating risk for each individual trade is a necessary but insufficient condition for capital preservation. Danger emerges at the portfolio level, when several formally independent positions turn out to be secretly interconnected through the correlation of their underlying assets. A trader who has opened five positions with a two percent risk on each, confident that total portfolio risk amounts to ten percent, may discover that the actual risk is significantly higher if all five instruments move in sync at the moment of market stress.

Correlation between assets is not a constant quantity. During calm periods, different asset classes may demonstrate weak interdependence, creating an illusion of diversification. But in moments of market panic, liquidity crises, or large-scale sell-offs, correlation among most risky assets tends toward one: investors simultaneously reduce exposure across the entire portfolio, regardless of the fundamental differences between individual positions. In such moments, diversification built on historical correlation coefficients from calm periods ceases to perform its protective function—and this happens exactly when protection is needed most.

The practical takeaway from this observation is that open positions should be viewed not as isolated bets but as a unified system, where aggregate risk can substantially exceed the sum of the nominal risks of individual trades. Before opening a new position, it is reasonable to assess how it interacts with existing ones: if the new trade adds exposure in a direction correlated with already-open positions, the portfolio's effective risk grows disproportionately to the nominal risk of a single trade. This is especially important when working with multiple instruments within a single asset class—for example, several currency pairs pegged to one reserve currency, or several cryptocurrency assets moving in the wake of the market's dominant asset.

Capital allocation between strategies and instruments should account for this hidden interdependence. Formal diversification by the number of open positions is not the same as diversification by sources of risk. A portfolio of ten positions all responding to the same macroeconomic factor represents a concentrated bet disguised as a distributed one. True diversification requires seeking out assets and strategies that respond to different factors, different time horizons, and different sources of volatility—only then does the aggregate risk of the portfolio actually decrease, rather than simply appearing to be spread across a greater number of rows in the trading terminal.

Dynamic Risk Adjustment Based on Performance

Risk management does not end at the moment of opening a position—it must continue throughout an entire series of trades, responding to changes in the state of capital. A static approach, in which risk per trade remains unchanged regardless of current drawdown or a streak of successful results, ignores an important principle: the capacity of capital to withstand risk changes together with its state.

After a series of losing trades, sound practice consists in reducing risk per trade rather than maintaining it at the previous level in an attempt to recover losses more quickly. This is counterintuitive from a psychological standpoint—the desire to compensate for a loss faster pushes toward increasing stakes—but mathematically, it is the reduction of risk during a drawdown period that protects capital from the very nonlinear recovery effect discussed at the beginning of this chapter. The deeper the drawdown, the more conservative the approach to subsequent trades must become, since the margin of safety for capital shrinks while the required percentage gain for recovery grows.

Similarly, a series of successful trades should not be automatically interpreted as a signal to increase risk. Capital growth following a fortunate period is often interpreted as confirmation of system effectiveness, which provokes a gradual increase in position size. However, system effectiveness is

measured not by a short streak of favorable outcomes but by statistics over a sufficiently long horizon that encompasses different market phases. Increasing risk at the peak of euphoria following a streak of successful trades is the classic mechanism by which traders give back to the market—in a matter of days during an unfavorable period—profits accumulated over months.

Конец ознакомительного фрагмента.

Текст предоставлен ООО «Литрес».

Прочитайте эту книгу целиком, [купив полную легальную версию](#) на Литрес.

Безопасно оплатить книгу можно банковской картой Visa, MasterCard, Maestro, со счета мобильного телефона, с платежного терминала, в салоне МТС или Связной, через PayPal, WebMoney, Яндекс.Деньги, QIWI Кошелек, бонусными картами или другим удобным Вам способом.