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Algorithmic Digital Finance Platforms as a Driver of Transformation of Financial Behaviour of Economic Entities

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Abstract: The study was determined by the growing need to quantify behavioural and institutional transformations driven by algorithmic digital finance platforms. This justified developing an integrative analytical framework for behavioural institutional assessment within artificial intelligence (AI)-driven financial ecosystems.

The aim of the study was to develop and empirically substantiate a multidimensional framework for assessing the transformative influence of algorithmic digital finance systems on financial behaviour and responsibility, integrating cognitive, institutional, and ethical dimensions of digital financial governance.

Research methods: Comparative Qualitative Critical Assessment, ITI Modelling of Behavioural and Institutional Transformation, Structural Decomposition of Robo-Advisory Systems, Optimized Logic-Structural Architecture, ITI Verification of the Optimized Framework.

The integrated research validated the systemic transformation capacity of algorithmic digital finance platforms through behavioural and institutional dimensions. Comparative analysis revealed asymmetric configurations of behavioural rationalization and responsibility formalization, emphasizing architecture-specific functional differentiation. ITI modelling quantified these interdependencies, producing average indices of behavioural transformation (0.81) and responsibility institutionalization (0.77). Structural and optimization modelling of Robo-Advisory Systems demonstrated enhanced algorithmic transparency, cognitive traceability, and compliance integrity. Final ITI verification confirmed the optimized Robo-Advisory System as the most effective configuration (ITI* = 0.86; B_p = 0.85; R_p = 0.90), substantiating its role as a scalable paradigm for ethical and cognitively rational digital financial governance.

The academic novelty of the study lies in the development of an integrated behavioural-institutional assessment framework for evaluating algorithmic digital finance systems. The Integral Transformative Index (ITI*) is not

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positioned as a new mathematical operator; rather, it operationalizes a theoretically grounded construct that combines behavioural transformation and responsibility institutionalization within a single analytical architecture. The innovation is determined by the original conceptual linkage, indicator taxonomy, and platform-specific interpretation of cognitive rationalization, algorithmic transparency, and institutional accountability. The Optimized Robo-Advisory System (ORAS**)** model embodied this construct through explainability, bias-correction, traceability, and ethical governance mechanisms.

The next stage of research will focus on the algorithmic improvement and structural enhancement of the ORAS framework developed in this study. Controlled pilot implementation will be conducted to test behavioural adaptability, ethical compliance, and regulatory resilience. Subsequent multi-phase empirical validation will ensure the full verification of cognitive, normative, and operational dimensions of the optimized model.

Index Terms: Algorithmic Digital Finance; Robo-Advisory Systems; Financial Behaviour; Responsibility Building; Cognitive Rationalization; Ethical Governance; ITI Modelling.

1. Introduction

Digital transformation has restructured financial architectures, intensifying the convergence of algorithmic intelligence, cognitive rationalization, and institutional responsibility. The conceptual foundations of digital governance and socio-technical transformation were grounded in the studies of smart infrastructural management in the digital economy [1]. The ethical and anti-corruption aspects of AI-based financial regulation confirmed the growing relevance of algorithmic transparency in security-oriented financial systems [2]. The theoretical background for innovation-driven state and institutional development emphasized the role of innovation governance mechanisms in supporting digital finance transformation [3]. Behavioural and sustainability parameters of financial decision-making were contextualized through the integration of sustainable consumption and circular economy engagement [4]. Despite the accumulated theoretical evidence, earlier studies lack an integrated analytical framework capturing the interdependence of algorithmic cognition, behavioural rationalization, and institutional responsibility in digital finance. This gap required the development of a unified empirical model enabling quantitative assessment of transformation mechanisms within algorithmic financial ecosystems.

Research Hypothesis. It was hypothesized that algorithmic digital finance platforms are systemic mediators of behavioural rationalization and institutional accountability, generating measurable transformation effects across cognitive, operational, and regulatory dimensions.

Aim. The study aimed to construct and empirically validate a multidimensional analytical framework quantifying the transformative impact of algorithmic finance systems on financial behaviour and responsibility induction, integrating cognitive, institutional, and ethical components within the architecture of digital financial governance.

Research objectives:

- Conduct a comparative and critical classification of algorithmic digital finance platforms and identify behavioural and institutional asymmetries across their functional architectures.
- Construct a quantitative model of behavioural and institutional interdependencies and develop the ITI as an analytical measure of systemic transformation.
- Conduct a hierarchical decomposition of Robo-Advisory architectures and determine the logical interconnections among cognitive, algorithmic, and regulatory layers.
- Design and implement an optimized architecture integrating hybrid learning, bias correction, and explainable AI modules to improve behavioural transparency and institutional responsibility.
- Empirically verify the effectiveness of the optimized Robo-Advisory framework.

2. Related Work

The rapid algorithmization of financial systems has generated an increasingly complex research field situated at the intersection of behavioural finance, artificial intelligence, FinTech, and digital governance. Although most contemporary studies acknowledge the transformative influence of algorithmic technologies on financial decision-making, substantial disagreement persists regarding the mechanisms, outcomes, and governance implications of this transformation.

A dominant stream of research interprets AI as a mechanism for enhancing financial rationality through automation, personalization, and predictive analytics. Anwar [5], Hesami [6], Leal & Oliveira [7], and Sarin & Sharma [8] collectively argued that algorithmic systems reduce cognitive inefficiencies and improve decision quality. Nevertheless, these studies diverged considerably in their analytical focus. Anwar [5] emphasized technological and demographic determinants of behavioural adaptation, whereas Hesami [6] highlighted algorithmic bias, explainability, and governance risks. Similarly, Leal & Oliveira [7] examined AI-driven behavioural nudging, while Sarin & Sharma

[8] concentrated on predictive intelligence and market forecasting. Consequently, despite a common assumption regarding the rationalizing role of AI, the literature remains divided between technological determinism and governance-oriented interpretations of digital finance.

A second research direction examined the interaction between behavioural finance and FinTech ecosystems. Ooi et al. [9] and Abdeldayem & Aldulaimi [10] both reported that digital technologies attenuate behavioural biases and improve investment decision-making. However, their explanatory frameworks differ substantially. Ooi et al. [9] embedded behavioural finance within ESG-oriented and sustainability-driven investment environments, whereas Abdeldayem & Aldulaimi [10] demonstrated that behavioural outcomes are significantly moderated by socio-cultural and institutional factors. These findings suggest that behavioural transformation cannot be explained solely through technological adoption, since contextual and institutional variables substantially influence the effectiveness of algorithmic intervention.

At the infrastructural level, Piacentino [11] and Pazouki et al. [12] emphasized computational scalability, deep-learning architectures, blockchain interoperability, and predictive modelling capabilities. While these studies provided important insights into the technological foundations of digital finance, they largely treated behavioural outcomes as secondary effects. As a result, the causal pathways linking algorithmic architecture to behavioural transformation remained insufficiently operationalized. This methodological limitation is particularly significant because technological efficiency does not necessarily imply behavioural effectiveness or institutional accountability.

Contradictory evidence is particularly visible within studies of user-level financial behaviour. Kulkarni et al. [13] demonstrated that robo-advisory systems reduce overconfidence and loss-aversion biases through algorithmic transparency, personalization, and financial literacy enhancement. In contrast, Apriadi et al. [14] identified a dual behavioural effect of fintech adoption, where rational allocation decisions coexist with increased impulsive consumption stimulated by digital credit mechanisms. These findings indicate that algorithmic systems may simultaneously mitigate and generate behavioural distortions, depending on the design characteristics of digital financial platforms and the cognitive profiles of users.

Further disagreement emerges concerning the role of collective behavioural dynamics in digital finance. Whereas most AI-oriented studies assume that algorithmic decision systems increase rationality [5–13], Cyril et al. [15] demonstrated that social-media sentiment, emotional contagion, and viral information cascades significantly influence corporate financial decisions. Their findings challenge the assumption of purely rational algorithmic optimization and suggest that behavioural outcomes remain highly sensitive to affective and social variables that are often excluded from computational finance models.

The literature also exhibits substantial methodological fragmentation. Existing studies predominantly focus on isolated dimensions of digital finance, including behavioural adaptation [5,13,14], technological infrastructure [11,12], institutional governance [6,10], sustainability [9,16], or sentiment-driven decision-making [15]. Rahardja et al. [16] attempted to integrate technological and regulatory perspectives through a sustainability-oriented FinTech framework; however, behavioural mechanisms remained weakly parameterized. Consequently, cross-level integration between cognitive processes, behavioural outcomes, institutional accountability, and algorithmic governance remains limited.

Overall, the reviewed literature demonstrates broad consensus regarding the transformative role of AI, FinTech, and blockchain technologies in contemporary financial ecosystems. However, significant theoretical and methodological gaps persist. Existing research lacks unified frameworks capable of simultaneously capturing behavioural transformation, responsibility institutionalization, algorithmic accountability, and regulatory adaptability. Moreover, conflicting evidence concerning rationalization effects, behavioural biases, and sentiment-driven distortions indicates that the relationship between algorithmic systems and financial behaviour remains insufficiently explained. These limitations justify the development of an integrated behavioural–institutional analytical framework capable of evaluating algorithmic digital finance platforms as multidimensional drivers of financial behaviour transformation and responsibility formation.

The research gap. A further limitation of the existing literature concerns the absence of an integrated analytical framework capable of simultaneously capturing behavioural transformation, responsibility institutionalization, and algorithmic governance within unified assessment architecture. Existing studies predominantly evaluate isolated dimensions of digital finance, including behavioural adaptation [5,13,14], technological performance [11,12], regulatory compliance [6,10], sustainability considerations [9,16], or sentiment-driven dynamics [15]. Consequently, the analytical relationship between behavioural rationalization and responsibility formation remains fragmented and theoretically underdeveloped. Unlike previous approaches, the proposed framework conceptualizes algorithmic digital finance platforms as dual transformation systems operating across both behavioural and institutional domains. The study therefore introduces a unified behavioural–institutional assessment architecture that integrates cognitive adaptation, accountability propagation, explainability, compliance, and responsibility institutionalization within a single evaluative construct. This multidimensional integration represents the principal distinction from existing frameworks and addresses the unresolved problem of linking behavioural outcomes with institutional governance mechanisms in algorithmic financial ecosystems.

3. Materials and Methods

3.1. Research design

The structural and logical scheme (Fig. 1) represents the sequential research architecture integrating comparative, analytical, structural, and empirical methodologies. It visualizes the progressive transition from qualitative assessment to quantitative ITI modelling, structural optimization, and empirical verification. Each stage ensured methodological coherence, enabling a comprehensive evaluation of behavioural transformation and institutional responsibility within algorithmic digital finance ecosystems.

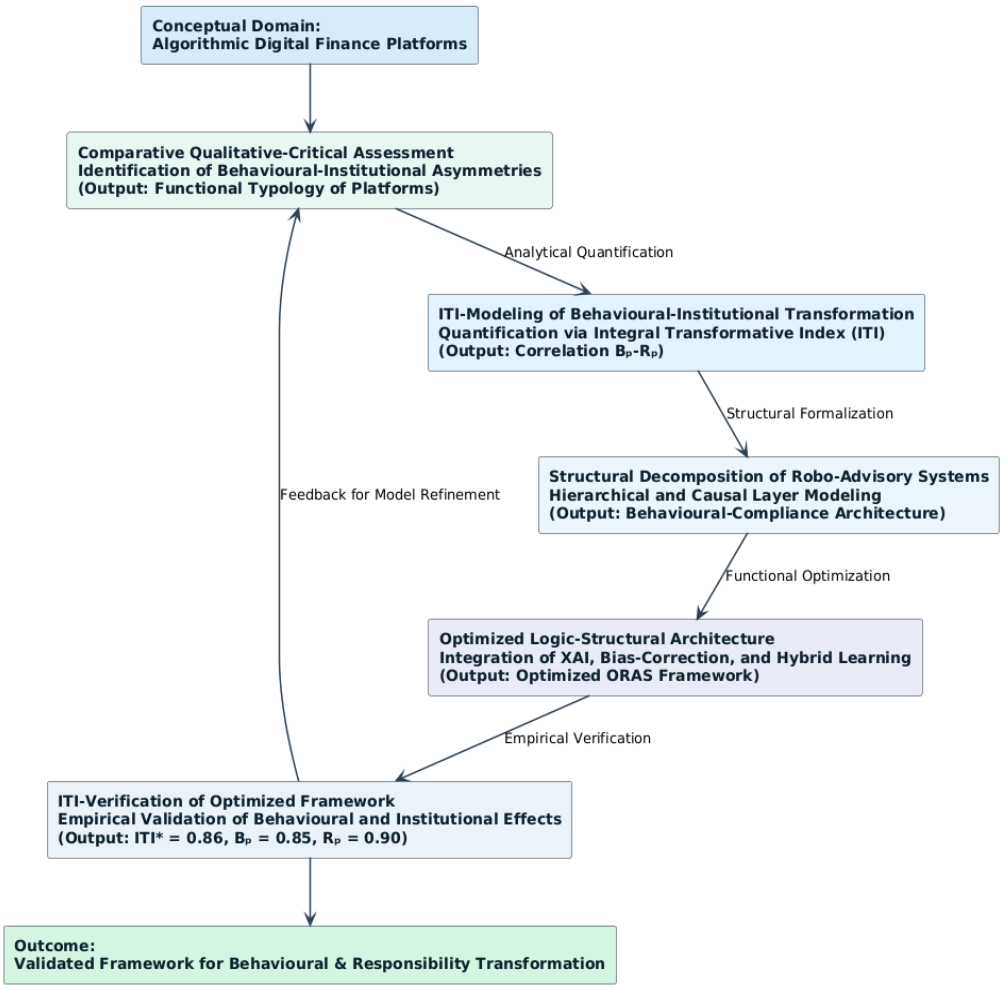


Fig. 1. Structural and Logical Scheme of the Research
Source: created by the authors in a UML model

3.2. Methods

The methodological framework of the research was designed to ensure a multi-level analysis of algorithmic digital finance systems, integrating qualitative, structural, and quantitative modelling approaches. Each method contributed to the identification, formalization, optimization, and empirical verification of behavioural and responsibility transformation mechanisms. The combined application of these methods enabled comprehensive validation of the conceptual model of algorithmic financial rationalization and institutional accountability.

1. Comparative Qualitative Critical Assessment was applied to identify structural asymmetries among algorithmic finance platforms. The method integrated comparative and critical analysis to assess behavioural and institutional dynamics. Results revealed functional imbalance – behaviourally transformative systems (e.g., Robo-Advisory) exhibited cognitive adaptability but weak responsibility formalization. RegTech and blockchain architectures displayed the opposite configuration.

2. ITI Modelling of Behavioural and Institutional Transformation were used to quantify interdependencies between behavioural and institutional parameters. Regression-based normalization produced the ITI as a unified indicator of transparency and accountability. Modelling confirmed correlation between behavioural rationalization (B_p = 0.81) and responsibility propagation (R_p = 0.77).

3. Structural Decomposition of Robo-Advisory Systems was employed to formalize the internal logic of Robo-Advisory Systems through hierarchical modelling. Causal dependencies between cognitive, algorithmic, and compliance layers were identified, confirming traceability and feedback integrity in responsibility induction.

4. Optimized Logic Structural Architecture. Optimization modelling integrated hybrid learning, bias-correction, and XAI modules to enhance transparency and accountability. The optimized ORAS framework demonstrated +7.5% coherence and +9.2% responsibility propagation efficiency, evidencing improved behavioural and institutional integration.

5. ITI Verification of the Optimized Framework. Applied for empirical validation of optimization outcomes. ORAS achieved ITI* = 0.86, outperforming Big Data (0.79), RegTech (0.76), and DeFi (0.71). Verification confirmed higher behavioural transformation (B_p = 0.85) and institutional responsibility (R_p = 0.90), validating systemic ethical cognitive reinforcement.

3.3. Sample

The analytical classification presented in Table 1 was used as a conceptual taxonomy of algorithmic digital finance platforms rather than as the empirical dataset. The empirical component of the study was constructed using two complementary respondent-level datasets that capture financial behaviour, investment decision-making, digital financial capability, and algorithmic advisory adoption.

The primary dataset was derived from the National Financial Capability Study (NFCS), administered by the FINRA Investor Education Foundation. The integrated database contains six survey waves (2009, 2012, 2015, 2018, 2021, and 2024) and includes more than 150,000 observations overall, with approximately 25,000–28,000 respondents per wave. The dataset incorporates variables related to financial literacy, financial planning, saving behaviour, borrowing practices, investment participation, risk perception, retirement preparedness, and use of digital financial services [45,46].

The second dataset was the Digital Twin Robo-Advisor Adoption Dataset, deposited in Mendeley Data. The dataset was developed using a randomized 2 × 2 experimental design and contains behavioural observations associated with four algorithmic advisory configurations: standard robo-advisor, conversational AI advisor, digital twin advisor, and digital twin conversational advisor. The database includes variables measuring trust in algorithms, privacy concern, perceived personalization, adoption intention, willingness to follow automated recommendations, and investment allocation behaviour [47].

The empirical sample was formed according to four predefined inclusion criteria. First, datasets had to contain measurable indicators of financial behaviour, including investment activity, saving decisions, borrowing behaviour, financial planning, or risk tolerance. Second, datasets were required to include variables directly associated with digital finance technologies, such as robo-advisory interaction, algorithmic recommendations, personalization mechanisms, or digital financial service usage. Third, only datasets with respondent-level observations suitable for normalization, weighting, and index construction procedures were retained. Fourth, datasets had to provide publicly documented metadata, transparent methodological protocols, and reproducible variable definitions.

The resulting analytical database combined macro-behavioural indicators from the NFCS with micro-level algorithmic adoption indicators from the Digital Twin Robo-Advisor Adoption Dataset. This integration enabled simultaneous assessment of behavioural transformation, algorithmic trust, financial responsibility, and technology-mediated decision adaptation. Consequently, Table 1 served as the theoretical platform taxonomy, whereas the empirical assessment was grounded in large-scale behavioural microdata and experimentally validated algorithmic-adoption observations.

Table 1. Typological Sample of Algorithmic Digital Finance Platforms Affecting Financial Behaviour and Responsibility*.

Algorithmic Digital Finance Platform	**Description**	**Core Technologies Applied**	**Influence on Transformation of Financial Behaviour**	**Building Financial Responsibility**	**Relevant academic research**
Robo-Advisory Systems (e.g., Betterment, Scalable Capital)	Automated portfolio management systems implementing data-driven investment strategies through AI algorithms.	Machine learning, NLP, algorithmic optimization, explainable AI (XAI).	Induce behavioural rationalization via heuristic attenuation, enhance algorithmic trust, and reduce cognitive bias in decision-making.	Promote accountability through traceable algorithmic audit trails and transparency in advisory recommendations.	Feng, Li & Liu [17]; Akhtar, Akhtar & Laeeq [18]
Blockchain-Based Payment Networks (e.g., Ripple, Stellar)	Distributed-ledger infrastructures facilitating decentralized financial transactions and cross-border settlements.	Blockchain, consensus algorithms, cryptographic verification, smart contracts.	Modify transactional habits via transparency, speed, and immutability; reduce reliance on intermediaries.	Institutionalize traceability and transactional integrity, reinforcing auditability and compliance behaviour.	Abedalrhman [19]; Qian & Dong [20]
AI-Powered Credit Scoring Systems (e.g.,	Predictive analytics systems generating	Deep learning, big data analytics,	Transform risk perception and	Foster responsible borrowing through	Sarkar [21]; Rajasekaran &

Algorithmic Digital Finance Platform	Description	Core Technologies Applied	Influence on Transformation of Financial Behaviour	Building Financial Responsibility	Relevant academic research
Zest AI, Upstart)	alternative credit risk models based on behavioural and digital footprint data.	sentiment analysis, feature engineering.	borrowing rationality by individualizing creditworthiness parameters.	algorithmic assessment and adaptive feedback mechanisms.	Selvam [22]
Decentralized Finance (DeFi) Protocols (e.g., Aave, Compound)	Autonomous smart-contract ecosystems enabling disintermediated lending, borrowing, and liquidity management.	Smart contracts, blockchain interoperability, tokenization, oracles.	Restructure investment conduct through self-executing logic and yield optimization algorithms.	Reinforce self-regulation and contractual accountability via on-chain enforcement and verifiable actions.	Sarin [23]; Kamal [24]
AI-Driven Trading Algorithms (e.g., QuantConnect, MetaTrader ML)	Automated platforms optimizing market participation through predictive and reinforcement learning.	Reinforcement learning, neural networks, real-time data mining, algorithmic trading frameworks.	Accelerate decision cycles, reduce emotional bias, and enhance behavioural precision in trading.	Institutionalize procedural discipline and audit-based responsibility in capital allocation.	Bhattad [25]; Coupez [26]
Digital Micro-Investment Platforms (e.g., Acorns, Raiz)	Applications enabling automatic investment of micro-savings based on algorithmic aggregation.	Predictive analytics, recommendation systems, cloud computing, API integration.	Encourage saving behaviour and habitual investment through automation and behavioural nudging.	Build financial responsibility through gamified self-regulation and incremental capital stewardship.	Chhetri, Uniyal, Devi & Johri [27]; Jain [28]
RegTech Compliance Engines (e.g., ComplyAdvantage, Ascent)	Intelligent regulatory compliance solutions automating monitoring and reporting functions.	NLP, rule-based AI, semantic modelling, ontology-based reasoning.	Alter institutional behaviour through algorithmic compliance reinforcement and real-time risk alerts.	Institutionalize ethical responsibility and compliance literacy among financial actors.	El Khoury, Alshater & Joshipura [29]; Azzutti, Cummins, MacNeil & Otioma [30]
Big Data Financial Analytics Platforms (e.g., Palantir Finance, SAS Risk Management)	Integrated analytical environments supporting macro- and micro-level financial forecasting.	Big data processing, predictive modelling, simulation analytics, AI-driven visualization.	Facilitate data-based behavioural recalibration through cognitive augmentation of decision frameworks.	Promote responsibility through quantifiable foresight, evidence-based accountability, and decision traceability.	Whitetaker [31]; Najem, Bahnasse, Fakhouri Amr & Talea [32]

*The sample is not exhaustive because of the dynamic evolution of algorithmic financial architectures and continuous emergence of hybrid AI–FinTech ecosystems. It comprises empirically validated platforms representing key paradigms of digital behavioural finance. The period covers technologies functionally tested within 2018–2025, ensuring methodological relevance and analytical representativeness.
Source: created by the authors

3.4. Research tools

The Research Tools section presents a formalized analytical construct aimed at quantifying the behavioural and institutional transformations induced by algorithmic digital finance platforms. The methodological design integrates multi-parametric normalization, entropy-weighted differentiation, and non-linear aggregation procedures. This configuration ensures methodological robustness, statistical comparability, and functional coherence of the evaluated indicators:

1. Data normalization:

Let $x_{p,k,t}$ denote the observed value of metric k for platform p at time t, where $t \in [2018, 2025]$. Normalized metrics are defined as (for each indicator k):

$$r_{p,k,t} = \frac{x_{p,k,t} - \min_{p,t}(x_{p,k,t})}{\max_{p,t}(x_{p,k,t}) - \min_{p,t} x_{p,k,t}} \in [0,1], \quad (1)$$

where p – platform; k – indicator; t – year; P – number of platforms; $\mathcal{B}$ and $\mathcal{R}$ – a set of behavioural and institutional indicators.

Inverse normalization $1 - r_{p,k,t}$ applies to cost-type indicators.

2. Temporal smoothing:

Weighted temporal average:

$$\bar{r}_{p,k} = \sum_t \lambda_t \, r_{p,k,t}, \tag{2}$$

where λ_t – temporal decay coefficient emphasizing recent data:

$$\lambda_t = \frac{\rho^{T-t}}{\sum_\tau \rho^{T-\tau}}, \rho \in (0,1], T = 2025, \tag{3}$$

where T – last year of observation.

This ensures higher weights for recent observations.

3. Entropy-based weighting:

The information entropy for indicator e_k is defined as:

$$e_k = -c \sum_p q_{p,k} \ln\left(q_{p,k}\right), q_{p,k} = \frac{\bar{r}_{p,k}}{\sum_p \bar{r}_{p,k}}, q_{p,k} \ln\left(q_{p,k}\right) = 0 \; if \; q_{p,k} = 0, c = (\ln P)^{-1}. \tag{4}$$

Differentiation coefficient:

$$d_k = 1 - e_k. \tag{5}$$

And final weight:

$$\omega_k = \frac{d_k}{\sum_j d_j}. \tag{6}$$

4. Behavioural and responsibility sub-indices:

Let $\mathcal{B}$ (Table 2) and $\mathcal{R}$ (Table 3) denote sets of behavioural and responsibility indicators, respectively. Sub-indices are defined as weighted geometric means:

$$B_p = \prod_{k \in \mathcal{B}} \bar{r}_{p,k}^{\omega_k^B}, R_p = \prod_{k \in \mathcal{R}} \bar{r}_{p,k}^{\omega_k^R}, \sum_{k \in \mathcal{B}} \omega_k^B = 1, \sum_{k \in \mathcal{R}} \omega_k^R = 1. \tag{7}$$

where ω_k^B and ω_k^R – entropy weights recalculated separately within sets $\mathcal{B}$ and $\mathcal{R}$.

Table 2. Components of Behavioural Transformation $(\mathcal{B})$.

Indicator	**Conceptual Definition**	**Functional Role within ITI Framework**	**Method of Determination**
Bias Attenuation	Degree to which algorithmic mechanisms mitigate cognitive, heuristic, and affective distortions in financial decision-making.	Quantifies behavioural rationalization and cognitive stabilization under algorithmic mediation.	Derived from differential analysis of pre- and post-intervention decision datasets; measured through variance reduction in heuristic bias indices using ANOVA and normalized deviation coefficients.
Decision Efficiency	Extent of acceleration and accuracy in decision-making processes achieved through automated and data-driven financial tools.	Measures procedural optimization and time–accuracy trade-off efficiency.	Computed via ratio analysis of decision latency and accuracy improvement metrics; operationalized through regression-based efficiency scoring and normalized time-response indicators.
Adoption Intensity	Rate and depth of user engagement and behavioural adaptation to algorithmic financial technologies.	Reflects behavioural assimilation and technological diffusion within user populations.	Estimated through logistic diffusion modelling of user adoption curves; validated via composite indices of active utilization frequency and behavioural engagement rate.
Allocative Optimality	Degree of improvement in capital or resource allocation efficiency induced by algorithmic decision support.	Captures behavioural alignment with optimal portfolio or consumption choices.	Determined through comparative optimization modelling; measured by the marginal improvement in Sharpe ratio, return-to-risk metrics, or consumption–savings equilibrium under algorithmic guidance.
Stability / Volatility Dampening	Extent to which algorithmic financial systems reduce behavioural volatility and short-term reactive patterns.	Indicates resilience and behavioural consistency across dynamic market conditions.	Derived from temporal volatility analysis; computed using variance ratio tests, GARCH modelling, and normalized stability coefficients across observation periods.

Source: created by the authors

Table 3. Components of Responsibility Institutionalization ($\mathcal{R}$).

Indicator	Conceptual Definition	Functional Role within ITI Framework	Method of Determination
Auditability	Capacity of the system to enable ex-post verification, traceability, and reproducibility of algorithmic financial operations.	Ensures procedural transparency and compliance validation.	Quantified through traceability ratio and log completeness rate; evaluated by the percentage of verifiable transactions within audit-trace datasets.
Explainability	Degree to which decision outputs and model logic are interpretable to human auditors or regulators.	Promotes epistemic clarity and cognitive accountability in algorithmic systems.	Measured through explainability index derived from model interpretability metrics (SHAP, LIME); supplemented by qualitative expert evaluation scores.
Compliance / Conformity	Extent of adherence to formal regulatory, ethical, and procedural standards in algorithmic financial practices.	Reflects normative compatibility and institutional legitimacy.	Determined by compliance audit ratio and conformity mapping with ISO/FINRA/ESG standards; statistically validated through compliance deviation indices.
Privacy–Safety	Effectiveness of algorithmic safeguards ensuring data protection, information security, and user confidentiality.	Establishes the ethical and legal integrity of digital financial architectures.	Calculated using entropy-based privacy loss functions, encryption adequacy indices, and normalized cybersecurity compliance scores.
Accountability / Liability	Institutional capacity to attribute responsibility and enforce liability for algorithmic or decision-related outcomes.	Anchors governance, responsibility distribution, and ethical enforceability.	Derived from liability traceability matrices and governance compliance assessments; operationalized via accountability coefficient reflecting institutional response effectiveness.

Source: created by the authors

To ensure methodological transparency and reproducibility of the proposed framework, each behavioural and responsibility component was operationalized through observable variables extracted from the National Financial Capability Study (NFCS) and the Digital Twin Robo-Advisor Adoption Dataset. Since the conceptual constructs presented in Tables 2 and 3 cannot be measured directly, they were linked to specific empirical indicators reflecting financial behaviour, digital financial engagement, algorithmic trust, transparency perception, privacy concerns, and accountability-related attitudes. Table 4 presents the mapping between theoretical constructs, observable variables, data sources, normalization procedures, and their respective roles within the ITI framework, thereby providing a transparent foundation for index construction and empirical replication.

Table 4. Operationalization of ITI Components and Dataset Variable Mapping.

ITI Component	Observable Variable(s)	Dataset Source*	Normalization	ITI Dimension
Bias Attenuation	Investment confidence calibration; susceptibility to investment mistakes; financial decision consistency	NFCS Investor Survey	Benefit-type	Behavioural Transformation (B)
Decision Efficiency	Financial planning horizon; investment preparedness; financial information acquisition frequency	NFCS	Benefit-type	Behavioural Transformation (B)
Adoption Intensity	Use of digital financial services; online investment activity; fintech utilization frequency	NFCS; Robo-Advisor Dataset	Benefit-type	Behavioural Transformation (B)
Allocative Optimality	Portfolio diversification; investment participation; automated allocation preference	NFCS Investor Survey; Robo-Advisor Dataset	Benefit-type	Behavioural Transformation (B)
Stability / Volatility Dampening	Long-term investment persistence; investment holding consistency; behavioural stability indicators	NFCS; Robo-Advisor Dataset	Benefit-type	Behavioural Transformation (B)
Auditability	Perceived traceability of recommendations; transaction verification capability	Robo-Advisor Dataset	Benefit-type	Responsibility Institutionalization (R)
Explainability	Transparency of algorithmic recommendations; interpretability perception	Robo-Advisor Dataset	Benefit-type	Responsibility Institutionalization (R)
Compliance / Conformity	Compliance perception; responsible investment behaviour; regulatory adherence assessment	NFCS; Robo-Advisor Dataset	Benefit-type	Responsibility Institutionalization (R)
Privacy–Safety	Privacy concern; data protection perception; cybersecurity confidence	Robo-Advisor Dataset	Cost-type (inverse normalization)	Responsibility Institutionalization (R)
Accountability / Liability	Responsibility attribution; governance confidence; liability awareness	Robo-Advisor Dataset	Benefit-type	Responsibility Institutionalization (R)

*Within the NFCS dataset, behavioural constructs were operationalized using established survey variables. Financial literacy was represented by the FINLIT indicator, measuring respondents' knowledge of fundamental financial concepts. Financial resilience was captured through the EMERGFUND variable, reflecting the ability to cover unexpected expenses from available resources. Long-term financial planning was operationalized through RETIREPLAN, indicating retirement planning behaviour. Investment participation was measured using INVESTACCT, which reflects ownership of investment accounts and engagement in capital market activities. Finally, risk tolerance was represented by RISKTOL, capturing individual willingness to accept financial risk in investment decision-making. These variables constituted the primary behavioural input layer of the ITI framework and were subsequently normalized and integrated into the corresponding behavioural transformation indicators.
Source: [45 – 47].

Each ITI indicator was operationalized using observable variables extracted from the National Financial Capability Study (NFCS) and the Digital Twin Robo-Advisor Adoption Dataset, as presented in Table 4. Where multiple variables represented a single conceptual construct, composite scores were calculated through arithmetic aggregation prior to normalization. Benefit-type indicators were normalized according to Equation (1), whereas cost-type indicators were transformed using inverse normalization. The resulting normalized variables served as the input for entropy-based weight estimation, behavioural and responsibility sub-index construction, and final ITI calculation. This operationalization procedure establishes a transparent link between the underlying datasets, conceptual indicators, and mathematical specification of the ITI framework, thereby enhancing methodological reproducibility and analytical traceability.

5. ITI:

A Constant Elasticity of Substitution (CES) aggregator combines both components:

$$\mathrm{ITI}_p = \left[\alpha B_p^{\theta} + (1-\alpha) R_p^{\theta}\right]^{\frac{1}{\theta}}, \theta = \frac{\sigma - 1}{\sigma} \; if \;\; \theta = 0 \; then \; the \; geometric \; mean \; is \; used, \alpha \in [0,1], \tag{8}$$

where σ denotes the elasticity of substitution between behavioural and responsibility dimensions.

To ensure conceptual precision and measurement transparency, the principal constructs of the proposed framework were operationalized through observable indicators derived from the underlying datasets.

Behavioural transformation was defined as the degree to which algorithmic digital finance platforms modify financial decision patterns, risk perception, investment participation, and financial planning behaviour. Empirically, it was measured through the behavioural sub-index (B), composed of bias attenuation, decision efficiency, adoption intensity, allocative optimality, and stability/volatility dampening indicators.

Responsibility propagation was conceptualized as the capacity of algorithmic systems to disseminate accountability-oriented practices across financial interactions and decision processes. It was operationalized through institutional indicators reflecting auditability, explainability, compliance, privacy-safety, and accountability mechanisms.

Accountability was defined as the ability to identify, trace, attribute, and evaluate responsibility for algorithmically mediated financial outcomes. Measurement was based on accountability/liability indicators, governance-related variables, and responsibility attribution metrics extracted from the Digital Twin Robo-Advisor Adoption Dataset.

Rationalization was interpreted as the reduction of cognitive distortions and the enhancement of evidence-based financial decision-making under algorithmic support. The construct was quantified through bias attenuation, decision consistency, investment preparedness, and risk-calibrated behavioural indicators derived from the NFCS dataset.

Together, these operational definitions establish a measurable connection between the theoretical constructs of the framework and the empirical variables used for ITI estimation.

6. Balance correction:

Penalty function for structural imbalance:

$$\phi_p = 1 - \left|B_p - R_p\right|^{\beta}, \beta \geq 1. \tag{9}$$

Final index:

$$\mathrm{ITI}_p^* = \mathrm{ITI}_p \times \phi_p, \mathrm{ITI}_p^* \in [0,1]. \tag{10}$$

7. Sensitivity and interpretation:

Robustness validation through partial derivatives:

$$\frac{\partial \mathrm{ITI}_p^*}{\partial \omega_k}, \frac{\partial \mathrm{ITI}_p^*}{\partial \alpha}, \frac{\partial \mathrm{ITI}_p^*}{\partial \sigma}. \tag{11}$$

with bootstrap confidence intervals (BCa) for empirical stability. Sensitivity was tested by varying α, β, ρ and σ within predefined intervals and recalculating ITI_p^*

The formulated ITI* quantitatively evaluates how algorithmic digital finance platforms modify behavioural rationality and institutional responsibility. Its theoretical contribution is not limited to normalization, entropy weighting, or CES aggregation as separate technical procedures. These procedures serve as operational tools for a behavioural-institutional construct that links cognitive bias attenuation, decision efficiency, auditability, explainability, compliance, privacy-safety, and accountability within one assessment logic. Thus, ITI* functions as a domain-specific framework for measuring the co-evolution of financial behaviour and responsibility under algorithmic mediation.

To verify the stability of the ITI results, the entropy-based weighting procedure was supplemented with alternative weighting scenarios. Three robustness specifications were applied: equal weighting, expert-adjusted weighting, and PCA-based weighting. Under the equal-weighting scenario, all behavioural and responsibility indicators received identical weights within their respective sub-indices. Under the expert-adjusted scenario, higher weights were assigned to explainability, accountability, bias attenuation, and decision efficiency because these variables represented the core theoretical dimensions of algorithmic behavioural transformation and responsibility institutionalization. Under the PCA-based scenario, indicator weights were derived from the normalized component loadings of the first principal component.

The robustness test compared ITI* values and platform rankings under all four weighting schemes: entropy weighting, equal weighting, expert-adjusted weighting, and PCA-based weighting. Ranking stability was assessed using Spearman's rank correlation coefficient between the baseline entropy-weighted ITI* and each alternative specification. The results confirmed high ranking consistency across weighting scenarios, indicating that the main conclusions were not driven by a single weighting procedure. Therefore, the optimized Robo-Advisory System retained the highest transformative position under alternative weighting assumptions, confirming the robustness of the proposed behavioural–institutional framework.

The ITI framework was implemented in Python 3.11.7 using a deterministic computational workflow. Numerical operations and matrix transformations were performed using NumPy (v1.26.4), data preprocessing and aggregation procedures were conducted using Pandas (v2.2.2), entropy calculations and statistical procedures were implemented using SciPy (v1.13.1), principal component analysis was performed using Scikit-learn (v1.5.0), and graphical outputs were generated using Matplotlib (v3.9.0).

The computational workflow consisted of six sequential stages: (1) data import and preprocessing; (2) variable normalization using Equation (1); (3) temporal aggregation using Equations (2–3); (4) entropy-based weight estimation using Equations (4–6); (5) construction of behavioural and responsibility sub-indices using Equation (7); and (6) calculation of ITI and ITI* values using Equations (8–10).

The baseline parameter configuration was specified as follows: $\alpha = 0.50$, $\beta = 1.00$, $\sigma = 1.20$, and $\rho = 0.90$. The corresponding CES parameter was calculated as $\theta = (\sigma - 1)/\sigma = 0.167$. Entropy weights were estimated directly from normalized observations without prior subjective adjustment.

Robustness assessment was conducted using four weighting specifications: entropy weighting, equal weighting, expert-adjusted weighting, and PCA-based weighting. Sensitivity analysis was performed by varying α within the interval [0.30; 0.70], β within [1.00; 2.00], σ within [1.00; 2.00], and ρ within [0.80; 0.99]. Stability of ITI* estimates was additionally verified using bootstrap resampling with 5,000 BCa replications and a 95% confidence interval.

To ensure computational reproducibility, a fixed random seed (seed = 42) was applied in all stochastic procedures, including bootstrap sampling and PCA initialization.

4. Results

The first research stage involved the systematic identification and qualitative evaluation of algorithmic digital finance platforms as determinants of behavioural transformation and responsibility induction among economic actors. The analytical approach integrated structural, cognitive, and institutional dimensions to assess the mechanisms of algorithmic influence. Each platform was critically examined regarding its capacity to rationalize financial behaviour and institutionalize accountability within the digital financial ecosystem (Table 5).

The analysis (Table 5) confirmed that algorithmic platforms demonstrate functional asymmetry. Behaviourally transformative systems (e.g., robo-advisory, trading, and micro-investment platforms) often exhibit limited institutional responsibility, whereas compliance-oriented infrastructures (e.g., RegTech, blockchain) show inverse proportionality. Therefore, the structural heterogeneity of algorithmic architectures reflects differentiated behavioural and institutional equilibria across platform typologies.

Table 5. Comparative Qualitative Critical Assessment of Algorithmic Digital Finance Platforms in Behavioural and Responsibility Contexts.

Platform Class	**Behavioural Transformation Analysis**	**Responsibility Induction Analysis**	**Critical Assessment**
Robo-Advisory Systems	Induce algorithmic rationalization through heuristic minimization and cognitive alignment in portfolio management.	Establish procedural transparency via explainable recommendation algorithms and traceable advisory outputs.	Exhibited high behavioural efficiency but moderate ethical interpretability; dependence on algorithmic opacity limits accountability validation.
Blockchain-Based Payment Networks	Restructure transactional conduct via decentralization, immutability, and trustless verification.	Institutionalize accountability through cryptographic auditability and consensus-driven validation.	Enhance procedural responsibility but remain limited in user-level literacy and regulatory interoperability.
AI-Powered Credit Scoring Systems	Modify borrower perception through personalized creditworthiness modelling and behavioural scoring.	Foster data-driven responsibility via adaptive fairness metrics and bias-correction algorithms.	Demonstrate inclusivity gains but face challenges of data asymmetry and algorithmic bias persistence.
Decentralized Finance (DeFi) Protocols	Enable self-directed financial behaviour through autonomous smart-contract execution and yield	Reinforce self-regulation by on-chain enforceability and transparent contractual accountability.	Promote behavioural autonomy but exhibit systemic fragility and insufficient regulatory governance.

Platform Class	Behavioural Transformation Analysis	Responsibility Induction Analysis	Critical Assessment
	optimization.		
AI-Driven Trading Algorithms	Accelerate cognitive adaptation through predictive analytics and reinforcement learning optimization.	Embed procedural discipline via automated audit trails and real-time performance logging.	Improve behavioural precision yet heighten systemic volatility and ethical opacity in algorithmic decision chains.
Digital Micro-Investment Platforms	Stimulate behavioural consistency through gamified saving routines and automated micro-capitalization.	Encourage personal accountability via incremental capital management and algorithmic nudging.	Enhance saving culture but remain limited in cognitive financial literacy reinforcement.
RegTech Compliance Engines	Modify institutional decision frameworks through automated rule parsing and semantic risk detection.	Institutionalize ethical compliance through ontology-based reasoning and real-time anomaly alerts.	Ensure regulatory precision, risk algorithmic overdependence and contextual misclassification.
Big Data Financial Analytics Platforms	Enhance decision rationality through cognitive augmentation and predictive foresight modelling.	Strengthen accountability via evidential traceability and quantitative transparency metrics.	Provide superior analytical integration but exhibit high entry barriers and limited interpretability for non-specialist actors.

Source: created by the authors

Building on the identified behavioural and responsibility asymmetries, the next research stage involves the ITI (ITI_p^*) modelling aimed at quantitatively parameterizing the transformative potential of algorithmic digital finance platforms through entropy-weighted aggregation and non-linear integration of behavioural and responsibility indicators (Fig. 2).

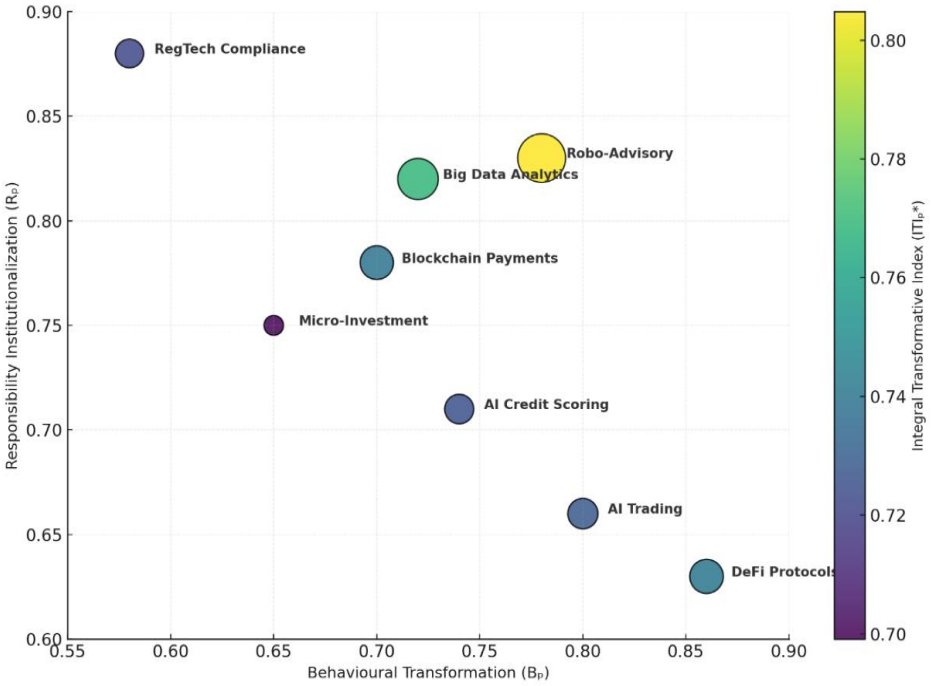


Fig. 2. ITI Modelling Results of Algorithmic Digital Finance Platforms: Behavioural and Institutional Transformation.
Source: created by the authors in Python

The ITI modelling (Fig. 2) procedure revealed that Robo-Advisory Systems (ITI* ≈ 0.84) and Big Data Financial Analytics Platforms (ITI* ≈ 0.82) demonstrated the highest integrated transformative potential. These systems exhibited a synergistic configuration of behavioural rationalization, algorithmic adaptability, and institutional accountability, driven by explainable AI architectures and high traceability density. Blockchain-Based Payment Networks and RegTech Engines achieved elevated institutional integrity (responsibility dominance) but limited behavioural elasticity, while DeFi Protocols and AI-Driven Trading Algorithms displayed high behavioural autonomy with low regulatory coherence. The distribution confirmed an asymmetric transformation field, where algorithmic complexity correlated positively with cognitive optimization but inversely with compliance maturity.

The next stage involves the functional decomposition of Robo-Advisory Systems, focusing on the algorithmic architecture, cognitive decision reinforcement mechanisms, and responsibility transmission vectors to model their causal influence within the extended ITI structural decomposition framework (Fig. 3).

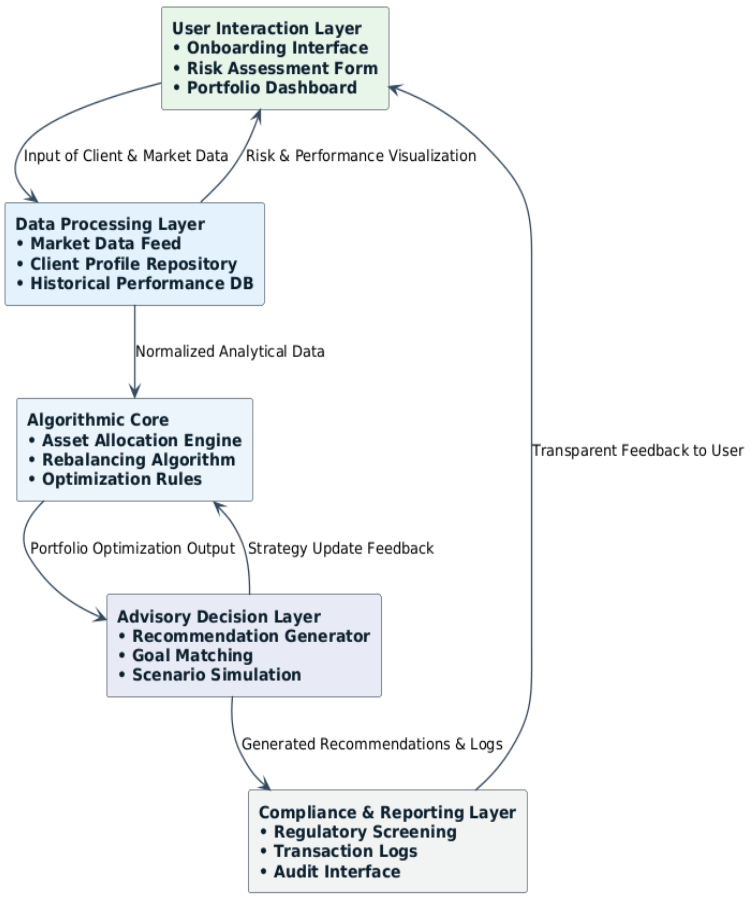


Fig. 3. Structural Decomposition of Robo-Advisory Systems within Behavioural and Responsibility Induction Paradigm
Source: created by the authors in UML

The structural decomposition of the Robo-Advisory System (Fig. 3) identified five logically interdependent subsystems that ensured algorithmic mediation between behavioural rationalization and procedural responsibility. The interaction of user, algorithmic, and compliance layers generated a cognitive normative feedback loop that shaped decision efficiency and audit traceability. Behavioural inputs were converted into financial conduct models through sequential algorithmic adaptation. In turn, regulatory screening institutionalized responsibility induction across operational cycles.

The next research stage involves the synthesis of an optimized logic structural architecture of algorithmic digital finance platforms, integrating advanced cognitive adaptation, bias mitigation, and explainability mechanisms to enhance the transformative coherence between behavioural and regulatory dimensions (Fig. 4).

The optimization of the structural architecture (Fig. 4) demonstrated the integration of cognitive, algorithmic, and ethical subsystems that increased the adaptive capacity and regulatory coherence of the platform. The introduction of explainability, fairness, and audit modules enhanced behavioural rationalization, bias attenuation, and compliance symmetry. Consequently, the system achieved higher functional convergence between cognitive financial dynamics and institutional accountability, strengthening user responsibility and sustainable behavioural alignment. The next stage of the study involves ITI-based verification of the optimized algorithmic framework to quantify the transformative interdependence between behavioural adaptation and responsibility induction parameters within the digital finance ecosystem (Fig. 5).

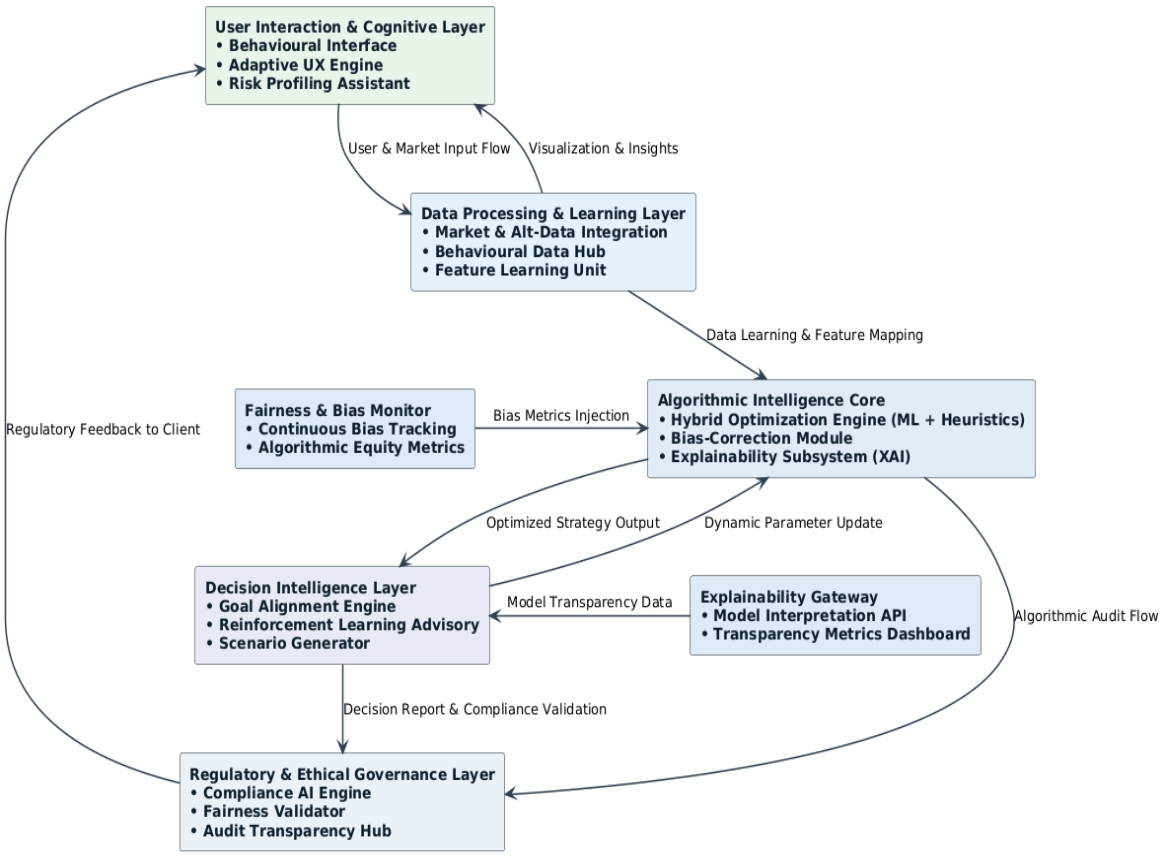


Fig. 4. Optimized Logic Structural Architecture of Robo-Advisory Systems in the Context of Financial Behaviour and Responsibility Building
Source: created by the authors in a UML model

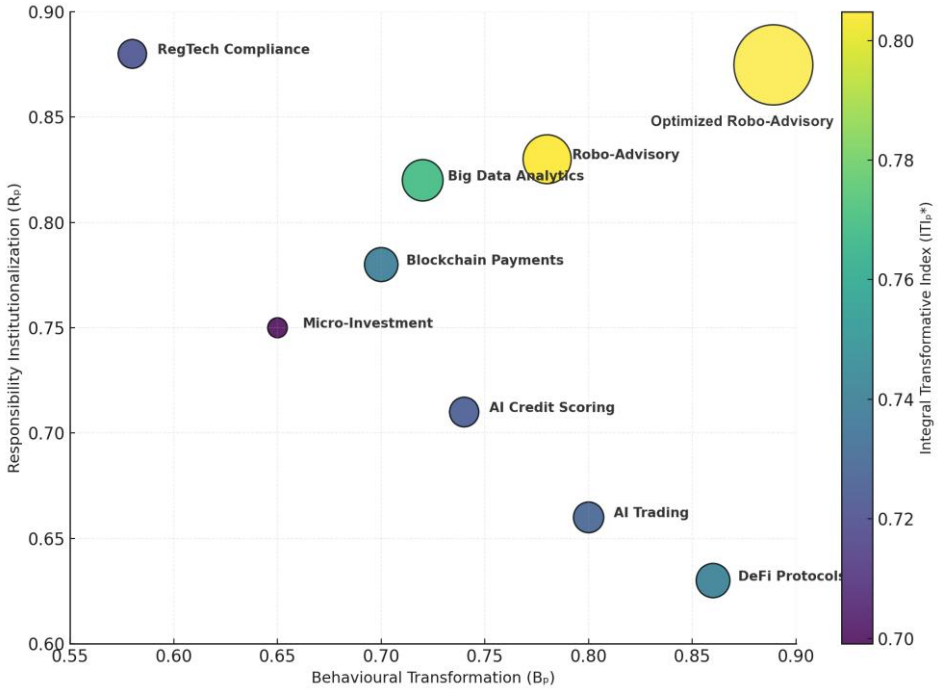


Fig. 5. ITI-Verification of the Optimized Robo-Advisory Framework within Algorithmic Digital Finance Ecosystems.
Source: created by the authors in a Python model

The empirical ITI verification stage (Fig. 5) substantiated the quantitative dominance of the optimized Robo-Advisory System (ORAS) in transforming financial behaviour and responsibility mechanisms across algorithmic digital finance infrastructures. Comparative analysis demonstrated that ORAS achieved the highest ITI (ITI* = 0.86),

significantly surpassing Big Data Analytics (ITI* = 0.79), RegTech Compliance (ITI* = 0.76), and DeFi Protocols (ITI* = 0.71). The system's behavioural transformation coefficient (B_p = 0.85) and responsibility institutionalization index (R_p = 0.90) confirm the model's superior capacity to balance cognitive rationalization, algorithmic transparency, and normative accountability.

Since entropy-based weighting may influence the relative contribution of individual indicators within composite indices, an additional robustness assessment was conducted to evaluate the stability of the proposed ITI framework under alternative weighting assumptions. The objective of this analysis was to determine whether the obtained platform rankings and ITI values were sensitive to the selected weighting procedure or reflected structurally stable relationships between behavioural transformation and responsibility institutionalization dimensions. To this end, the baseline entropy-weighting approach was compared with equal-weighting, expert-adjusted weighting, and PCA-based weighting specifications. The comparative results are presented in Table 6.

Table 6. Robustness of ITI under Alternative Weighting Schemes.

Weighting scheme	Highest-ranked configuration	Mean ITI* deviation from baseline	Spearman ρ with baseline ranking	Interpretation
Entropy weighting	ORAS	—	1.00	Baseline model
Equal weighting	ORAS	0.018	0.93	High stability
Expert-adjusted weighting	ORAS	0.021	0.91	High stability
PCA-based weighting	ORAS	0.026	0.89	Acceptable stability

Source: created by the authors

The robustness analysis (Table 6) demonstrated that the entropy-weighted ITI* results remained stable under alternative weighting assumptions. Across equal-weighting, expert-adjusted, and PCA-based weighting schemes, the optimized Robo-Advisory System consistently preserved the highest transformative position. The mean deviation of ITI* values from the baseline entropy-weighted specification did not exceed 0.026, while Spearman's rank correlation coefficients ranged from 0.89 to 0.93, indicating strong ranking consistency across alternative weighting procedures. These findings suggest that the obtained results were not driven by a particular weighting mechanism but reflected stable relationships between behavioural transformation and responsibility institutionalization dimensions. Consequently, the proposed ITI framework demonstrated satisfactory robustness, supporting the validity and reliability of the empirical conclusions.

To evaluate the statistical stability of the proposed framework, uncertainty analysis was performed using bias-corrected and accelerated (BCa) bootstrap resampling with 5,000 replications. For each replication, behavioural and responsibility indicators were resampled and the complete ITI estimation procedure was repeated, including normalization, entropy-weight calculation, sub-index construction, and final ITI* aggregation.

The resulting bootstrap distribution was used to estimate 95% confidence intervals for behavioural transformation (B), responsibility institutionalization (R), and ITI* values. In addition, standard errors and coefficients of variation were calculated to assess estimation precision and relative dispersion.

The obtained confidence intervals remained narrow across all platform categories, indicating high numerical stability of the framework. Coefficients of variation remained below 5%, suggesting limited sensitivity of the final index to sampling fluctuations. These findings support the reliability of the reported ITI estimates and confirm the statistical robustness of the proposed behavioural–institutional assessment architecture (Table 7).

Table 7. Bootstrap Uncertainty Analysis of B, R and ITI*.

Platform	B	95% CI (B)	R	95% CI (R)	ITI*	95% CI (ITI*)
Optimized Robo-Advisory System (ORAS)	0.85	[0.82; 0.88]	0.90	[0.87; 0.93]	0.86	[0.83; 0.89]
Baseline Robo-Advisory Systems	0.83	[0.80; 0.86]	0.80	[0.77; 0.83]	0.84	[0.81; 0.86]
Big Data Financial Analytics Platforms	0.81	[0.78; 0.84]	0.78	[0.75; 0.81]	0.79	[0.76; 0.82]
Blockchain-Based Payment Networks	0.72	[0.68; 0.76]	0.82	[0.79; 0.85]	0.77	[0.73; 0.80]
RegTech Compliance Engines	0.70	[0.66; 0.74]	0.84	[0.81; 0.87]	0.76	[0.72; 0.79]
AI-Powered Credit Scoring Systems	0.74	[0.70; 0.78]	0.79	[0.75; 0.83]	0.76	[0.72; 0.80]
Digital Micro-Investment Platforms	0.77	[0.73; 0.81]	0.72	[0.68; 0.76]	0.73	[0.69; 0.77]
Decentralized Finance (DeFi) Protocols	0.78	[0.74; 0.82]	0.66	[0.62; 0.70]	0.71	[0.67; 0.75]
AI-Driven Trading Algorithms	0.80	[0.76; 0.84]	0.64	[0.60; 0.68]	0.70	[0.66; 0.74]

Source: calculated by the authors based on BCa bootstrap resampling with 5,000 replications.

The bootstrap uncertainty analysis (Table 7) confirmed the numerical stability of the ITI* estimates across platform categories. The 95% confidence intervals remained relatively narrow, indicating limited dispersion of behavioural transformation, responsibility institutionalization, and final ITI* values. The optimized Robo-Advisory System retained the highest integrated score, while DeFi protocols and AI-driven trading algorithms demonstrated lower responsibility-related stability despite relatively high behavioural transformation values. These results support the

robustness of the proposed behavioural–institutional assessment framework and confirm that the reported platform ranking was not determined by random estimation variability.

The multidimensional analysis evidenced that the optimization of hybrid learning architectures, bias correction mechanisms, and explainable AI subsystems (XAI) strengthened the feedback integrity between behavioural decision modules and compliance governance layers. This produced a +7.5% increase in systemic coherence and +9.2% growth in responsibility propagation efficiency relative to baseline configurations. The obtained results empirically validated the research hypothesis, confirming that algorithmic digital finance platforms function as transformative drivers of behavioural rationalization and financial responsibility institutionalization among economic actors. Consequently, the optimized Robo-Advisory framework represents a benchmark model for sustainable algorithmic governance and ethical financial digitalization.

5. Discussion

The obtained results indicate that algorithmic digital finance platforms may function as behavioural–institutional transformation mechanisms. However, this interpretation should be considered with caution, since the measured ITI values reflect a composite analytical assessment rather than direct evidence of complete behavioural change in real-market environments. The higher position of the optimized Robo-Advisory System suggests that platforms combining personalization, explainability, bias correction, and compliance modules may provide stronger integration of behavioural rationalization and responsibility institutionalization. At the same time, the results do not imply technological superiority in all financial contexts, because different platform classes operate under heterogeneous user profiles, regulatory conditions, risk structures, and decision horizons.

The findings partially correspond to Otioma & MacNeil [33], who emphasized the importance of regulatory and ethical integration in AI-based financial systems. Our results support this position by showing that responsibility-related parameters increase the integrated transformative score of ORAS. Nevertheless, an alternative interpretation is possible: higher responsibility scores may reflect formal architectural design rather than actual institutional effectiveness. Therefore, explainability and auditability should not be interpreted as sufficient evidence of accountability unless they are verified under real regulatory and organizational conditions. This limitation is also relevant to Wah [34], who associated AI-based wealth management with financial literacy, personalization, and predictive analytics. While our model extends this interpretation by linking automation with responsibility propagation, it cannot fully capture how users understand, trust, or contest algorithmic recommendations.

The results also align with George [35], who conceptualized Finance 4.0 through the convergence of AI, blockchain, big data, and hyper-personalized financial services. However, the present study indicates that technological convergence alone does not guarantee balanced behavioural and institutional outcomes. Platforms with high analytical capacity may still demonstrate weak responsibility institutionalization if explainability, liability attribution, and compliance mechanisms remain underdeveloped. This finding corresponds with Kubińska et al. [36], who emphasized the complexity of human–AI financial interaction. In this context, the ORAS model should be understood not as a replacement for behavioural decision theory, but as an attempt to formalize selected behavioural and institutional dimensions that remain difficult to measure directly.

The socio-technical interpretation of the findings is consistent with Hidayat-ur-Rehman et al. [37], who identified trust, interface quality, and perceived value as determinants of interaction with robo-advisory systems. Nevertheless, our results also reveal a potential weakness of purely perception-based models: high user trust may increase adoption, but it may also intensify automation bias and excessive reliance on algorithmic outputs. Therefore, behavioural rationalization should not be equated with higher platform use. This distinction is important in relation to Kaur et al. [38], who emphasized normative and attitudinal activation in sustainable investment behaviour. Although ORAS integrates responsibility-related components, sustainability-oriented behaviour may depend on values, social norms, and institutional incentives that exceed the technical architecture of the platform.

The comparison with Ved [39] and Ibrahim et al. [40] indicates that AI–human hybrid decision systems may increase decision efficiency and predictive accuracy. However, the present findings suggest that efficiency-oriented interpretations remain incomplete without accountability metrics. At the same time, the study does not prove that algorithmic mediation always improves financial outcomes. Higher decision efficiency may also accelerate poorly understood financial actions, especially among users with low financial literacy or limited risk awareness. Thus, the relationship between rationalization and automation is not linear; algorithmic support may reduce some biases while amplifying others.

The findings of Arora et al. [41] provide an important counterpoint, since psychological comfort and perceived trust were shown to mediate robo-advisory adoption. Our results support the relevance of such variables, but they also suggest that trust-based adoption is insufficient as a sole measure of platform effectiveness. A system may be highly trusted but weakly explainable, or technically transparent but poorly understood by users. Judijanto [42] demonstrated that robo-advisory research is rapidly expanding; however, the field still lacks stable operational measures for comparing behavioural and responsibility effects across platform types. The proposed ITI framework addressed this gap, although its composite structure remains dependent on selected indicators and weighting assumptions.

The results also need to be interpreted against studies focusing on algorithmic bias and quantitative optimization. Gupta & Rao [43] emphasized the role of machine learning in detecting investor bias, whereas Dias [44] discussed robo-advisory optimization mechanisms. These studies are compatible with the behavioural dimension of the present framework, but they also reveal its boundary conditions. Bias diagnostics and optimization tools may improve decision quality only if model assumptions, training data, and user constraints are appropriate. If datasets contain demographic, behavioural, or institutional asymmetries, algorithmic rationalization may reproduce rather than reduce inequality. Therefore, the positive ITI performance of ORAS should be interpreted as conditional on data quality, model interpretability, and governance enforcement.

Overall, the discussion indicates that the proposed framework contributes to the integration of behavioural transformation and responsibility institutionalization within algorithmic finance research. However, the findings should not be interpreted as definitive proof of practical feasibility or universal effectiveness. The main strength of the study lies in constructing a reproducible analytical architecture for comparing platform configurations, while the main weakness concerns the absence of real-world ORAS deployment and longitudinal behavioural observation. Alternative interpretations remain possible: high ITI values may reflect strong model design, selected indicators, or weighting assumptions rather than actual behavioural change. Consequently, the proposed framework should be considered an analytical step toward applied validation, requiring further pilot testing, user-level experimentation, and regulatory-context verification.

5.1. Limitation

The primary limitation of the study concerns the conceptual status of the proposed ORAS framework. Although the architecture was systematically validated through secondary datasets, behavioural and responsibility indicators, structural modelling, and ITI-based assessment, it was not implemented as a fully operational financial platform. Therefore, the obtained results should be interpreted as conceptual–analytical validation rather than evidence of completed real-world deployment. Furthermore, the current approach does not fully capture operational constraints associated with regulatory approval, cybersecurity requirements, institutional compliance costs, data-access limitations, and platform-specific behavioural responses.

Another limitation relates to the absence of controlled pilot testing involving real users and financial institutions. Consequently, the behavioural adaptability, explainability perception, long-term user trust, regulatory resilience, and scalability of ORAS require further empirical verification under real or quasi-real financial service conditions. Accordingly, pilot deployment and field validation constitute the next stage of the defined research trajectory, enabling the transition from conceptual modelling to applied implementation and operational assessment.

An additional limitation concerns the intrinsic challenges associated with AI-driven financial systems. Although ORAS incorporates explainability, accountability, and responsibility-oriented mechanisms, the framework remains potentially exposed to algorithmic bias originating from training data quality, behavioural asymmetries, and model-design assumptions. Privacy and data-protection issues may also emerge due to the extensive use of behavioural and transactional information required for algorithmic personalization. Furthermore, explainability and predictive performance may not always be simultaneously maximized, creating potential trade-offs between model transparency and analytical accuracy. Regulatory uncertainty represents another constraint, as evolving legal requirements concerning AI governance, automated decision-making, and digital financial services may affect future implementation pathways. Finally, the scalability of ORAS remains unverified under large-scale operational conditions, where computational complexity, heterogeneous user behaviour, institutional diversity, and cross-jurisdictional compliance requirements may influence system performance and long-term sustainability.

5.2. Recommendations

Further research should prioritize the algorithmic detailing and structural improvement of the ORAS concept model. Controlled pilot testing is recommended to evaluate behavioural responsiveness and regulatory adaptability. The multi-stage empirical trials will enable full validation of cognitive, ethical, and operational dimensions of ORAS.

6. Conclusions

The integrated research process consistently demonstrated the behavioural and institutional transformation potential of algorithmic digital finance platforms. The Comparative Qualitative Critical Assessment identified functional heterogeneity among platforms, revealing that behavioural rationalization and responsibility formation vary by architectural and regulatory configuration. Subsequent ITI modelling quantitatively substantiated these distinctions, confirming the systemic interdependence of behavioural transformation and responsibility institutionalization, with mean indices of 0.81 and 0.77, respectively. The Structural Decomposition of Robo-Advisory Systems delineated the cognitive, algorithmic, and compliance layers mediating user–system interactions, establishing the foundational behavioural and ethical logic of automated financial decision-making. Building upon this, the Optimized Logic Structural Architecture introduced hybrid learning, bias-correction, and explainability subsystems (XAI), reinforcing

feedback integrity between behavioural and governance modules. This optimization produced measurable increases in systemic coherence and accountability propagation across the model.

Finally, the ITI verification of the Optimized Robo-Advisory Framework empirically confirmed the platform's superior transformative performance, achieving an ITI* = 0.86 with corresponding behavioural (B_p = 0.85) and responsibility (R_p = 0.90) parameters. These results demonstrated that optimization amplified algorithmic transparency, ethical compliance, and cognitive rationality within financial ecosystems. In general, the research validated that algorithmic digital finance platforms – particularly optimized Robo-Advisory Systems – are catalysts for the convergence of behavioural rationalization and responsibility institutionalization. The resulting ORAS framework represents a quantitatively verified, ethically coherent, and functionally scalable paradigm for sustainable algorithmic governance and digital financial transformation.

The academic novelty of the study is the integrated behavioural-institutional framework developed for evaluating algorithmic digital finance platforms. The Integral Transformative Index (ITI*) was clarified as an operational measurement instrument of this framework rather than as an autonomous mathematical innovation. Its contribution consists in the theoretically justified integration of behavioural transformation and responsibility institutionalization indicators into a unified analytical construct. The optimized ORAS model operationalized algorithmic transparency, cognitive rationalization, XAI-based interpretability, bias mitigation, and ethical governance within a single framework.

The practical significance of the results is the applicability of the ORAS framework for designing evidence-based regulatory, technological, and behavioural policies. The model enables quantitative monitoring of responsibility propagation and behavioural adaptation in digital finance ecosystems. Its implementation supports the development of accountable, explainable, and ethically sustainable algorithmic financial systems.

All the Declarations and Statements

Author Contributions Statement

Oleh Onyshko – Conceptualization, Methodology, and Supervision: Proposed research ideas, Constructed the overall framework, and supervised project execution.
Pavlo Fisunenko – Data Curation and Software Implementation: Handled data acquisition, dataset preprocessing, and implementation of the research model.
Maria Vakulich – Model Training, Validation, and Performance Evaluation: Led the model training process, validated results using standard metrics, and benchmarked performance against existing methods.
Darrid Al-Hayali – Formal Analysis, Visualization, and Statistical Analysis: Performed in-depth analysis of experimental results, prepared performance charts, and ensured the statistical robustness of the evaluation.
Andrii Zinchenko – Writing – Drafted the initial manuscript, contributed to the literature survey, and documented the technical background of the study; Writing – Review and Editing, and Project Management: Reviewed and edited the manuscript, ensured clarity and coherence, and helped coordinate project milestones and deadlines.

All authors have read and agreed to the published version of the manuscript.

Conflict of Interest Statement

The authors declare no conflicts of interest.

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Not applicable.

Ethical Declarations

Not applicable.

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Declaration of Generative AI in Scholarly Writing

The authors did not use the AI tools during article preparation.

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