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Strengthening Consumer Protection and Growth Investment Management: Application of Data-driven Framework in Fintech

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Abstract: In the fintech landscape, rapid platform expansion has amplified consumer exposure to concentrated financial risks while widening gaps in risk compensation and protection. To address these challenges, this study proposes and empirically evaluates a unified data-driven framework that integrates customer profiling, behavioral monitoring, and complaint mining to enhance targeted consumer protection. The framework further incorporates multi-source data into goal-oriented asset allocation, scenario-based investment advisory, and sentiment-aware risk management to improve medium- and long-term investment outcomes. Using a 12-month pre-post observation of a large-scale internet wealth management platform, the empirical analysis examines changes in consumer risk exposure, complaint incidence, transaction risk control, portfolio drawdown, target achievement rates, and customer retention. Results show that the proportion of high-risk products held in protected accounts and complaint rates declined substantially following implementation, while abnormal transaction interception rates improved. At the portfolio level, maximum drawdowns of education and pension target portfolios narrowed, and the probability of achieving predefined return objectives increased. Overall, these findings have broader implications for digital financial governance and consumer risk mitigation in advanced fintech markets, including the United States.

Keywords: Fintech; Consumer protection; Data-driven governance; Behavioral risk management; Goal-oriented investment management

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1. Introduction

In recent years, fintech platforms have rapidly expanded across payments, credit, and wealth management, driven by data-intensive and algorithmic decision-making systems. While these technologies improve efficiency and broaden investment choices, they also introduce structural risks, including complex risk transfer mechanisms, increased product opacity, and heightened information asymmetry between platforms and consumers [1]. Consequently, tensions between consumer protection and growth-oriented investment objectives have become increasingly pronounced in digital wealth management.

Prior research has primarily addressed these challenges through regulatory design, disclosure standards, product innovation, or investor education. However, limited empirical attention has been given to how risk identification, suitability management, and investment allocation can be jointly operationalized and evaluated within an integrated data-driven framework. In practice, consumer protection mechanisms often remain static and compliance-oriented, while investment management systems continue to emphasize return optimization without systematically incorporating behavioral risk and vulnerability indicators.

To fill this gap, this study proposes and empirically evaluates a unified data-driven framework that integrates customer profiling, behavioral monitoring, complaint mining, and goal-oriented asset allocation. Using a large-scale internet wealth management platform as a representative case [2], the study applies a before-and-after quasi-empirical design to assess changes in consumer risk exposure, complaint incidence, portfolio drawdown, target achievement rates, and customer retention. The findings provide empirical evidence that data-driven governance mechanisms can simultaneously enhance consumer protection and the stability of long-term investment outcomes, while highlighting practical limitations in real-world fintech implementation.

2. The Coordination Status of Consumer Protection and Growth Investment under the Fintech Scenario

2.1. Platform Business Expansion and Risk Transfer to Consumers

Fintech platforms have increasingly consolidated payment, credit, and wealth management services into integrated applications, significantly lowering access barriers for consumers. However, their business models have shifted from "self-operation with on-balance-sheet risk" toward "matchmaking with technology service fees." Although risks appear dispersed across financial institutions, they are effectively concentrated in end-investor accounts through high-yield wealth management products and asset transfer arrangements. Algorithmic recommendations and default settings-such as simplified purchase flows and automatic subscriptions-encourage investors to enter higher-risk portfolios without fully understanding asset concentration, leverage exposure, or liquidity constraints.

When macroeconomic conditions or specific asset classes experience sharp fluctuations, platforms can rapidly adjust partnerships or product offerings to reduce their own exposure. In contrast, individual investors often face limited exit options and accelerated net asset value drawdowns. This asymmetry in risk transfer and risk-bearing capacity establishes the structural background against which consumer protection and growth-oriented investment management must be jointly evaluated.

2.2. Displacement of Consumer Protection Rules and Product Innovation

Existing consumer protection frameworks are largely designed around contract disclosures, offline sales practices, and traditional financial institutions. In fintech environments, however, critical risk transmission points have migrated to algorithmic decision rules, interface design, and data-driven recommendation mechanisms. Regulatory adaptation has lagged behind rapid product iteration and scenario innovation, leaving a governance gap between formal compliance and actual consumer understanding.

In practice, platforms often prioritize conversion rates, user retention, and asset scale, simplifying complex financial structures into surface-level return labels while relegating key risk disclosures to lengthy clauses or secondary pages [3]. Compliance is reduced to procedural confirmation-such as "check and agree"-without effective mechanisms to assess whether investors genuinely comprehend structural risks or potential losses under adverse scenarios. This divergence between "what is disclosed" and "what is understood" weakens consumer protection and increases reliance on data-driven monitoring and intervention mechanisms [4].

2.3. Growth-oriented Investment Preference and the Gap in Risk Compensation Mechanism

Against a backdrop of declining interest rates, constrained asset allocation options, and rising wealth anxiety, both platforms and investors increasingly favor growth-oriented investment strategies. Marketing narratives commonly emphasize "stable medium-to-high returns," while risk compensation mechanisms-such as loss-sharing arrangements, reserve funds, or targeted safeguards for vulnerable investors-remain underdeveloped.

When significant losses occur, responsibility is typically confined to the principle that "risks were disclosed and borne by investors." Ordinary investors face persistent disadvantages in information access, financial expertise, and the cost of dispute resolution, resulting in a concentration of downside risk at the consumer level. Without measurable and enforceable compensation or shared liability mechanisms, improvements in growth-oriented investment outcomes are achieved at the expense of consumer protection. This imbalance highlights the need for data-driven systems capable of identifying risk accumulation, triggering early warnings, and supporting compensatory interventions.

3. Data-driven Consumer Protection Application Framework

3.1. Customer Profile Construction and Vulnerable Group Identification

To enhance consumer protection in fintech environments, protection strategies must evolve from uniform, average-based approaches toward targeted and differentiated mechanisms. Within legal and regulatory boundaries, platforms can integrate real-name verification data, asset structures, transaction histories, and device-level behavioral information to construct multidimensional customer profiles capturing risk tolerance, asset stability, and liquidity constraints. These profiles enable the identification of vulnerable groups, including elderly users, low-income households, and individuals with elevated debt burdens [5].

Based on profiling outcomes, platforms can implement differentiated protection measures such as tiered product whitelisting, dynamic credit limit controls, and context-specific risk alerts, thereby avoiding one-size-fits-all safeguards and rigid static labeling. Importantly, customer profiles are updated dynamically as financial conditions, family responsibilities, and investment experience evolve, reducing the risk of discriminatory or opaque "black-box" classification. In this way, profiling functions not only as a compliance tool, but as an operational foundation for aligning consumer protection with platform-level decision-making (As shown in Figure 1).

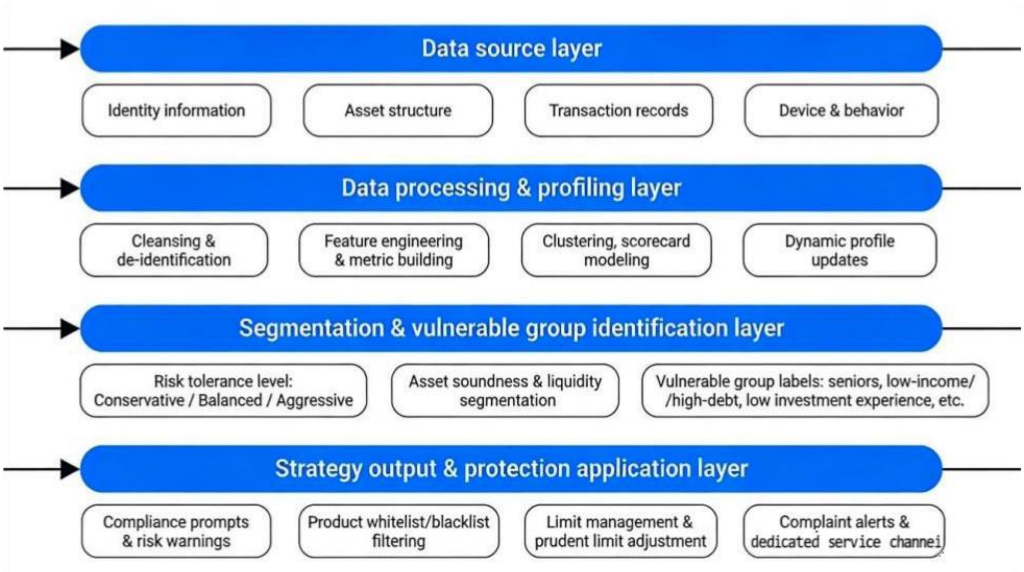

Figure 1. Data-driven workflow for customer profiling and vulnerable group identification.

As illustrated in Figure 1, the platform integrates, cleanses, and models heterogeneous multi-source data within a legally compliant framework. Customers are stratified using risk tolerance and asset stability indicators, allowing vulnerable groups to be identified through transparent and revisable criteria. The stratification outputs are then linked directly to protection mechanisms, including product access controls, credit limit management, and risk alert rules. This closed-loop design ensures that customer profiling supports both precise customer segmentation and effective consumer protection, rather than static classification or symbolic compliance.

3.2. Behavioral Monitoring, Early Warning, and Real-Time Risk Interception

While customer profiling identifies groups requiring enhanced protection, risk exposure frequently materializes during discrete, high-impact transactions. To address this, the data-driven framework establishes behavioral baselines at the account level by integrating device fingerprints, login locations, transaction timing, amount distributions, trading frequency, and product switching patterns. Rule-based systems and machine learning models are then used to detect significant deviations from established behavioral norms.

When abnormal behavior is identified-such as accounts with no prior equity exposure rapidly purchasing high-leverage products, or initiating large withdrawals from atypical devices or locations-the system activates graduated intervention mechanisms. Low-risk cases trigger mandatory, high-salience risk alerts prior to transaction execution, emphasizing potential principal loss and liquidity constraints and requiring explicit user confirmation. Moderate-risk cases invoke enhanced identity verification measures, while severe cases may result in temporary transaction suspensions pending automated or manual verification.

In parallel, behavioral monitoring generates product- and channel-level risk indicators. Products exhibiting concentrated subscriptions followed by rapid redemptions, or simultaneous increases in complaints and negative sentiment, automatically experience reduced recommendation weights and restricted exposure to vulnerable users. Channels repeatedly associated with misleading sales practices trigger incentive structure reviews or scale reductions. Through this multi-layered design, behavioral monitoring evolves from a narrow anti-fraud function into a core mechanism for continuous consumer risk management.

3.3. Complaints and Disputes Mining and Pre-incident Risk Prevention

From an operational perspective, consumer complaints and disputes are often treated as isolated negative outcomes. Within a data-driven governance framework, however, they constitute a high-value source of structured risk signals. Platforms can aggregate customer service records, call transcripts, online chat logs, app store reviews, and public social media content into a unified analytical system. Using natural language processing techniques such as keyword extraction, sentiment analysis, and topic modeling, recurring risk points and structural deficiencies can be systematically identified.

For example, frequent co-occurrence of terms such as "automatic renewal," "non-transparent fees," and "delayed redemption" may indicate deficiencies in product design, interface defaults, or disclosure practices. Complaints from elderly users referencing comprehension difficulties or low interface visibility may signal inadequacies in suitability management. Repeated allegations of exaggerated returns within specific sales channels often reflect incentive structures that encourage systematic rule violations.

Once identified, these insights are embedded back into business rules and algorithmic systems. High-risk contractual clauses are rewritten and tested on limited user samples, interface risk alerts are redesigned based on observed behavior, misleading language is removed from marketing and customer service templates, and high-complaint channels are scaled down pending remediation. Regulators may also utilize anonymized complaint data to identify cross-platform systemic risks. By shortening the feedback loop from issue emergence to rule adjustment, complaint mining transforms post-incident remediation into proactive, pre-incident risk prevention.

4. Data-driven growth investment management system

4.1. Multi-source Data Fusion and Asset Allocation Optimization

In growth-oriented investment management, the objective of the data-driven framework is not the pursuit of higher nominal returns, but the achievement of predefined financial goals with greater confidence under explicit risk constraints. To this end, the platform integrates multi-source data-including customer characteristics, account behavior, product attributes, market pricing, and macroeconomic conditions-into a unified analytical view [6]. Based on investor-specific risk budgets, return-volatility trade-offs, and maximum drawdown constraints, the system generates goal-oriented asset allocation strategies and dynamically adjusts portfolios through periodic rebalancing and scenario-based stress testing.

Unlike static allocation models that rely primarily on historical returns and volatility, this framework incorporates behavioral and liquidity constraints, such as investors' actual tolerance for drawdowns and the likelihood of irrational decision-making under stress. Asset allocation decisions are therefore conditioned not only on market efficiency, but also on empirically observed investor behavior. As summarized in Table 1, the framework achieves this by jointly applying data across four complementary dimensions-customer profiling, account behavior, market risk, and macroeconomic environment-rather than optimizing along any single metric.

Table 1. Illustration of multi-source data dimensions in portfolio optimization.

Data dimension	Examples	Main data sources	Role in portfolio optimization
Client profile data	Age, income level, occupation, household debt ratio, risk tolerance score	Account/onboarding information, risk profiling questionnaires	Defines risk budget and investment horizon; separates conservative, balanced and aggressive profiles
Account behavior data	Portfolio turnover, SIP/regular investment persistence, redemption frequency, "chasing gains & panic selling" score	Historical transaction records, account cash-flow logs	Reveals real volatility tolerance and discipline; narrows the gap between model and actual behavior
Market pricing & risk factors	Historical returns, volatility, max drawdown, correlations, factor exposures	Market data vendors, index/fund NAV histories	Supports efficient frontier building, scenario tests, and rebalancing/hedging decisions
Macro environment & liquidity	Interest rates, inflation expectations, business cycle indices, capital flows, liquidity tiers	Macroeconomic databases, capital-flow monitoring systems	Guides dynamic risk budget and position sizes; helps manage drawdown and liquidity risk

Table 1 illustrates how each data dimension contributes to a distinct but interlocking component of the allocation process. Importantly, these dimensions do not operate independently. Client profile data establishes structural suitability constraints, while behavioral data introduces empirical validation of real-world investor responses. Market risk factors provide the quantitative backbone for optimization, and macro-liquidity indicators dynamically recalibrate exposure in response to systemic conditions.

By integrating these layers within a unified decision architecture, the framework addresses a critical limitation of traditional mean-variance optimization - namely, its reliance on static assumptions and representative-agent behavior. The result is a portfolio construction process oriented not merely toward short-term return efficiency, but toward improving the probability of long-term goal attainment under realistic behavioral and macroeconomic constraints.

4.2. Scenario-based Intelligent Investment Advisory and Target-oriented Allocation

For growth-oriented investment management to align with consumer welfare, abstract return-risk trade-offs must be translated into concrete, goal-based financial scenarios. Leveraging the data-driven framework, scenario-based advisory systems evaluate household income structures, family responsibilities, debt levels, existing protections, and risk tolerance to identify key financial objectives, such as education funding, retirement preparation, housing-related expenditures, and health-related contingencies [7].

Each objective is decomposed into multiple investment pathways differentiated by contribution levels, investment horizons, and risk ranges. Using historical performance data and scenario simulations, the system estimates the probability of achieving each goal under alternative configurations and presents these outcomes in a transparent and comparable manner. As market conditions and personal financial circumstances evolve, progress toward each objective is continuously monitored. When deviations from planned trajectories occur, the system provides actionable adjustment options-such as modifying contribution amounts, extending time horizons, recalibrating targets, or adjusting risk exposure-while explicitly illustrating their implications for household cash flow and overall portfolio risk. This goal-oriented structure anchors investment decisions in long-term outcomes rather than short-term market fluctuations, reducing the likelihood of emotionally driven trading.

4.3. Market Sentiment Recognition and Risk Hedging Strategies

In the short term, market sentiment often exerts a stronger influence on price movements than fundamental factors and is a primary driver of irrational trading behavior. Fintech platforms generate rich behavioral data that implicitly capture sentiment dynamics, including capital flows across risk tiers, subscription and redemption imbalances, frequent portfolio reallocations, search and click patterns, and asset-specific discussion intensity. By aggregating these signals into multidimensional sentiment indicators aligned with historical price movements and major market events, the framework identifies periods of excessive optimism or pessimism [8].

Rather than serving speculative purposes, sentiment indicators are incorporated as risk management inputs within the growth investment framework. For conservative investors, elevated sentiment levels trigger recommendations to moderately reduce exposure to high-volatility assets and increase allocations to liquid or defensive positions. For more aggressive investors, scenario simulations illustrate potential drawdowns associated with excessive concentration during peak sentiment phases, supporting disciplined position sizing and predefined risk controls. During periods of extreme pessimism, the system compares long-term outcomes of panic-driven liquidation with more gradual adjustment strategies, discouraging irreversible one-time decisions. In this manner, sentiment recognition functions as an additional layer of drawdown control and behavioral stabilization, reinforcing consistency between growth-oriented investment management and consumer protection.

5. Empirical Strategy and Case Evaluation

To assess the real-world effectiveness of the proposed data-driven framework, this study conducts a quasi-empirical evaluation using a large-scale internet wealth management platform as a representative case. The analysis compares platform-level transaction records, account behavior data, complaint reports, and portfolio performance outcomes across two observation windows: a 12-month period prior to framework implementation and a 12-month period following implementation. The platform's core product structure and user base remained stable during the observation period, allowing observed changes to be primarily attributed to framework implementation rather than major exogenous shocks.

An integrated evaluation system is constructed across three dimensions: consumer protection outcomes, growth-oriented investment management performance, and customer relationship stability. Key indicators include the proportion of high-risk products held by protected accounts, complaint rates related to high-risk products per 10,000 households, success rates in intercepting high-frequency abnormal transactions, maximum annual drawdowns of education and pension target portfolios, target return range achievement rates, and one-year customer retention rates. Collectively, these indicators capture changes in consumer risk exposure, dispute incidence, transaction risk control, portfolio robustness, and long-term engagement (As shown in Table 2, Figure 2).

Table 2. Comparison of key indicators before and after implementation of the data-driven framework (12-month pre-post observation).

Indicator category	Indicator Description	Before implementation	After implementation
High-risk exposure	Proportion of high-risk products (R4/R5, etc.) in key protection accounts	23.6%	15.2%
Complaint status	Complaint rate per 10,000 households for high-risk products (complaints per 10,000 households per year)	3.8	2.1
Transaction risk control	High-frequency abnormal transaction interception success rate	82.4%	94.3%
Portfolio robustness	The maximum drawdown of the education fund/pension target portfolio within the year	−18.5%	−12.3%
Goal achievement	Percentage of accounts meeting the target return range	57.8%	71.9%
Customer and asset retention	One-year customer retention rate	86.2%	92.7%

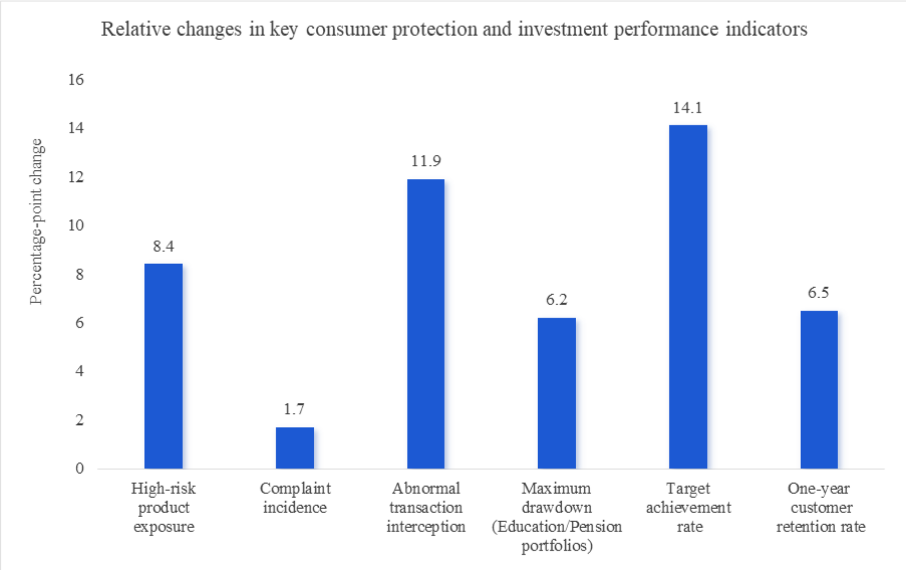

Figure 2. Relative changes in key consumer protection and investment performance indicators following implementation of the data-driven framework (Values represent percentage-point changes relative to pre-implementation levels over a 12-month observation window).

Table 2 reports the raw values of each indicator before and after framework implementation, while Figure 2 visualizes the relative magnitude of changes across indicators. Following implementation, the proportion of high-risk products in protected accounts declined from 23.6% to 15.2%, indicating a substantial reduction in concentrated risk exposure among vulnerable users. Complaint rates related to high-risk products decreased from 3.8 to 2.1 cases per 10,000 households per year, suggesting improved suitability management and disclosure effectiveness. The success rate of intercepting high-frequency abnormal transactions increased from 82.4% to 94.3%, reflecting enhanced real-time risk control capabilities.

In terms of investment outcomes, the maximum annual drawdown of education and pension target-oriented portfolios narrowed from −18.5% to −12.3%, while the proportion of accounts achieving predefined target return ranges increased from 57.8% to 71.9%. Customer relationship stability also improved, with one-year retention rates rising from 86.2% to 92.7%. Taken together, these results are consistent with the interpretation that the data-driven framework contributed to improvements in consumer protection and the stabilization of growth-oriented investment outcomes, without evident trade-offs between the two dimensions.

While this analysis does not claim strict causal identification, the consistent directional improvements across multiple independent indicators provide convergent empirical evidence supporting the operational effectiveness of the framework in real-world fintech settings. Although the design does not rely on a formal difference-in-differences specification, macro-level volatility indicators and platform-level product structures remained broadly stable across the observation window. Moreover, the consistent directional improvement across consumer protection, portfolio robustness, and retention metrics reduces the likelihood that results are driven solely by external market cycles [9].

6. Conclusion

This study demonstrates that a unified data-driven framework integrating customer profiling, behavioral monitoring, complaint mining, sentiment recognition, and goal-oriented asset allocation can deliver measurable improvements in both consumer protection and growth-oriented investment management within fintech platforms. Empirical evidence from a real-world implementation shows reduced exposure to high-risk products among vulnerable users, lower complaint incidence, stronger transaction risk interception, improved drawdown control, higher target achievement rates, and enhanced customer retention.

More broadly, the findings suggest that consumer protection in fintech environments need not rely solely on static disclosure rules or post-incident remedies. Instead, protection can be operationalized as a continuous, data-driven governance process that identifies risk accumulation, intervenes at critical decision points, and dynamically adjusts investment strategies based on behavioral and market signals. At the same time, growth-oriented investment management can move beyond short-term return optimization toward improving the probability of long-term financial goal attainment under explicit risk constraints.

Future research should further examine governance boundaries related to data usage, potential model bias, and cross-platform or cross-institutional coordination mechanisms to prevent data-driven systems from becoming opaque or exclusionary. Ensuring transparency, accountability, and proportional intervention will be essential for scaling such frameworks in a manner that supports financial stability, consumer welfare, and broader social equity.

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