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A Model of the Transition from Human to Algorithmic Decision-Making in the Financial Sector

Igor K. Klioutchnikov[1], Oleg I. Kliuchnikov[2]
Autonomus Nonprofit Organization of Higher Education "International Banking Institute named after Anatoliy Sobchak", St. Petersburg, Russian Federation

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Abstract: This article examines the transition from human to algorithmic decision-making in the financial sector. It demonstrates the potential of algorithmic governance, which is unlocked through the development of financial institutions and algorithms that transform the decision-making process. The article presents a periodization of the development of algorithmic governance in finance and discusses the benefits and challenges associated with this transition. It emphasizes the importance of algorithmic decision-making in the formation of new financial practices and addresses issues of legitimization, institutionalization, and social acceptance. A simplified transition model is presented, illustrating the replacement of human decisions with algorithmic ones in the financial industry. To illustrate this process, dynamic equations are presented for key variables such as F, S, A, and R. It is shown that changes in decision making have led to the development of proactive financial management, which makes extensive use of modern algorithmic systems, including data analysis, risk assessment, and the interaction of financial and non-financial systems, the legitimization of algorithms, and the emergence of algorithmic institutionalism.

1 INTRODUCTION

Algorithmic decision-making processes in the financial sector have recently evolved significantly, revolutionizing management and business operations. The rapid adoption of algorithmic artificial intelligence (AI) systems has enabled financial institutions to significantly reduce the costs associated with decision-making and core management functions. Furthermore, the full potential of data has been unlocked, leading to increased efficiency in financial decision-making. To fully realize the potential of algorithmic decisions and their socioeconomic significance in the financial industry, it is necessary to understand the underlying technologies and sociotechnical and financial processes. Advanced algorithmic technologies open new possibilities for their potential impact on the market and the behavior of market participants.

Financial institutions increasingly rely on AI systems to perform tasks such as reporting and decision-making on key issues. These decisions play a critical role in ensuring the resilience of individual institutions and the financial system. Researchers from various fields, including mathematics, computer science, and sociology, are interested in studying these AI systems and their socioeconomic and financial implications. The success of these systems depends largely on the technologies used to develop solutions. New technologies are not only transforming the way financial institutions operate and make decisions, but also changing the way financial services are provided and business is conducted.

The key aspects of modern algorithmic decision-making include the transformation of management into a computational process and the transition to an automated conveyor system. Predictive algorithms play a significant role in this process, creating the basis for a more manageable and computationally

[1] https://orcid.org/0000-0002-6132-6632
[2] https://orcid.org/0009-0002-9128-0994

efficient future. An important aspect of this transformation is building trust in algorithmic decisions, which is largely achieved through legitimization and positive perception by market participants. The rapid spread of these methods is linked to the institutionalization of algorithms, implying their integration into organizational structures and financial processes.

The process of institutionalizing decision-making involves three key aspects: first, the formalization and integration of algorithms into standard management processes; second, the regulation of the use of algorithms and establishment of accountability for decisions they make; third, the adaptation of stakeholders to algorithmic processes, formalization of algorithm systems as independent market entities, and ensuring their socio-cultural acceptance.

A defining feature of this system is the transition to algorithm-based solutions that compete with human decisions. This paper examines algorithmic decision-making from a socio-technical and financial-economic perspective, allowing us to understand and model it as an institutionalized process in the financial sector.

2 LITERATURE

There is a vast body of literature dedicated to the evolution of financial management (Challoumis, 2024). Researchers examine various aspects of private management, such as risk management, transition to big data-driven management (Malz, 2011), compliance with regulatory requirements (Judiijanto, Kartika, Yusuf, 2023), introduction of distributed ledger technologies (Nzomiwu, Nwobodo, 2024), management specifics in green finance (Wang, Wang, Zhai, 2024), and algorithmic trading (Addy, Ajayi-Nifise, Bello, Tula, Odeyemi, Falaiye, 2024). Bibliometric studies have been conducted to analyze management issues, allowing us to track the main trends in this field (Shi, Ali, Leong, 2025).

Recently, there has been an increasing interest in automating managerial tasks and decision-making processes, as well as integrating algorithmic decision-making into basic financial functions (Thekkethil, Shukla, Beena, Chopra, 2021) and financial event modeling (Chen, Zhou, Li, 2025). In this context, the integration of artificial intelligence (AI) with concepts of trust and reliability presents a significant challenge from a theoretical, empirical, and ethical perspective (Lahusen, Maggetti, Slavkovik, 2024). Researchers are attempting to develop models that can adequately understand the complex dynamics of trust within a socio-technical setting (Liu, Fu, 2024).

Of particular interest is the analysis of the institutionalization of automated trading in financial assets. Researchers are trying to understand why the automation of trading operations and resource allocation necessitates institutionalization and regulatory protection (Arnoldi, 2016). Scientists and practitioners have recently become interested in the overall process of algorithmic system institutionalization (Mendonça, Almeida, Filgueiras, 2024). In this context, special attention has been paid to issues of legitimacy and the institutionalization of algorithmic solutions (Prietl, Raible, 2025). The transition to algorithmic management has led to a new area of research – algorithms as institutions (Almeida, Filgueiras, Mendonça, 2022) – attracting the attention of scholars (Almeida, Mendonça, Filgueiras, 2025). However, there is insufficient attention paid to the transition from human to algorithmic decision-making processes. To our knowledge, there are no comprehensive studies on the decision-making of financial algorithmic institutions. Modeling of the transition from human to algorithmic decision-making in the financial sector is also lacking.

3 STAGES OF THE TRANSITION OF DECISION-MAKING PROCESSES FROM HUMANS TO ALGORITHMIC INSTITUTIONS

Overall, the transition from human decision-making to algorithmic systems in finance is a complex process that requires careful planning and development. It involves the use of advanced technologies and the creation of new structures to ensure the efficient operation of financial institutions.

One of the key aspects of this transition is the automation of routine tasks. This includes the use of data analysis, decision-making algorithms, and machine learning. This improves accuracy and efficiency, reducing the time spent on tasks and minimizing human error risk. Robotic process automation (RPA) and ETL tools are used to consolidate data and make it more accurate. Business intelligence (BI) systems help visualize data. These technologies automate repetitive tasks, providing a more efficient way to manage information. Data consolidation and financial algorithms are also important. They manage various functions and make

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informed decisions based on data. Algorithms help businesses optimize operations and increase profitability.

From a socio-technical perspective, this transition involves the development of new technologies, changes to business processes, and adjustments to the regulatory framework. Data consolidation is achieved through the formation of algorithmic institutional structures that perform management functions.

The transition from human decision-making to algorithms in the financial sector is a gradual process involving several key stages. These stages are associated with technological advances, changes in business processes, and adjustments to the regulatory framework. From a socio-technical and institutional point of view, this transition can be divided into five main stages.

From a socio-technical and institutional perspective, this transition involves five main stages:

The first stage involved the automation of routine financial processes: Systems were implemented to automate repetitive tasks such as data entry, reporting, reconciliation, and asset transfers within the financial institution. Technologies such as robotic process automation (RPA), ETL (extract, transform, load) tools for data consolidation, and BI (business intelligence) systems were used for visualization. This reduced the time spent on routine tasks and reduced the risk of human error.

The second stage involves the implementation of algorithms for data analysis. The advent of advanced algorithmic technologies has made it possible to work more efficiently with big data, leading to the ability to identify patterns more accurately. In lending, new technologies make it possible to assess credit risk by analyzing not only financial indicators but also alternative data, such as social media behavior and utility bills. In trading, algorithms are used for high-frequency trading, arbitrage, and risk management.

The third stage involves the transition to complex AI-based models and systems. Artificial intelligence algorithms become capable of learning and adapting. Neural networks and machine learning methods are used to create generative systems capable of predicting market trends, detecting fraud, providing personalized investment advice, and developing investment strategies based on client data.

The fourth stage involves the legitimization of algorithmic decisions. This stage involves integrating algorithmic solutions into the regulatory framework and strengthening trust in them. As the use of algorithms expands, the need for regulation increases. To address this challenge, countries are implementing standards and regulations aimed at ensuring transparency, security, and preventing discrimination in algorithmic models. For example, Russia has adopted laws on personal data protection and anti-money laundering, which affect the use of algorithms in financial services.

The fifth stage involves the emergence of financial and algorithmic institutions. Specialized organizations and platforms are being formed, based entirely or partially on algorithms. Various electronic platforms, mobile operators, social networks, and messaging apps, as well as Internet of Things devices and smart services, are being developed. The scale, forms, and content of communication are also changing, accelerating the emergence of algorithmic financial institutions.

As data sources expand, messages become more personalized, barriers to entry are lowered, and decision-making cycles accelerate, new interaction formats are emerging, and the roles of participants are shifting. This impacts costs and risks, and ultimately leads to the creation of a unified information space where algorithmic institutions and their financial communications become an integral part of users' everyday digital experiences.

During the institutionalization of financial algorithms, several specialized organizations have emerged - algofunds, RegTech companies that provide risk management solutions, and fintech startups that develop new financial products. Additionally, there are algortraders that rely on solutions related to assessing speculative, fundamental and current price changes. The transfer of decision-making responsibility from humans to machines is part of the technological process and leads to economic benefits. Automation reduces costs, accelerates processes and improves the efficiency of decisions. This transition also enhances the competitiveness of pioneer companies, providing an important incentive for its acceleration.

This transition is accompanied by certain risks and challenges. Among them, the following are notable: first, increased dependence on technology - algorithm failures or cyber-attacks can cause significant financial losses. Secondly, increased pro-cyclicality and volatility - the consistency of algorithms can amplify market fluctuations and lead to sudden crashes. Thirdly, ethical and regulatory concerns - algorithms may be biased or based on incomplete data, necessitating strict control and standardization. Lastly, staff resistance - the shift to algorithmic solutions often faces resistance from employees used to traditional methods.

4 SIMPLIFIED MODEL OF THE TRANSITION FROM HUMAN TO ALGORITHMIC DECISIONS IN FINANCIAL MARKETS

The transfer of financial decision-making from humans to algorithms in the context of financial and social network interactions plays a crucial role in the development of financial algorithms. The mathematical formulation of the shift from human-based to algorithm-based decisions in financial organizations is based on hybrid models that combine dynamic systems (ODEs/SDUs), game theory, multi-agent systems, machine learning, and statistical techniques, as well as network models for interaction graphs. The key components of this formalization process include comparative models of human and algorithmic decision-making, as well as models of system interaction and social-algorithmic decision making.

4.1 The transition from humans to algorithms

The model of transition from human to algorithmic solutions is a hybrid dynamic system with four subsystems: financial networks (*F*), social networks (*S*), algorithmic solutions (*A*), and regulators (*R*). The interaction between these systems leads to the emergence of financial and algorithmic systems as stable structures.

System state vector:

$$X(t) = [F(t), S(t), A(t), R(t)]^T, \quad (1)$$

where *F(t)* is financial indicators (prices, volumes, volatility).

S(t) is social signals (tonality, social media activity, reach).

A(t) is the level of algorithmic activity (share of algorithmic trades).

R(t) is regulatory restrictions/risk metrics.

System dynamics:

$$\frac{dX}{dt} = G(X, t; \theta(t)), \quad (2)$$

where *θ(t)* are the adjustable parameters of the algorithms with the ability to learn.

4.1.1 Decision-making model: human vs. algorithm

a) Human decision. Described as a stochastic choice with cognitive biases:

$$D_h(t) = \mathbb{I}[U_h(X(t), \phi) + \varepsilon_h(t) > \tau_h], \quad (3)$$

where U_h is subjective utility (depends on psychological parameters ϕ);

$\varepsilon_h(t)$ is noise (emotions, limited attention);

τ_h is the activation threshold.

b) Algorithmic solution. Deterministic or quasi-optimal solution:

$$D_a(t) = \mathbb{I}[U_a(X(t), \theta(t)) > \tau_a], \quad (4)$$

where U_a is the algorithm's objective function (e.g., maximizing profitability while limiting risk).

θ(t) are parameters updated online with the ability to use reinforcement learning.

4.1.2 Substitution dynamics: growth of the algorithmic share

The share of algorithmic solutions $A(t) \in [0, 1]$ evolves according to the ODE:

$$\frac{dA}{dt} = k \cdot [Benefit_a(\text{e}) - Benefit_h(t)] \cdot (1 - A(t), \quad (5)$$

where κ is the adaptation rate;

$[Benefit_a]$ *and* $[Benefit_h]$ are the comparative efficiency of algorithms and humans (e.g., by ROI or Sharpe ratio);

($1-A$(t)) is the saturation constraint.

4.2 Interaction and Optimization of Systems

Interaction is built on the "ecosystem principle"—financial services are integrated into non-financial platforms, creating a unified user experience. Key mechanisms for system integration include API gateways and microservices, a single ID and user profiles, end-to-end analytics, and shared processes (from scoring and credit approval at the point of purchase to integrating product insurance into the checkout process).

4.2.1 Model of interaction between financial and social networks

a) Information propagation (reaction-diffusion type equation):

$$\frac{\partial S_i}{\partial t} = a \sum_{j \in neighbours(i)} (S_j - S_i) + \beta \cdot F_i(t) + \gamma \cdot \xi_i(t), \quad (6)$$

where S_i is the social signal of agent i;
α is the diffusion rate across the network;
$\beta \cdot F_i$ is the link to financial data;
ξ_i (t) is external noise.

:

$$\frac{dP}{dt} = \mu P + \eta \cdot \bar{S}(t) + \sigma P dW(t), \quad (7)$$

4.2.2 Optimization of algorithmic behavior

The algorithm selects an action u(t) by maximizing the functional:

$$J = \mathbb{E}\left[\int_0^T e^{-pt}(R(X(t), u(t)) - \lambda \cdot Risk(X(t), u(t))dt\right], \quad (8)$$

subject to constraints: dynamic ($dX / dt = G\ (X, u, t)$) and regulatory ($h\ (X, u) \leq 0$),
where R is the return;
Risk is the risk measure (VaR, CVaR);
ρ is the discount;
λ is the risk weight.

4.2.3 Multi-agent market model

Each agent i (human or algorithm) has: state x_i(t); bias $\pi_i\ (x_i, t;\ \theta_i)$; utility function U_i.

System dynamics:

$$\frac{dx_i}{dt} = f_i\left(x_i, u_i, \{x_j\}_{j \neq 1}, t\right), \quad (9)$$

where $u_i = \pi_i\ (\cdot)$ is the agent's control.

Algorithms can learn from history ($\theta_i \leftarrow$ RL) and/or adapt to the behavior of other agents (π_i depends on $\{\pi_j\}$).

4.2.4 Switching metrics

The following were used to evaluate the process: Algorithmizing index A(t) and Efficiency coefficient: $Eff(t) = \frac{Profitability_{alg}(t)}{Profitability_{hum}(t)}$. The stability and optimization of the system can be determined through the eigenvalues of the Jacobian matrix ∂G/∂X.

4.3 Social Development of Algorithmic Decisions

Social acceptance of algorithmic decisions is a complex process that depends on many factors, including the transparency of algorithms, their impact on society, the level of trust, and criteria for understanding their operation. There is no single universal formula for this process, but key components and models can be identified that help analyze it.

The key factors influencing automated algorithmic decision making include transparency and explainability of algorithms; fairness and lack of bias; participation and oversight by society; alignment with specific norms and values; and the ability to manage risks and consequences.

The following model can be proposed, which reflects social acceptance of algorithmic decisions:

$$Accept(t) = \frac{1}{N}\sum_i^N \mathbb{I}[Trust_i(t) > 0. \quad (10)$$

Social acceptance of algorithmic decisions depends on the complex interaction of technical, social, psychological, and regulatory factors. Successful implementation of algorithms requires considering not only their functionality but also how they are perceived and accepted by society.

4.4 Example of a Simplified Model

Let P(t) be the asset price, A(t) the share of algorithmic trades in the market, and S(t) a social signal influencing the price P. The system of ordinary differential equations is:

$$\begin{cases} \frac{dP}{dt} = (\mu + \eta S(t))P(t) + \sigma P(t) dW(t), \\ \frac{dS}{dt} = -aS(t) + \beta A(t), \\ \frac{dA}{dt} = k(R_a(t) - R_h(t))(1 - A(t)), \end{cases} \quad (11)$$

where R_a, R_h represent the returns from algorithmic and human decisions, respectively.

The proposed system includes dynamic equations for key variables (F, S, A, R), two decision-making models (human and algorithmic), network effects representing the impact of social connections, optimization tasks for algorithms aimed at optimizing interaction with the system, and metrics for the transition from humans to machines. This model allows you to predict the growth of algorithmic trading, assess market stability, optimize algorithm parameters, and analyze the impact of social media.

5 CONCLUSIONS

The transition from human decision-making to algorithmic institutions in the financial sector is a complex process that requires careful balancing of innovation, regulation, and control over financial transactions. The successful implementation of this transition depends on the willingness of companies to embrace change, the development of technology, and adaptation to regulatory requirements.

The interaction of financial and non-financial systems using algorithms leads to the formation of new institutions that make decisions based on data. This data synergy, which combines financial and behavioral metrics, enhances decision accuracy. The resulting flexibility in services allows for personalization in real-time, reducing barriers to access financial services and increasing competitiveness through revenue growth from cross-selling and dynamic pricing.

The transition to algorithmic decision-making in financial management represents a significant shift. This change has led to the emergence of proactive financial management, which makes extensive use of modern algorithms. As a result, predictive models and analytical tools based on data and machine learning have become the foundation for informed decision-making. The fundamental elements of modern algorithmic decision making involve the transformation of control into a computational process and the transition to an automated system. Predictive algorithms play a significant role in this transformation, laying the groundwork for a more rational and computationally efficient future.

A key component of this process is building trust in algorithmic solutions through validating them and receiving positive feedback from market participants. The rapid adoption of these methods is closely linked to the institutionalization of algorithms through their integration into organizational structures and financial processes.

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