

Fair Value Accounting in Algorithmic Markets: Rethinking Measurement Neutrality, Bias, and Financial Reporting Integrity

Furqan ¹

¹ Harvard University, US, United States

Abstract

The introduction of algorithmic trading, together with high-frequency trading systems and data-driven predictive modelling methods, has resulted in fundamental changes to financial markets. Automated systems and proprietary trading algorithms, together with recursive feedback mechanisms, now control price movements in financial markets rather than relying on human market participants to establish prices. Fair value accounting methods still depend on market prices because they serve as objective measurement standards according to accounting principles. The study asserts that algorithmic market microstructures

require researchers to rethink the foundational knowledge that supports fair value accounting. Accounting theory investigates liquidity stress and procyclicality issues, but it has not yet examined how algorithmic bias, system opacity, and feedback loops will change the market price information system. Researchers have treated value relevance evidence as a basis for determining

neutrality instead of studying it as a construct that involves societal and technical dimensions. The presence of hidden financial algorithms that produce market prices creates situations where financial reports deliver technological distortions while people think these reports present unbiased information. The Algorithmic Fair Value Risk Framework developed in this paper addresses

existing research gaps by showing how algorithmic input bias and model opacity together produce market distortions that impact

financial statements. The research study defines neutrality through its dependence on technology while showing how this relationship affects digital market governance, audit practices, and regulatory control

Keywords: Fair value accounting, Algorithmic finance, Market microstructure, financial reporting integrity, Algorithmic bias, Socio-technical governance, Audit digitalization

***Corresponding Author:** Furqan (furqanahmed.engineer@gmail.com) .

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1. INTRODUCTION

In the last twenty years, financial markets have experienced a paradigm shift in that the human-dominated trading landscape has changed to machine-mediated ecosystems that run on a machine-logical code (Sunil Kumar Das, 2024). It was empirically demonstrated that nowadays, algorithmic trading and high-frequency trading (HFT) occupy an important portion of the market activity, radically changing the way liquidity is provided, the price formation, and the market microstructure (Hendershott et al., 2011; Menkveld, 2013). Although early studies indicated that algorithmic trading can indeed lead to increased liquidity and an improved part of the price discovery (Hendershott et al., 2011; Brogaard et al.,

2014), the later studies make this sunny story more complicated. The instability of the market prices and the information quality is questioned due to the power of speed competition, the location of the strategic orders, and the use of automated feedback loops (Kirilenko et al., 2017).

The Flash Crash of 2010 is a great example of how algorithmically related markets can be so delicate. Kirilenko et al. (2017) show that automated strategies reinforced each other in a vicious cycle to create extreme volatility that was unrelated to underlying fundamentals. On a similar note, Menkveld & Yueshen (2019) describe fragmented and highly automated markets as vulnerable to the evaporation of liquidity. Policy analyses also

highlight structural weaknesses brought about by high-frequency trading and arms races that are technological in nature (Miller & Shorter, 2016). These changes hold the implication that the current market prices are not simply a product of scattered human information, but a product of highly intertwined algorithmic systems operating at velocities that are beyond human control.

At the same time, AI and sophisticated data analytics have gone beyond trading floor environments into financial reporting and auditing areas. There is an increasing adoption of big data applications, predictive analytics, and robotic process automation in the accounting profession in the valuation, risk estimation, and audit processes (Alles, 2015; Vasarhelyi et al., 2015). The advent of AI-based auditing also points to the direction of increasingly fast assurance through algorithmic mediation (Kokina & Davenport, 2017), and recent systematic reviews report on the quick adoption of AI and robotic process automation in accounting practice (Kassar & Jizi, 2026). This two-fold change, algorithmic market pricing on the one hand and AI-aided financial reporting and auditing on the other hand, is fundamentally challenging the way in which the valuation signals are produced, deciphered, and confirmed.

The conceptual underpinnings of fair value accounting are directly in conflict with these structural changes. Fair value measurement, especially within the market-based logic of exit prices, assumes that market prices are a rather objective aggregation of information (Barth et al., 1995). The assertion that market prices are related to economically relevant information by the fair value reporting has been backed by empirical evidence historically (Barth et al., 1996). Tacit within this logic is an implicit assumption of neutrality: that the market prices, though imperfect, are not being systematically poisoned by opaque, myopic technological processes.

But the worldwide economic crisis has rekindled the argument as to whether fair value accounting increases volatility and passes the instability in the markets into financial reporting. Leuz (2009) doubted simplified accounts that put the blame of the crisis dynamics on fair value, & Laux & Leuz (2010) described the possibility of mark-to-market measurement being procyclical. Barth & Landsman (2010) went on to examine the interaction of financial reporting with the conditions of crisis. These debates, despite the fact that they were concerned more with liquidity spirals and distressed market pricing, implicitly held on to the premise that the prices, despite being volatile, were a product of the human interaction in the market under stress. An ontological change of the human-controllable markets towards algorithmically designed price systems was not fully theorised.

This change, in turn, maintains the arguments provided in the present paper that suggest that the neutrality of fair value accounting requires a more thorough re-evaluation. The assumption that modern market prices are becoming increasingly influenced by non-transparent algorithmic structures, which are defined by model bias, data dependence, speed asymmetry and self-reinforced feedback loops, is a condition that calls into question the epistemic status of market prices as being an objective standard (Seele et al., 2019). The main research question that will inform this research is thus:

If market prices are increasingly shaped by opaque algorithmic systems, can fair value accounting still claim neutrality and integrity?

To answer this question, it is necessary to go beyond empirical measurements of volatility to the conceptual analysis of the mediation of valuation signals through algorithmic infrastructures. In two main aspects, this paper is a contribution. First, it provides a conceptual re-conceptualisation of neutrality in fair value accounting, reassessing market price as an algorithmic design and strategic automation of dispersed information rather than as a neutralising aggregation of this information. Second it determines what is known as the algorithmic transmission risk: the mechanism by which biases, feedback effects and opacities inherent in algorithmic market systems are passed onto financial reporting through fair value measurement. This research places fair value accounting in the context of technological transformation of the entire algorithmic finance domain and forms a new question of whether financial reporting is honest in technologically mediated markets.

2. THEORETICAL FOUNDATIONS OF FAIR VALUE ACCOUNTING

2.1 Market-Based Measurement, Value Relevance, and the Neutrality Assumption

The basis of fair value accounting is that the market prices have decision-useful and economically meaningful indicators of the underlying asset values. The idea of market-based measurement has fancied a superiority within the conceptual architecture of financial reporting, wherein market-based measurement is held superior to historical cost since it expresses the present exit prices and brings all dispersed information into a single observable measure (Gentry & Shen, 2010). This logic has been historically supported through empirical research. Barth et al. (1996), discussing the fair value disclosure of banks in the context of SFAS No. 107, indicate that the disclosed fair value shows an incremental value relevance to the historical cost measures. They have often interpreted their findings to

heroise the existence of market prices that are economically important in the sense that they are captured by and impounded by investors in the form of share values.

Likewise, Barth et al. (1995) record that the fair value accounting system results in volatile earnings and changes regulatory capital requirements to banks. Increased volatility was also sometimes interpreted as a liability, but it was also interpreted as a true measure of the underlying economic risk, more accurately than a smoothed historical cost figure. According to this perspective, volatility is economic and not a measurement error. It means that fair value improves transparency because it passes market risk into financial statements.

Bell et al. (2002) also show the effect of market-based accounting treatments on the valuation assessment and illustrate that recognition and measurement options do influence the manner in which investors price firms. These studies altogether contributed to the institutionalisation of the concept that fair value measurement can bring the numbers of accounting in agreement with those of the market to improve relevance and comparability.

However, within this mass of evidence, there exists a strong yet frequently unspoken assumption that market prices in themselves are good enough neutral measures. The value relevance does not imply neutrality; it only shows some association between accounting numbers and market prices. The conceptual jump between relevant to values and objective lies in the fact that markets are believed to be efficient marketers of information and have no systematic bias. This assumption, in fact, is the one that must be put under fresh scrutiny in algorithmically mediated markets.

2.2 Historical Evolution and Crisis-Era Controversies

The emerging fair value accounting has been characterised by controversy. In their work, Emerson et al. (2010) give a historical summary of how fair value has swung the whole process between advocacy and resistance, especially at the time of financial turmoil. The issue of whether market-based measurement increases cyclical volatility and spreads the short-term price changes into long-term financial reports has long been an issue of debate among critics.

These debates were enhanced by the global financial crisis. According to Valentin & T (2011), crisis conditions revealed the tension between market pricing and the stability of financial reporting because the extreme adjustments in valuations were realised in the distressed markets. Leuz (2009) criticises simplified narratives, which hold systemic collapse as only being caused by fair

value accounting, and it is necessary to analyse it in a nuanced way. Laux & Leuz (2010) focus on the issue of whether mark-to-market rules actually increased procyclicality, and eventually conclude that fair value might have played a role in the interaction between fair value and crisis, but the causal narrative is complicated. Barth & Landsman (2010) also explore the role of financial reporting in crisis perceptions with the focus on accounting standards interaction and investor reactions.

The debates of this crisis era, however, to a large extent, assumed that the market prices, in spite of their volatility, were the result of human trading behaviour under stress. They also questioned the liquidity spirals, fire sales and capital adequacy pressures, but not the ontological position of the market itself. The market was still conceptualised as a human information-processing mechanism that was temporarily impaired by panic or illiquidity.

With a more critical view, Barlev & Haddad (2003) claim that fair value accounting is not just a neutral measurement device, but it belongs to the wider managerial and institutional power structures. According to their analysis, measurement regimes influence the organisational behaviour and strategic decision-making. This is especially applicable to the modern situation: if the systems of measurement affect the behaviour of organisations, then the market prices that are preset by algorithms can have a recursive effect on the managerial policy, as well as the financial reports. Accordingly, there is no way in which the neutrality of fair value can be assessed free and clear of the social-technical environment where market prices are generated.

2.3 IFRS, Global Harmonization, and Measurement Tensions

With the internationalisation of the International Financial Reporting Standards (IFRS), fair value as a fundamental measurement principle became further established. Ball (2006) points out the strengths and weaknesses of adopting IFRS, stating that although harmonisation can lead to improved comparability, it fails to do away with incentive, enforcement variations, and interpretation discretion. In this global context, fair value is a technical choice of measurement, as well as a governance mechanism integrated into different institutional settings.

The fair value framework under codified by IFRS 13 was exit-based fair value logic. Wage et al. (2017) comment on the impact of IFRS 13 on the UK banking sector concerning the disclosure requirements and hierarchies. The standard institutionalises the use of observable market inputs where possible, which enhances the centrality of market prices in financial reporting.

Nevertheless, the study of the presentation and quality of income statement forecasts (Henry & Yang, 2020) indicates that measurement and disclosure are inextricably linked because the choices of classifications and presentation can affect the quality of interpretability and forecasts. The cross-country evidence also indicates that the degree and use of fair value measurement differ (van Zijl & Hewlett, 2022), meaning that the institutional context can mediate the neutrality rather than the strictly technical requirements. Sellhorn and Stier (2019) conduct a review of the evidence on long-lived operating assets and conclude with mixed implications on reliability and relevance, especially in the absence of active markets.

McDonough et al. (2020) summarize the latest studies and reveal the persistent conflicts in aspects of relevancy,

reliability, and comparability of fair value accounting. Notably, a good portion of this literature still considers market prices as external reference values instead of the outputs of technological mediated infrastructures.

Combined, the theoretical underpinnings of fair value accounting are based on three pillars, including empirical value relevance, procyclicality and volatility debate in crises, and global standard taking under IFRS. However, in these spheres, the objectivity of market price is hardly questioned as a socio-technical form of construct. The literature presumes that the markets are observable benchmarks, although imperfect. The unexplored aspect is the way the changes in market microstructure, especially algorithmic intermediation, can change the informational qualities of such benchmarks.

TABLE 1: Summary of Fair Value Accounting Debates and Empirical Evidence

Study	Context / Setting	Research Focus	Key Empirical or Theoretical Findings	Implicit Assumption About Market Prices	Implications for Neutrality and Integrity
Barth, Landsman, & Wahlen (1995)	U.S. banks; SFAS implementation	Earnings volatility & regulatory capital	Fair value increases reported volatility and affects capital ratios	Market volatility reflects economic reality	Neutrality equated with transparency; volatility treated as informative rather than distortionary
Barth, Beaver, & Landsman (1996)	U.S. banks; SFAS 107 disclosures	Value relevance of fair value disclosures	Fair value estimates are incrementally associated with share prices	Market prices aggregate relevant information efficiently	Value relevance interpreted as evidence of measurement objectivity
Bell et al. (2002)	Software firms; stock option accounting	Valuation implications of accounting recognition	Accounting treatment affects investor valuation judgments	Investors rationally process market-based information	Suggests measurement choices influence valuation but does not question price neutrality
Emerson, Karim, & Rutledge (2010)	Historical review	Evolution of fair value controversy	Recurring debates during instability periods	Market benchmarks assumed fundamentally legitimate	Reveals cyclical trust/distrust in markets but not structural critique of price formation
Valentin & T (2011)	Financial crisis reporting	Impact of crisis on reporting stability	Crisis-induced valuation instability affects financial statements	Market distress seen as temporary dysfunction	Neutrality challenged during crises but not reconceptualized
Leuz (2009)	Crisis-era policy debate	Fair value and systemic risk	Cautions against oversimplified blame on fair value	Markets reflect underlying liquidity conditions	Preserves assumption of price informational content
Laux & Leuz (2010)	Global financial crisis	Procyclicality of mark-to-market	Limited evidence that fair value alone caused crisis	Market illiquidity, not accounting, drives distortions	Neutrality framed as conditional on liquidity
Barth & Landsman (2010)	Financial reporting during crisis	Reporting-market interaction	Financial reporting interacts with investor perceptions	Markets react to accounting signals rationally	Reinforces mutual dependence of reporting and pricing
Barlev & Haddad (2003)	Critical accounting perspective	Managerial implications of fair value	Measurement shapes organizational behavior and incentives	Prices embedded in institutional power structures	Challenges neutrality as socially constructed, not purely technical
Ball (2006)	IFRS adoption globally	Pros and cons of IFRS	Institutional differences affect reporting outcomes	Market efficiency varies by enforcement context	Neutrality contingent on governance quality
Wage et al. (2017)	UK banks; IFRS 13	Impact of exit price framework	Greater reliance on observable inputs and hierarchy disclosure	Observable markets presumed reliable	Neutrality dependent on active market existence

Henry & Yang (2020)	IFRS income statement presentation	Forecasting quality implications	Presentation format influences predictive usefulness	Market users process structured disclosures effectively	Neutrality mediated by presentation and interpretability
van Zijl & Hewlett (2022)	JSE Top 40 firms	Extent and use of fair value	Variation in fair value application across firms	Market comparability assumed but unevenly applied	Institutional variation challenges uniform neutrality
Sellhorn & Stier (2019)	Long-lived operating assets	Evidence on reliability and relevance	Mixed support for fair value reliability in illiquid markets	Active markets required for neutrality	Absence of liquidity undermines measurement objectivity
McDonough, Panaretou, & Shakespeare (2020)	Literature synthesis	Future research in fair value	Ongoing tension between relevance and reliability	Market prices remain primary benchmark	Neutrality remains foundational but increasingly contested

3. ALGORITHMIC FINANCE AND MARKET MICROSTRUCTURE TRANSFORMATION

The financial market's modern architecture is no longer sufficiently characterised by the decentralised synthesis of human convictions. It is becoming a highly technological space where algorithmic agents are competing, interacting and co-creating prices. To the accounting scholarship, and especially in the critical and socio-organisational orientation of accounting, this change demands a conceptual focus on the way that market prices are formed, stabilised, and even perverted in algorithmic infrastructures.

3.1 High-Frequency Trading, Liquidity, and the Reconfiguration of Price Formation

Initial empirical studies included algorithmic trading as a process, which improves the liquidity and informational efficiency. The paper by Hendershott et al. (2011) records that narrower spreads and better liquidity in the NYSE are related to algorithmic trading, which implies the possibility that automation can improve the quality of the market. According to Menkveld (2013), high-frequency traders are described as new market makers whose major contribution is to provide liquidity in fragmented electronic markets. Brogaard et al. (2014) go ahead to state that high-frequency trading also plays a role in price discovery as information is quickly introduced into prices.

Biais et al. (2011) theoretically describe high-frequency trading as the result of strategic interaction and speed competition by having an equilibrium. Algorithmic trading is within the realm of market structure in its paradigm, and in some circumstances, it may increase allocative efficiency.

But these efficiency-based accounts are based on a very restricted definition of liquidity and informational incorporation. They are likely to make the correlation between speed and volume with the quality of information. This story is overshadowed by empirical studies of extreme events. Using the example of the 2010 Flash Crash, Kirilenko et al. (2017) show that automated trading

policies fed on each other in self-reinforcing feedback loops and increased volatility, briefly breaking the linkage between prices and fundamentals. Menkveld & Yueshen (2019) define highly fragmented and automated markets as susceptible to quick liquidity draws, whereby market makers leave at the same time in reaction to algorithmic indications.

These observations imply that liquidity availed by the high-frequency traders can be conditional and pulled back in times of stress. In forming the price, algorithmic reflexivity, then, is not merely a faster way of doing so, but may be destabilising. The epistemic position of price, which is the essence of fair value accounting, is conditional on the stability of technological infrastructures, and not only on scattered human information.

3.2 Market Fragmentation, Technological Arms Races, and Risk Amplification

The technological competition has also altered the market microstructure by fragmentation of trading venues, latency arbitrage and co-location techniques. In their report to Congress, Miller & Shorter (2016) note the issues of speed-based benefits, systemic risk, and regulatory issues that relate to high-frequency trading. The fragmentation makes the process more complex and less transparent in forming prices, as the origin of price formation and localisation becomes hard to track.

The question of fair value reference to a particular market brings about a more problematic question in terms of accounting, though: which market? When prices form at algorithmic venues linked together, where there are heterogeneous latency and liquidity conditions, the assumption of a single, coherent market benchmark is problematic. Collectivisation of several algorithmic order books does not always result in a stable informational equilibrium, but rather it can increase microstructural noise and temporary distortions.

In this way the shift in market microstructure creates a structural conflict between the dependence of accounting on the observation of market prices and the processes

that are becoming more obscure and technologically mediated as the source of such prices.

3.3 Algorithmic Bias, Opaqueness, and the Socio-Technical Construction of Markets

On top of liquidity and volatility issues, normative and technical bias is embedded within algorithmic systems. Zwitter (2014) places Big Data in a larger moral argument, which points to how data-based systems can replicate structural inequalities. Barocas & Selbst (2016) show that even when there is no explicit form of discrimination, the results of algorithmic decision systems may prove disproportionate. Kleinberg et al. (2018) also examine the complexity of constraints of fairness in algorithmic systems, and in this regard, multiple definitions of fairness cannot be reached at the same time. Barocas et al. (2023) build on this discussion, stating that fairness in machine learning is necessarily limited by the design-based trade-offs.

Although most of this literature exists beyond the field of finance, its implications on the system of algorithmic price formation are extensive. Algorithms of financial trading are based on the past data, optimization algorithms and strategic prediction models. Market prices can be biased by systematic errors in case training data encodes structural biases or when optimisation objectives put more emphasis on speed and profit maximisation rather than stability (Sonkavde et al., 2023).

Olorunju (2019) explains that predictive algorithms in legal settings can introduce so-called machine bias and highlights the overall danger of transferring consequential decisions to black box models. Pasquale (2015) frames the concept of algorithmic systems as black boxes, in which proprietary logic prevents any form of open and

transparent decision-making. Diakopoulos (2016) points out the problem of accountability lapse that arises when the automatic systems affect socially consequential results without clear control.

Zuboff (2023, 2024) also applies the analysis to surveillance capitalism, saying that the digital infrastructures are turning the behavioural data into predictive products, and that the informational power is concentrated on the corporate platforms. Her analysis is rather general concerning the idea of digital economies, but it highlights how the development of algorithmic systems transforms institutional authority and knowledge generation.

In the field of finance, the explainability and interpretability of algorithmic models are questioned due to the opaqueness of these models. Černevičienė & Kabašinskas (2024) describe explainable artificial intelligence (XAI) in finance and find that there are long-standing difficulties in explaining complex models. O'Neil (2017) defines an opaque system of algorithms as a weapon of math destruction, highlighting the ability of scale, opaqueness, and feedback loops to cause damage.

When applied to market valuation, these criticisms hint at the likelihood that algorithmically generated prices can reflect model risk, bias in data, and strategic manipulation that are not easily discernible to the outside world. In the case of accounting, it is not a peripheral issue. When the measurement of fair value is based on the prices being generated by opaque algorithmic processes, then the principle of neutrality is not to be assumed, and it should be critically evaluated as a socio-technical finding (Huang & Liu, 2025).

Table 2: Algorithmic Market Features and Risks to Price Integrity in Fair Value Measurement

Algorithmic Market Feature	Key Literature	Underlying Mechanism	Potential Impact on Market Price Formation	Implications for Fair Value Measurement
High-frequency liquidity provision	Hendershott et al. (2011); Menkveld (2013)	Speed-based automated market making and order routing	Narrow spreads in normal conditions; liquidity withdrawal during stress	Increased short-term volatility transmitted into fair value estimates
Algorithmic price discovery	Brogaard et al. (2014); Biais et al. (2011)	Rapid incorporation of information via automated strategies	Acceleration of price adjustment processes	Market price reflects algorithmic processing speed rather than deliberative human assessment
Flash event amplification	Kirilenko et al. (2017); Menkveld & Yueshen (2019)	Self-reinforcing trading loops and synchronized liquidity exits	Extreme, temporary price dislocations	Transitory distortions potentially embedded in reporting dates
Market fragmentation and latency competition	Miller & Shorter (2016)	Multiple trading venues and speed asymmetries	Reduced transparency and coherence of reference prices	Ambiguity regarding which observable market price constitutes fair value
Data-driven model bias	Barocas & Selbst (2016); Kleinberg et al. (2018); Barocas et al. (2023)	Training data limitations and fairness trade-offs	Systematic skew in predictive outputs	Embedded bias within valuation-relevant price signals

Algorithmic opacity ("black-box" models)	Pasquale (2015); Diakopoulos (2016)	Proprietary algorithms and limited transparency	Reduced accountability and interpretability	Difficulty in assessing neutrality of input prices used in fair value hierarchy
Feedback effects at scale	O'Neil (2017); Zuboff (2023, 2024)	Predictive optimization and recursive data extraction	Concentration of informational influence and reinforcement cycles	Structural amplification of distortions affecting financial reporting integrity
Explainability constraints in financial AI	Černevičienė & Kabašinskas (2024)	Complex machine learning architectures with limited interpretability	Incomplete understanding of pricing drivers	Challenges for auditors and standard setters in verifying measurement reliability

4. THEORETICAL TENSION

The theoretical fair value accounting legitimacy relies on a premise that market prices offer a neutral and information-efficient benchmark that is sufficiently useful to measure. Although previous discussions were concerned with volatility and liquidity in stressed market conditions, the algorithmic change of market microstructure brings into being a qualitatively new issue. It is not only a question of whether markets are in a state of illiquidity or cyclical, but whether it is structurally determined by opaque, recursive, and maybe biased algorithmic systems that determine price formation.

4.1 Feedback Loops and the Endogeneity of Price Formation

Price-based traditional finance theory views prices as reflections of diffuse information. But when automated agents interact at extreme speeds in algorithm-dominated markets, prices are increasingly being determined out of interactions between automated agents. Biais et al. (2011) describe high-frequency trading as the result of a strategic competition, in which the speed and information asymmetry determine the trading. Although the model indicates that there is a possibility of efficiency gains, it also means that the price formation is endogenous to algorithmic strategy, and not simply conducive to exogenous information.

This issue is supported through empirical evidence provided by the Flash Crash. Kirilenko et al. (2017) illustrate the interactions between automated trading strategies, which have driven the extreme volatility with no changes in fundamentals, by self-reinforcing feedback loops. Instead of acting as passive mirrors of economic value, algorithmic systems also co-produce price paths. Price is made a recursive product of machine interaction, which is formed by coded rules, optimisation routines, and latency benefits.

This poses a conceptual conflict in the case of fair value accounting. When prices are partly the product of algorithmic reflexivity, in which strategies of trading are driven by signals caused by other trading strategies, then the price ceases to be just an aggregation of independent human judgments. It is a socio-technical artefact that is

created under the influence of strategic automation. Fair value neutrality, therefore, does not necessarily rely on market participation, but on algorithmic interaction architecture.

4.2 Altered Price Discovery and Informational Quality

Advocates of algorithmic trading suppose that swiftness improves price discovery. Brogaard et al. (2014) discovered that the contribution of information in prices is faster through high-frequency traders. However, the speeding up of the information processing does not always mean a better informational quality. Speed can squash reaction times without improving deliberative evaluation. The difference between technological efficiency and informational efficiency comes to the fore.

In cases where the algorithms give priority to short-term predictive signals, order-flow imbalances, or microstructural arbitrage eventualities, the price discovery can be decoupled from longer-term economic fundamentals. When this occurs, fair value measurements based on observable market prices can be associated with microstructural noise and strategy distortions. What has been identified as fair value can portray the competitive speediness as opposed to the actual economic evaluation.

4.3 Fragmentation, Liquidity Withdrawal, and Benchmark Instability

Dividend markets enhance these apprehensions. Menkveld & Yueshen (2019) demonstrate that the highly fragmented and automated markets are more likely to experience liquidity withdrawal swiftly during the stress events. In fragmented systems, liquidity providers can all bow out at the same time in reaction to algorithmic communications, leading to sudden price dislocations. In these circumstances, market price has ceased to be a stable reference point of value and is a temporary agreement between retreating algorithms.

The accounting side of this causes the exit price assumption within fair value systems to be challenging. In the instance where the liquidity situation in two or more trading venues is inconsistent, which price is the orderly transaction benchmark? Fragmentation questions the

assumption of an integrated market price and concentrates on the dependability of the observable inputs into the fair value pyramid.

4.4 Opacity and the Accountability Deficit

In addition to volatility and fragmentation, there is the problem of transparency. Pasquale (2015) characterises algorithmic systems as black boxes, in which proprietary models and trade secrets prevent the decision logic in such systems from being scrutinised. According to Diakopoulos (2016), the problem of accountability is a lack of accountability that emerges with the use of automated systems that affect socially significant outcomes without clear control. Generally, algorithmic trading strategies in financial markets are regarded as confidential, and it is not easy to judge the way price signals are developed.

This obscurity compromises the justificatory pillar of transparency, which is one of the major tenets of fair value accounting. However, the mechanisms behind the observed market prices may be highly unobservable, whereas fair value is based on them. The disconnection between measurement and accountability is formed by the epistemic gap between observable output (price) and unobservable mechanism (algorithmic model). The fair value can look smooth on the surface level, but it can be based on cloudy technological sub-systems.

4.5 Bias Transmission and Structural Inequality

There is also a vulnerability of algorithmic systems to bias in training data, model architecture and optimisation criteria. Barocas & Selbst (2016) reveal the example of how data-driven systems can cause unequal effects without the intention of discrimination. Kleinberg et al. (2018) demonstrate that constraints of fairness in an algorithmic system are trade-offs that are unavoidable, which means that no model may be able to meet all normative fairness requirements at the same time.

Although a significant part of this literature deals with areas like credit scoring or criminal justice, the logic that drives this is applicable to financial markets. Trading algorithms that are conditioned on past value data can copy the structural biases, magnify the momentum effects, or respond more to some signal than to others. In case the biases affect the price curves, fair value measurement becomes a vessel to convey algorithmic bias to financial statements.

O'Neil (2017) claims that unregulated, large-scale, opaque, and algorithmic systems can multiply harm in feedback loops and scale effects. Zuboff (2023) also places algorithmic systems in the context of larger regimes of data capitalism, in which predictive architecture transforms institutional power and knowledge

production. In financial markets, this view implies that algorithmic infrastructures are not neutral technologies, but rather entrenched within incentive systems that serve to give preference to speed, profit and the extraction of data.

The aggregate impact of the feedback loops, speeded up price discovery, fragmentation, opacity, and algorithmic bias is a structural restructuring of the price formation. Market prices are no longer aggregations of dispersed human information; they are co-produced by opaque algorithmic systems that operate within a set of incentive and design constraints (Grace & Friday Okoh Onum, 2025).

This paper is therefore proposing the following core:

The bias of algorithms and structural distortions that appear in the modern market microstructure are inherent in fair value accounting.

This hypothesis does not mean that market prices are generally inefficient. Instead, it questions the unquestioned factor that observable market prices are neutral factors. The concept of neutrality, in algorithmically mediated markets, has to be redefined depending on the technological design, governance of data, and institutions. In the absence of such reconceptualisation, fair value accounting will be vulnerable to passing on algorithmic distortions into the financial reporting in the interest of objectivity.

5. CONCEPTUAL FRAMEWORK: THE ALGORITHMIC FAIR VALUE RISK MODEL

The above discussion indicates that the neutrality of fair value measurement cannot be considered at either the accounting standards or disclosure practices level. It needs to be analyzed on the very level of price making. In furthering this investigation, this section constructs the Algorithmic Fair Value Risk Model (AFVRM)- a conceptual framework that underlines how distortions inherent in the algorithmic market infrastructures can be transferred to the financial reporting and eventually impact the reporting integrity.

This model is based on six connected constructs, which are (1) algorithmic input bias, (2) model opacity, (3) feedback amplification, (4) market price distortion, (5) reporting transmission risk, and (6) erosion of integrity. Collectively, these constructs form a socio-technical route towards the influence of algorithmic finance on accounting outcomes.

5.1 Algorithmic Input Bias

Algorithm systems are trained and optimised based on past data and predetermined goal functions. Barocas et al. (2023) underline that machine learning systems have

limitations and biases in the training data and model structure. Algorithms are discriminatory even without a clear discriminatory intent; the output of algorithms represents the arrangement, choice, and prioritisation of input variables. The existence of fairness trade-offs lies in the fact that fairness normative criteria cannot be fulfilled together when they compete (Barocas et al., 2023).

Moved to financial markets, algorithmic trading methods are based on past price patterns, order flow, volatility and predictive indicators. In case historical data encodes structural market asymmetries, e.g., momentum effects, liquidity concentration, or sectoral bias, algorithms can enhance such behaviours. In this way, systematically distorted price paths incurred through algorithmic interaction can be encoded in data architecture.

In the AFVRM, the bias of algorithmic input is the structural bias that is captured in data selection, modelisation, and optimisation criteria affecting trading behaviour and the formation of prices. This construct is in opposition to the belief that market prices are the aggregation of dispersed human judgments that are neutral.

5.2 Model Opacity

The price-generating mechanisms are always opaque, even in the case of observable price outputs. The idea of algorithmic systems described by Pasquale (2015) as black boxes is reserved by proprietary rights and technical complexity. Opacity restricts the power of external observers such as regulators and auditors to inquire about the process of decision-making.

The algorithmic trading models are not often transparent in the financial markets. Their reasoning is contained within proprietary code, which is coded to be fast and competitive. This opaqueness generates an epistemic imbalance: the accounting standards hold that it is necessary to resort to observable market prices, but the process of pricing the market is highly opaque.

In the AFVRM, model opacity reflects the lack of accountability due to lack of transparency in creation of algorithmic prices. It is a structural impediment to the assessment of market prices on the grounds of neutrality and reliability criteria incorporated in fair value theory.

5.3 Feedback Amplification

Algorithmic systems do not perform on their own. They are dynamic in the way they interact with other automated systems and tend to react to their signals. Kirilenko et al. (2017) show how feedback between high-frequency traders led to extreme volatility in the Flash Crash. Recursive algorithmic responses, instead of fundamental information, only increase price movements in these situations.

Feedback amplification is the process of self-reinforcing dynamics in trading algorithms that act on the price signal produced by other trading algorithms. The result of this recursive process can be fast price overshooting or liquidity withdrawal. Though Hendershott et al. (2011) demonstrate that algorithmic trading can increase liquidity in normal circumstances, it may result in conditional and fragile liquidity in a stressful situation.

Feedback amplification is the mechanism that, in the AFVRM, localised algorithmic biases become amplified to large market price distortions. It translates the micro-level design characteristics into the macro-level pricing impacts (Mansoury et al., 2020).

5.4 Market Price Distortion

Market price distortion does not mean systematic mispricing as compared to intrinsic value. Instead, it refers to fluctuations of price formation which are stable and deliberative, based on algorithmic structures. Price is then sensitive to technological and not informational variables when liquidity is being quickly withdrawn, fragmented across venues and being influenced by latency competition.

Distortion can be in the form of higher volatilities, temporary dislocations, or price trend systematic skewness. In fair value accounting, these signals of prices are directly included in the measurements of balance sheets and income statements. The concept of market price distortion in the AFVRM understands it to be the medium effect of the algorithmic bias, the processes of opacity, and feedback.

5.5 Reporting Transmission Risk

The fair value measurement passes market prices to financial reports. Barth et al. (1995) illustrate the impact of fair value on earnings volatility and regulatory capital. Volatility in the market is captured in the reported earnings and equity when the market prices are not stable.

The AFVRM proposes a new concept called reporting transmission risk that describes how the algorithmically manipulated price signals make it into financial reporting in the form of fair value measurement. This is not a risk of temporary volatility, but the possibility of structural algorithmic biases in the accounting numbers.

When algorithmic amplification or bias are observed in the market prices, it is possible that financial statements are reproducing these distortions under the assumption of objectivity. Volatility, as it is reported out as transmission risk, is therefore more a question of transparency, or rather, contamination.

5.6 Integrity Erosion

The last construct is integrity erosion, which is based on

the critical perceptiveness of Barlev and Haddad (2003), who declare that fair value measurement influences the behaviour of managers and the results of an organisation. In case fair value is seen to be objective with an opaque algorithm underpinning it, trust in this reporting neutrality can eventually degrade.

Loss of integrity does not entail blatant misstatement. It can be achieved by making slight changes in trust, interpretability and accountability. The validity of financial reporting systems can be compromised when there is no way to determine whether artificially low or artificially high prices in the market are caused by structural bias or technological distortion.

5.7 Link to Audit Digitalization and Professional Transformation

The digital transformation of auditing and accounting also overlaps with the AFVRM. The integration of big data opens new possibilities for data analysis and new governance issues (Alles, 2015; Vasarhelyi et al., 2015). It

is also possible that AI-powered auditing systems are more and more based on automated pattern recognition and anomaly detection (Kokina and Davenport, 2017). A recent systematic review by Kassar & Jizi (2026) includes reports on the recent fast proliferation of AI and robotic process automation in the practice of auditing.

Gulin et al. (2019) emphasise the fact that digitalisation is transforming the accounting profession and changing the skills and foundational mechanisms of oversight. However, when auditors are using algorithmically generated market prices without questioning the nature of model structures, digitalisation can recreate instead of reducing algorithmic transmission risk.

Therefore, the AFVRM places fair value accounting in a wider socio-technical ecosystem where there are algorithmic market infrastructures and AI-leveraged auditing practices. According to the model, neutrality in financial reporting is not only dependent on the adherence to the standards, but also on the technological governance on the market and audit grounds.

Table 3: Conceptual Constructs of the Algorithmic Fair Value Risk Model

Construct	Definition	Key Literature	Role in Framework
Algorithmic Input Bias	Structural bias embedded in data selection and model optimization	Barocas et al. (2023)	Origin of potential distortion
Model Opacity	Limited transparency of proprietary trading algorithms	Pasquale (2015)	Reduces accountability and verifiability
Feedback Amplification	Recursive interaction among automated trading systems	Kirilenko et al. (2017)	Scales micro-bias into macro-distortion
Market Price Distortion	Instability or skewness in price formation due to algorithmic structures	Hendershott et al. (2011)	Intermediate outcome affecting valuation
Reporting Transmission Risk	Incorporation of distorted prices into financial statements	Barth et al. (1995)	Channel through which distortion enters reporting
Integrity Erosion	Gradual weakening of confidence in neutrality and objectivity	Barlev & Haddad (2003)	Long-term consequence for reporting legitimacy

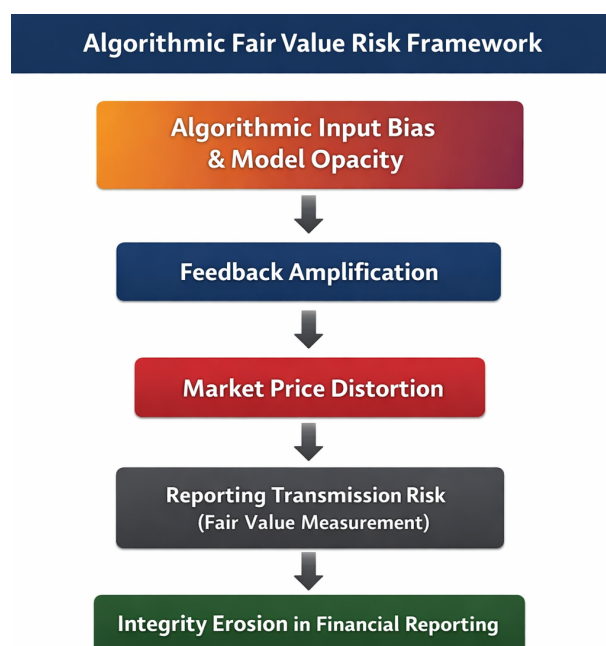


Figure 1: Algorithmic Fair Value Risk Framework

6. IMPLICATIONS FOR ACCOUNTING THEORY AND GOVERNANCE

The above discussion not only has an implication on the method of measurement but also on the very nature of accounting theory. Value relevance evidence has long been used to legitimize fair value accounting (Barth et al., 1996) in which the link to market prices is construed as evidence of the informational utility. Neutrality, however, does not come about through value relevance. It is correlated, but not epistemically independent. When the market prices are determined by obscure algorithmic structures, the argument about objectivity based on market association is theoretically unstable.

When revising the contentious debates surrounding the crisis, Leuz (2009) warns about the easy aetiology of systemic failure of the accounting standards. Even this subtle defence, however, assumes that market prices will show the underlying economic conditions, though under strain. The current structure proposes a more radical change: the concept of neutrality should be redefined as technologically conditional instead of being intrinsically tied to visible prices. The market price can no longer be a social aggregation of dispersed information, but rather a socio-technical product of algorithmic agencies,

proprietary models, and competitive infrastructures that are jointly produced by algorithmic agents and proprietary models.

This reconceptualisation demands a more inclusive concept of socio-technical accountability. Diakopoulos (2016) says that algorithmic systems that affect the consequential outcomes must have mechanisms of transparency, control and explanation. This is obviously the case with the financial markets. However, market prices are generally an exogenous input in the accounting regulation, as opposed to a construct that is technologically mediated. When price formation cannot be scrutinised due to the use of algorithmic opacities, then there is a risk of an accountability gap when these prices are used in financial reporting.

In such a situation, explainability comes into play. According to a document by Černevičienė & Kabašinskas (2024), there are still problems with the implementation of explainable artificial intelligence in the financial industry, which is characterized by tension between the performance and explainability of models. From an accounting governance point of view, the lack of ability to describe pricing mechanisms impairs the ability of the auditors to determine whether observable inputs are

indicative of orderly transactions or algorithmically exaggerated distortions. This casts doubt on the practicability of fair value hierarchies which value observable market data.

The implication goes with international standard setting. Ball (2006) stresses that the success of IFRS requires institutional implementation and incentives. Nonetheless, IFRS frameworks such as the exit price logic incorporated in IFRS 13 implicitly suppose that active markets create credible benchmarks. To the extent to which algorithmic microstructures systematically transform the dynamics of prices, then regulatory frameworks need to revisit the terms and conditions in which market prices might be considered neutral measures of anchoring.

As a result, disclosure reform can be required. The reporting transmission risk could be addressed by providing superior transparency on the liquidity conditions of the market, the existence of algorithmic trading, or the source of volatility. Standard setters might also have to rethink the manner in which the assumptions of orderly transaction are to be operationalised in highly fragmented and automated markets. Without these reforms, the accounting standards will expose themselves to technologically mediated distortions in financial statements in the name of objectivity.

7. CONCLUSION AND RESEARCH AGENDA

The paper has stated that the conceptual basis of fair value accounting needs to be re-examined with regard to algorithmic change in financial markets. The conventional neutrality assumption that observable market prices can be the anchors of objective measurements is based on a perception of markets as an aggregator of dispersed human information. Evidence, however, based on high-frequency trading, market fragmentation and algorithmic feedback loops, suggests that the formation of prices is being mediated to an increasing degree by opaque technological mechanisms.

Its outcome is not always systematic mispricing, but a structural change to the process of price generation. Distortions can be created by algorithmic input bias, model opacity and feedback amplification, and passed on into financial statements via fair value measurement. The fair value neutrality is not absolutely collapsed but made contingent and contingency-based. Observability of the market by itself cannot ensure measurement objectivity in the case of underlying opaque infrastructures that are strategically designed.

This higher conclusion is the necessity of a socio-technical theory of accounting, and a theory that combines financial reporting analysis with technological governance, data ethics, and algorithmic accountability.

Markets will not be exogenous black boxes when accounting uses the results of their operations as input measures of objectivity.

The direction of future research should take a number of directions. Empirically, research might be done to test explicit channels of distortions, testing the fair value volatility or earnings sensitivity of algorithmic trading intensity. Second, qualitative audit case studies may examine how practitioners evaluate algorithmically affected prices in the market through the fair value hierarchy. Third, the response to algorithmic market structures by different IFRS enforcement settings could be compared in cross-jurisdictional research.

Placing the concept of fair value accounting into the changing framework of algorithmic finance, this paper aims to redefine neutrality as a technologically optimistic phenomenon and to invite additional theoretical and empirical analysis of the socio-technical premises of financial reporting integrity.

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