Human Factors, Business Management and Society, Vol. 215, 2026, 253–263
https://doi.org/10.54941/ahfe1007606

Algorithmic Institutional Financial Intermediaries: Formation and Development

Igor Klioutchnikov, Maria Sigova, and Anna Klioutchnikova

International Banking Institute, Saint-Petersburg 191023, Russia

ABSTRACT

Algorithmic systems have transformed financial markets by automating services, driving new business models, and engaging new population segments. These algorithms prioritize service openness, inclusivity, and the removal of human intermediaries from trading and asset management. This study investigates the emergence of algorithmic financial intermediation through institutional, sociotechnical, and network lenses, incorporating the "arrow of time" concept.

Objective: To trace the evolution of algorithmic intermediation as an institutional shift replacing traditional structures. The research examines how integration into online networks and computational optimization shape market dynamics, requiring updated conceptual frameworks for analysis.

Results: The analysis demonstrates the intermediary mission and institutional form of financial algorithms, highlighting their specific influence on user behavior. A system of models characterizing the development of algorithmic intermediation and its market impact is established.

Conclusions: Financial algorithms are defined as intermediation institutions operating within online networks. The study outlines the conditions for their development and their impact on financial inclusion while identifying new challenges and risks that market participants and regulatory authorities must address.

Keywords: Financial algorithms, Financial intermediation, Institutional economics, Social networks, Network theory

INTRODUCTION

Financial algorithms integrated into non-financial networks fundamentally transform the financial industry, influencing the development of social and commercial networks as well as the behavior of internet users. By processing financial data and aggregating external information from social, commercial, and other networks, these algorithms rapidly learn, enabling automated systems to replace financial clerks in service provision to the population.

The integration of financial algorithms into non-financial networks marks a pivotal stage in the fintech revolution (Dong, 2024). This study addresses the resulting shifts in user behavior and the evolution of algorithmic intermediation institutions within these online networks.

Most existing studies of financial markets from a network perspective focus on financial stability and impulse transmission across systems (Gabauer, 2020;

Received February 7, 2026; Revised April 3, 2026; Accepted April 18, 2026; Available online July 20, 2026

Hou et al., 2025; Liu, 2025). This approach facilitates examination of how network connections propagate price shocks and liquidity between markets, as well as the spillover of crises to new markets. While researchers of financial networks emphasize network effects, they often overlook the conditions for forming and scaling new network links and nodes, interactions between financial and non-financial networks, and the embedding of algorithmic financial applications into networks. Nevertheless, inter-network linkages and the integration of financial algorithms into non-financial networks largely define the nature of the contemporary transformation of financial markets.

Institutional economics provides robust tools for analyzing the emergence of algorithmic financial institutions as a pivotal result of integrating financial algorithms into non-financial networks. The methodology and analytical framework of institutional economics enable a comprehensive understanding of the institutional nature of such integration, its market impacts, and effects on network architecture and dynamics. Combined with sociotechnical analysis and methods drawn from the arrow-of-time concept, this opens avenues for formalizing and modeling these processes, allowing simulation of various algorithmic system development scenarios, their external dependencies, and market influences. Grasping these mechanisms is crucial for effective regulation, risk management, and innovation stimulation in the financial sector.

Financial algorithmic systems are advancing and disseminating rapidly yet remain in early stages of implementation and development (Judijanto et al., 2025). Their institutional status has not been fully delineated. Analysis from sociotechnical perspectives and the arrow-of-time concept traces their reliance on the technological shifts and illuminates the irreversibility of algorithmic transformations in financial markets toward algorithmic financial intermediation.

INTEGRATION OF FINANCIAL ALGORITHMS INTO NETWORKS AS A PREREQUISITE FOR ALGORITHMIC INTERMEDIATION

Modern financial intermediation relies on the capacity of networks to function as channels for asset and information transmission (Siedlarek, 2025). The transition from human-centric to algorithmic systems occurs when these computational agents are deeply embedded within social and commercial architectures. This integration removes traditional organizational and sociocultural barriers, allowing universal interfaces to erase the boundaries between fragmented domains.

Practically, this is evidenced in payment systems, crowdfunding, and high-frequency trading (HFT), where automated processes replace manual data collection and decision-making. Such markets increasingly utilize algorithmic agents that interact via price systems, aligning with the Walrasian paradigm and the Arrow-Debreu-McKenzie model (Jukl and Lansky, 2025). By optimizing routes to bypass legacy channels, these agents minimize trading frictions and establish computationally achieved network equilibrium (Bardoscia et al., 2021).

Networks function as institutional structures wherein participant interactions are governed by a combination of formal rules and informal norms (Lazega, 2017). These rules and norms form the basis for integrating financial algorithms into networks and organizing their operations, ensuring predictability and order in relations among diverse actors. Thus, the institutional environment serves as the foundation for financial algorithm functionality.

The institutional nature of financial and non-financial networks manifests, in their capacity to reduce transaction costs through standardization of market participant interactions. The drive to lower costs and scale operations largely determines the prospects for integrating financial algorithms into networks. Standardization of procedures and agreements minimizes the need for continual renegotiation of transaction terms, thereby boosting the efficiency of market operations and reducing expenses on information search, bargaining, contracting, and enforcement.

The system-forming role of institutions in networks involves ensuring interaction stability and minimizing information asymmetry. Moreover, institutions create mechanisms that foster trust among market participants, promote the dissemination of reliable data, and mitigate risks of opportunistic behavior. This strengthens overall system stability (Shahrabi et al., 2025).

Conceptualizing financial algorithms as institutional entities constitutes a critical aspect of understanding modern financial market operations. Networks themselves operate as complex institutional structures, where interactions among participants are shaped not only by formal rules but also by informal norms that play a substantial role. These rules and norms provide a robust foundation for organizing and coordinating activities within networks, guaranteeing predictability and order in relations among investors, creditors, borrowers, and regulators.

Thus, the institutional network environment acts not merely as a backdrop but as a pivotal element shaping the dynamics of financial algorithm operations.

CONCEPTUAL FRAMEWORK OF THE INSTITUTION OF ALGORITHMIC FINANCIAL INTERMEDIATION

The integration of applications with financial algorithms into non-financial networks drives the development of embedded finance, which leverages intra-network and inter-network effects to scale and enhance the efficiency of financial services (Yan et al., 2024). Network analysis makes it possible to identify key nodes in financial, social, and commercial systems, as well as to trace communication channels both within each network and across networks, thereby revealing the impact of integrating financial algorithms into network interactions.

Currently, seamless integration of financial services into non-financial platforms (clusters of major network nodes) is rapidly evolving (Kopperapu, 2025). Under these conditions, algorithmic systems gain the capacity to perform intermediation functions, providing users with additional conveniences such as diversified payment options and personalized financial advice embedded in everyday online communication scenarios.

A deeper understanding of the emergence of algorithmic financial intermediaries requires clarifying how technological processes have led to the formation of new institutions, taking into account the irreversibility of these processes (Gołosz, 2025). Algorithmic financial intermediation (AFI) constitutes a complex system operating on the basis of predefined computational procedures. The key characteristics of an algorithmic financial intermediary include autonomy, adaptability, self-learning, and self-optimization (see Table 1).

This self-organizing capacity is driven by the pursuit of formal economic rationality through systemic calculation. By subjecting financial management to rigorous computational optimization, these algorithms process vast datasets and automate complex operations with minimal human interference. This transition toward algorithmic decision-making prioritizes objective efficiency and control, allowing financial logic to be applied consistently across diverse digital markets without the subjective constraints of traditional human intermediation.

As system-forming elements, algorithmic financial institutions replace physical infrastructure and human agents with automated digital channels, fundamentally restructuring the sector's institutional architecture. These entities act as catalysts, connecting previously fragmented financial and non-financial networks to facilitate novel forms of economic interaction. This evolution creates a hybrid architecture where algorithmic systems coordinate the majority of transactions and redefine governance procedures. In areas like HFT, these systems operate independently, while in others they support human decisions. This results in a new hybrid model of financial intermediation.

ALGORITHMIC FINANCIAL INTERMEDIARIES

Distinctive Features of Algorithmic Financial Intermediaries

Algorithmic financial intermediation is emerging as a fully fledged institution that evolves within the financial system, adapting traditional functions to digital technologies and creating new tools and mechanisms. Its development requires a balance between innovation, regulation, and risk management.

Table 1: Comparative characteristics of traditional and algorithmic intermediaries.

Criteria	Traditional Intermediaries	Algorithmic Intermediaries
Basis of activity	Expert-led, Human management	AI-driven, Automated algorithms, Machine Learning
Speed of operations	Constrained by human capabilities	Near real-time
Data Scale	Analyst-dependent	Large-scale Big Data
Main Risks	Subjectivity, human error	Technical failures, algorithmic errors, systemic risks
Regulation	Classical norms for financial institutions	Special regulations for algorithmic and high-frequency trading

Algorithmic intermediation arises as a response to technological innovations introduced into traditional financial institutions (Table 1). Technological change also brings forth new institutions like fintech firms, algorithmic trading platforms and marketplaces, whose emergence necessitates the design of new formal and informal rules. The economic rationale for these new institutions is primarily linked to cost savings, operational scaling, and profit growth, which give them advantages over traditional institutions and enhance their competitiveness. The state acts as a catalyst for innovation by supporting pilot projects (for example, digital currencies) while simultaneously tightening control.

Dynamics of the Diffusion of Financial Algorithms

The diffusion of financial algorithms across the market can be described by a logistic growth equation with additional technological, regulatory, and cost-related constraints. One key constraint stems from the high energy consumption required to maintain data centres: as energy usage approaches a critical threshold, the further expansion of algorithmic systems slows down. Regulatory barriers and implementation costs also limit the rate of diffusion.

$$\frac{dA(t)}{dt} = k \cdot A(t) \cdot \left(1 - A(t)\right) \cdot \left(1 - \frac{E(t)}{E_{\max}}\right) \cdot R(t) \cdot C\left(I(t)\right) \tag{1}$$

In Eq. (1), $A(t)$ is the automated process share; k is the baseline diffusion rate; $1 - A(t)$ is the saturation effect; $E(t)$ and $E_{\max}$ are current and maximum energy consumption; $R(t) \in [0,1]$ is regulatory freedom; and $C\left(I(t)\right)$ is implementation cost as a quadratic function of investment scale $I(t)$. Parameters $(k, \alpha, \beta, \gamma, \theta)$ are estimated via maximum likelihood or machine learning.

The change in the aggregate state of the market under the influence of algorithms can be written as

$$F(t) = F_0 + \alpha \cdot A(t) - \beta \cdot A(t)^2 + \gamma \cdot \xi(t) \tag{2}$$

where $F(t)$ is a synthetic indicator of market performance (for example, efficiency or stability); F_0 is the initial state; $\alpha > 0$ measures the positive effect of automation through cost reduction; $\beta > 0$ captures the negative effect of market over-saturation with algorithms, such as cascading failures; and $\gamma \cdot \xi(t)$ is a stochastic term representing external shocks, with $\xi(t)$ modelled as Gaussian white noise whose integral generates a Wiener process.

One of the key indicators of market transformation is financial inclusion, captured by an inclusiveness index:

$$II(t) = II_0 + \frac{\tau \cdot A(t)}{1 + \chi \cdot \left(1 - R(t)\right)} \tag{3}$$

where II_0 is the initial level of inclusion; $\tau > 0$ quantifies the effect of algorithmic penetration on access to financial services; and $\chi > 0$ reflects the strength of regulatory constraints. A higher level of algorithmic adoption $A(t)$ tends to improve inclusion, while tighter regulation (a lower value of $R(t)$) dampens this effect.

Taken together, models (1)-(3) incorporate technological limits (energy consumption), regulatory barriers, and social outcomes (financial inclusion). The term $k \cdot A(t)$ corresponds to exponential growth at early stages; the logistic factor $(1 - A(t))$ captures market saturation once most processes have been automated; the factor $(1 - E(t) / E_{max})$ accounts for energy-related frictions; the fraction in (3) reflects the potential improvement in access to services and the dampening role of regulation as $R(t)$ decreases.

At a more general level, the institutional dynamics of algorithmic financial intermediation can be written as

$$\frac{dI(t)}{dt} = f\left(T(t), C(t), I(t)\right) \tag{4}$$

where $I(t)$ denotes the set of institutions governing algorithmic intermediation; $T(t)$ represents technological change; $C(t)$ stands for transaction costs at time t; and $f(\cdot)$ is a (potentially nonlinear) function describing how technology and costs shape the evolution of institutional arrangements.

The diffusion patterns established in this section provide a macro-level navigation, yet they lack explanation of the structural changes occurring within the network. To move beyond mere adoption rates, one must examine the thermodynamic state of the system. The following sections transition to an entropy-based analysis, exploring how micro-scale automated transactions aggregate into the macro-scale institutional irreversibility defined by the Arrow of Time.

COMPARATIVE ANALYSIS OF APPROACHES TO MODELING ALGORITHMIC FINANCIAL INTERMEDIATION

Institutional economics makes it possible to analyze the emergence of algorithmic financial intermediation through the lens of institutional change, transaction costs, and the regulatory environment. Mathematical models help formalize these processes, but they must account for technological factors, behavioral patterns of economic agents, and the accelerated development of algorithms together with their changing position in the overall system.

From a sociotechnical perspective, algorithmic financial intermediation is viewed as a system in which technologies and social structures are interconnected and mutually constitutive. This approach emphasizes that algorithms do not merely automate processes; they transform organizational structures and relationships, business models, participant roles, information flows, and cultural norms in the financial sphere.

The application of methods inspired by the arrow-of-time concept to the analysis of algorithmic financial intermediation makes it possible to trace the irreversibility of change and the dynamics of institutional transformations as old structures are dismantled and new ones formed in a temporally ordered sequence of transformations (Table 2). Unlike static models, the arrow-of-time approach highlights directionality and potential asymmetry of processes, underscoring that a return to a "pre-algorithmic" state is impossible.

Overall, this perspective stresses that algorithmic financial intermediation is not merely a tool facilitating interactions within networks but a new regime of the financial market. This regime reshapes temporal rules by making operations instantaneous and irreversible, executed with computational precision, so that the future is constructed through a sequence of irreversible transformations.

Table 2: Approaches to modelling algorithmic financial intermediation.

Aspect	Institutional	Sociotechnical	Arrow-of-time
Focus	Rules, norms and institutions	Tech-social co-evolution	Path dependency and trajectory
Key Changes	Institution evolution, ↓ transaction costs	Automation, shifting participant roles	Irreversible structural shifts
Key variable	*I(t)* - a set of institutions	*T(t)* - technological changes affecting institutions systems	*H(t)* - historical dependence
Dynamics model	$\frac{dI(t)}{dt} = f\begin{pmatrix} T(t), \\ C(t), I(t) \end{pmatrix}$ *C(t)* - transaction costs, *R(t)* - regulatory changes	$\frac{dS(t)}{dt} = f\begin{pmatrix} T(t), \\ A(t), S(t) \end{pmatrix}$ *S* - system status, *A(t)* - adaptability of agents	$X(t) = h(X(t-1)), \int(t)$ *X(t)* - state of the system at time t, *ε(t)* - exogenous shocks
Target function	$\min C(t)$ s.t. $R(t) \geq R_{\min}$	$\max U(S)$ s.t. $T(t) \leq T_{cap}$	Maintain $H_{stab}(t)$ given H_{hist}
Restrictions & Sustainability criteria	$R(t) \geq R_{\min}$ $R_{\min}$ - regulatory requirements $\frac{dC}{dt} \approx 0$ -cost stability	$T(t) \leq T_{cap}$ T_{cap} - technological limits	$H(t) - H(t-1) \leq \Delta H_{crit}$ ΔH_{crit} - critical growth of entropy
Examples of parameters	C_{reg} - regulation costs, I_{API} - openness index	T_{HFT} - the share of high-frequency trading, A_{adapt} - speed of adaptation of agents	H_{data} - volume of historical data, Δt_{lag} - reaction lag to shocks
Mathematical tool	Optimization, game theory	System Dynamics, Agent-based models (ABMs)	Stochastic differential equations, Markov processes
Forecast horizon	Short/ Medium $t \in [0, T_{reg}]$	Medium $t \in [T_{tech}, T_{evol}]$	Long-term $(t \to \infty)$

(Continued)

Table 2: Continued.

Aspect	Institutional	Sociotechnical	Arrow-of-time
Risks	Inefficient institutions; regulatory gaps $\left(R(t) < R_{reg}\right)$	Cascading failures; technological vulnerabilities $\left(T(t) > T_{cap}\right)$	Information asymmetry; ↑ inequality; entropy collapse $\left(H(t) \to \infty\right)$
The Role of the State	Regulation, enforcement	Support for innovation, infrastructure creation	Formation of a legal framework for new technologies
Examples	Open APIs, RegTech, smart contracts	HFT, robo-advisors, recommendation systems, digital currencies	Forecasting based on historical data

MODEL OF ALGORITHMIC FINANCIAL INTERMEDIATION THROUGH THE LENS OF THE ARROW OF TIME

The arrow-of-time (AoT) concept implies that temporal priority relations constantly arise, some of which persist while others fail in the market (Gołosz, 2025). This perspective can be expressed as a system-state dynamics equation (the "arrow of time" of the system):

$$\frac{dx_i}{dt} = f_{\text{int}}\left(x_i, t\right) + \sum_{j=1}^{N} w_{ij}\left(t\right) g\left(x_j, x_i, t\right) + \sum_{a_k \in A_i} h_k\left(x_i, a_k, t\right) + r_i\left(R, t\right) \qquad (5)$$

Where $f_{\text{int}}\left(x_i, t\right)$ represents internal dynamics (e.g., liquidity depletion); $g(\cdot)$ denotes network contagion and risk propagation; $h_k(\cdot)$ captures algorithmic impacts such as automatic rebalancing; and $r_i\left(R, t\right)$ indicates regulatory constraints, including margin requirements and position limits.

The entropy of an algorithmic intermediary $H(t)$effects the disorder of interactions:

$$H(t) = -\sum_{i=1}^{N} \sum_{j=1}^{N} p_{ij}(t) \ln p_{ij}(t) \qquad (6)$$

where $p_{ij}(t) = \dfrac{w_{ij}(t)}{\sum_{m,n} w_{mn}(t)}$ is the normalized weight of the link between nodes i and j.

An increase in entropy $H(t)$ indicates intensifying micro-chaos (a proliferation of heterogeneous algorithmic strategies), whereas a decrease in $H(t)$ corresponds to the centralization of control.

System stability can be characterized by a stability function $U(t)$:

$$U(t) = \alpha \cdot R(t) + \beta \cdot \left(1 - D(t)\right) - \gamma \cdot Y(t) - \chi \cdot C_{\text{total}}(t) \qquad (7)$$

Here, $R(t)$ is the giant connected component node share; $D(t)$ is the digitization index (the share of algorithmic agents); $Y(t)$ is aggregate computational complexity; $C_{total}(t)$ is the sum of computational costs $\Sigma C_k(t)$; and $\alpha, \beta, \gamma, \chi$ are weighting coefficients.

A higher $R(t)$ and lower $D(t)$ and $Y(t)$ ceteris paribus increase system stability, while higher complexity and costs reduce it.

Irreversibility of transformation is captured by the digitization index $D(t)$, which measures the growth of the share of algorithmic agents in the system:

$$D(t) = \frac{|A(t)|}{|A(t)| + |V(t)|} \tag{8}$$

where $|A(t)|$ is the number of algorithmic agents and $|V(t)|$ is the number of human participants. Once introduced, algorithms do not disappear completely due to network effects and economies of scale, which is expressed as

$$\frac{dD(t)}{dt} \geq 0 \text{ for all } t \geq t_1 \tag{9}$$

This inequality states that, beyond a certain time t_1, digitization is non-decreasing: even if some algorithms are removed, the overall share of algorithmic agents does not revert to pre-algorithmic levels.

A critical point (bifurcation) of the system is associated with a sharp drop in stability when $dU(t)/dt < \theta$, where θ is a negative threshold indicating a loss of resilience.

The system aims to maximize efficiency $E(t)$ under an entropy constraint:

$$\max_A E(t) = \frac{\text{Total profit}}{\text{Transaction costs} + C_{\text{total}}(t)} \quad \text{subject to} \begin{cases} H(t) \leq H_{\max} \\ U(t) \geq U_{\min} \end{cases} \tag{10}$$

where $H_{\max}$ is the admissible entropy level and $U_{\min}$ is the minimum acceptable stability threshold.

The arrow of time defines the direction from past to present to future. First, technological changes $D(t)$ are irreversible; second, structural changes accumulate in the system (new links, rules, and agents); third, entropy $H(t)$ tends to increase, generating potential chaos; fourth, bifurcations may occur when $U(t)$ falls below the critical level; and fifth, systemic complexity $Y(t)$ grows. As a result, the very nature of the system changes, while regulators systematically lag behind innovation.

From an econophysics perspective, entropy production serves as a measure of the correlation between algorithmic financial intermediaries and their broader environment. While micro-level operations (such as transaction reversals, contract cancellation or asset substitutions) may be locally reversible, the aggregate system remains strictly irreversible. This reflects the second law of thermodynamics within a networked environment: as algorithmic systems diffuse, causal relations emerge and solidify, transforming the market's thermodynamic state.

Initial integration phases are characterized by high order and low entropy, but as millions of stable micro-processes accumulate, they drive a macro-level entropy increase. This process creates a "thermodynamic arrow of time" where the future state of the market exhibits high correlation between distant network nodes. Consequently, the institutionalization of financial algorithms is directly tethered to the directionality of network development. In this framework, the future is defined by the transition from human-led exceptions to a state where algorithmic institutions are the systemic norm.

If the arrow of time for the institutionalization of financial algorithms is directly linked to the expansion and integration of new network, then the resulting development follows an irreversible path. The future, by definition, is the transition from a human-centric system with algorithmic exceptions to a state where algorithmic institutions represent the systemic norm.

CONCLUSION

Algorithmic financial intermediation emerges at the intersection of technological innovation, institutional change, and irreversible development processes. Sociotechnical transition provides the technical foundation for automating financial operations, institutional economics determines the rules and mechanisms that sustain system stability, and the arrow-of-time concept highlights the directionality and irreversibility of these transformations. Successful development in this domain requires balancing technological progress with adaptation of the institutional environment, while systematically accounting for historical and social factors.

REFERENCES

Bardoscia, M., Barucca, P., Battiston, S., et al. (2021). The physics of financial networks. *Nature Reviews Physics*, Vol. 3, pp. 490–507.

Dong, P. (2024). Research and analysis of financial crisis prediction model based on the fusion of financial and non-financial data with CSO algorithm. *Academic Journal of Business & Management*, Vol. 6, No. 11, pp. 56–60.

Gabauer, D. (2020). Volatility impulse response analysis for DCC-GARCH models: The role of volatility transmission mechanisms. *Journal of Forecasting*, Vol. 39, No. 5, pp. 788–796.

Gołosz, J. (2025). Does the thermodynamic arrow explain the psychological arrow of time?. *Minds & Machines*, Vol. 35, No. 48.

Hou, Y., et al. (2025). The spillover effect of US monetary policy on the international financial market: Evidence from network analysis. *Journal of Management Science and Engineering*, Vol. 10, No. 1, pp. 111–125.

Judijanto, A. L., Rizani, A. and Devita, H. (2025). Implementation of artificial intelligence in financial crisis early warning system. *International Journal of Social Science Education Communication and Economics (SINOMICS JOURNAL)*, Vol. 3, No. 6, pp. 1737–1744.

Jukl, D. and Lansky, J. (2025). Systematic review on algorithmic trading. *Acta Informatica Pragensia*, Vol. 14, No. 3, pp. 506–534.

Kopperapu, R. (2025). Embedded finance: how non-financial companies are shaping the future of financial services. *Journal of Science and Technology*, Vol. 10, No. 2, pp. 23–38.

Lazega, E. (2017). Networks and institutionalization: A neo-structural approach. *Connections*, Vol. 37.

Liu, X. (2025). Unraveling systemic risk transmission: An empirical exploration of network dynamics and market liquidity in the financial sector. *Journal of Knowledge Economy*, Vol. 16, pp. 6629–6664.

Pazouki, S., Jamshidi, M., Jalali, M. and Tafreshi, A. (2025). Artificial intelligence and digital technologies in finance: a comprehensive review. *Journal of Economics, Finance and Accounting Studies*, Vol. 7, No. 2, pp. 54–69.

Shahrabi, A., et al. (2025). Data-driven stability analysis of complex systems with higher-order interactions. *Communications Physics*, Vol. 8, No. 1, p. 239.

Siedlarek, J. P. (2025). Intermediation in networks. *Economic Theory*, Vol. 79, pp. 1083–1105.

Yan, Y., Hu, Y., Zhou, Q., et al. (2024). Pacer: Network embedding from positional to structural. *Proceedings of the ACM Web Conference 2024*, pp. 2485–2496.