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Machine Learning Analysis of Key Features in Household Financial Decision-Making

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Abstract: This paper explores the potential and challenges of mobile Internet in household investment decisions. The rapid development of mobile Internet has brought opportunities and challenges to household asset allocation, especially in promoting greater participation in venture asset investment. This paper focuses on the application potential of machine learning in analyzing household investment behavior patterns and trends. It reveals the potential household income rules, consumption patterns and asset allocation preferences through extensive data analysis. However, machine learning faces many challenges, such as data privacy protection, algorithmic interpretation, and data acquisition costs. Finally, the paper calls for further research and exploration to deepen understanding of how technological innovation can drive intelligent and optimized household financial decisions.

Keywords: Machine Learning; Financial Decisions; Financial Risk Management; Household Investment Decision.

1. Introduction

When households, as microeconomic entities, make asset allocation decisions, they often face the dilemma of choosing between various forms or combinations of investments. This includes decisions between financial and non-financial assets, such as housing, or between risky assets (such as stocks, bonds, funds, etc.) and risk-free assets (such as cash, deposits, etc.). In China's capital market, investors are predominantly retail investors, primarily from households. Despite this, the "China Household Wealth Survey Report 2019" highlights that China's households exhibit a simplistic financial asset allocation structure, with cash, demand, and time deposits accounting for nearly 90%. The likelihood and extent of household participation in risky asset investments remain low, a phenomenon known as the "limited participation mystery."

The advent of the mobile internet marks the fifth technological development cycle in the computing realm, following mainframes, minicomputers, personal computers, and desktop internet, and is considered a significant breakthrough in the internet domain. With the proliferation of mobile devices like smartphones and tablets, services such as instant messaging and mobile payments have flourished. As the latest phase in internet evolution, the mobile internet differs markedly from traditional internet in its application scenarios, business models, and connectivity ports. Exploring whether the mobile internet can mitigate the "limited participation" of households in venture asset investments and its impact on the investment decisions of Chinese families warrants further investigation.

Machine learning holds immense potential in examining how the mobile internet influences household investment decisions. It excels in leveraging extensive data analysis to uncover the underlying patterns and trends in household investment behaviours. By analysing multidimensional data—including household income, spending patterns, and asset allocation preferences—machine learning can offer personalised investment recommendations to optimise asset allocation and enhance investment returns. Moreover, machine learning can automate the processing of vast datasets, thereby improving decision-making efficiency and accuracy.

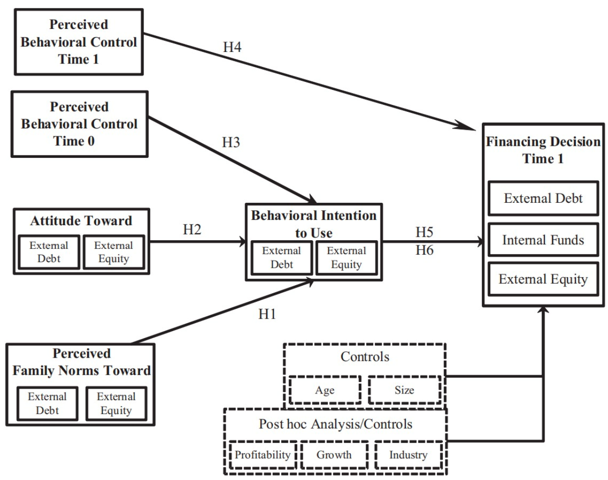

Figure 1. Hypotheses model of financial decision making in the family firm

However, machine learning encounters several challenges in this domain. Chief among them is data privacy protection, particularly concerning sensitive personal financial and investment information. Addressing this issue is crucial to ensuring data security and privacy. Another significant challenge lies in the interpretability of algorithms, especially in financial decision-making contexts where decision-makers require insights into how models generate recommendations to build trust and acceptance. Additionally, the complexities and costs associated with data acquisition pose practical challenges, especially for complex models requiring data integration from multiple sources. Lastly, bridging the gap between the predictive capabilities of machine learning models and the practical needs of financial decision-making requires further research and exploration.

This paper explores the potential and challenges of the mobile internet in household investment decision-making. The rapid evolution of the mobile internet presents opportunities and challenges in household asset allocation, particularly fostering greater participation in venture asset investments. Effectively harnessing machine learning to analyse complex patterns and motivations in household investment behaviour is key to unlocking this potential. The article aims to delve into the current applications of machine learning in analysing household investment decisions and the critical challenges they face, ultimately seeking to deepen our understanding of how technological innovation can drive intelligent and optimised household financial decisions.

2. Related Work

2.1. The Logic of Family Finance Development

The financial system is inherently characterised by pro-cyclicality, vulnerability and externality, and residents, as essential participants in the financial market, have significant differences in education level, cognitive ability, financial literacy, etc. Such differences will be reflected in family financial activities through two dimensions: financial equity and efficiency.

According to the theory of financial subject ability, there are congenital and significant differences among residents in capital strength, professional knowledge, information searching, thinking and cognition, etc. Such differences lead to differences in residents' income and family financial activities, ultimately resulting in financial inequity. It includes financial exclusion, credit constraint, financial availability, financial literacy difference, etc. The main starting point of ensuring financial equity is to prevent the congenital internal capacity gap from widening through external effects such as financial leverage through practical means, including financial inclusion.

The difference in household financial efficiency is the ultimate manifestation of the economic equity gap. Regarding household asset allocation, the excess return of unit risk bearing in the two-dimensional framework of "reap-risk" has attracted more attention, which can better reflect the differences in subjective abilities such as cognitive ability and financial literacy of different resident investors. In terms of borrowing and financing, factors such as credit constraints, income levels and financing guarantees faced by households will also exclude some residents, making their reasonable financing needs unable to be met, thereby reducing their financing efficiency and further losing financial equity. Under the current background of high-quality economic development promoting shared prosperity, discussing the family financial logic of shared prosperity realisation from the two dimensions of fairness and efficiency and exploring the underlying economic laws is essential.

2.2. The Development of Household Finance Balances Fairness and Efficiency.

Finance is the core of the modern economy, and financial resources are also the primary resources for economic subjects to achieve optimal goals in modern economic society. The primary function of inclusive finance is to help all economic entities obtain financial resources for their development without distinction and ultimately achieve shared prosperity by optimising income structure, rationally distributing wealth, and improving development efficiency.

The first is to narrow the structural differences in the degree of financial resource inclusion. Capital movement symbolises the "blood" flow of the national economy and is also an essential embodiment of the movement of finance as modern economic resources gather among different economic sectors. As an important economic sector in the development of the national economy, the family forms capital exchanges with other economic sectors mainly through participating in various transactions. By measuring the total scale of capital flows in different sectors, it is found that the proportion of financial resources shared by the household sector ranks behind financial institutions and non-financial enterprises for a long time and is generally higher than that of government departments and overseas departments, and shows a steady and rising trend, indicating that the degree of financial resources "benefiting" the household sector is still relatively high. From the perspective of family internal structure, there are also significant differences in the level of financial inclusion among different families: farmers, low-income families, low-income families, and elderly families enjoy a significantly lower level of financial inclusion. The participation of households in the formal credit market is low, and the accessibility and quality of financial services need to be improved.

The current situation shows that the efficiency of securities investment in non-financial enterprises, financial institutions and government departments is significantly higher than in the household sector. The specific reasons for this can be analysed from information asymmetry and financial literacy specialisation. In terms of information asymmetry, compared with the characteristics of families that are linked by marriage and blood, non-financial enterprises, financial institutions and government departments all belong to legal organisations and have natural advantages in information search and acquisition. However, families are inevitably always at the end of the information transmission chain and cannot obtain the corresponding information asymmetry rent. This, combined with the longstanding position of households as the primary providers of capital, has limited the benefits of asset allocation. In terms of the specialisation of financial literacy, with the continuous improvement of the level of economic financialisation, more and more economic departments need more professional teams with high-level financial literacy to take charge of the financial investment business, which means that financial literacy has entered the production link of enterprises and other economic departments as an exclusive production factor. The allocation of assets in the securities market has become a specialised element combining allocation behaviour with the characteristics of a scale economy.

3. Machine Learning in Financial Decision-Making

3.1. Artificial Intelligence and Financial Risk Management

Artificial intelligence and machine learning can be used to manage risks through earlier, more accurate risk assessments. ML is highly beneficial to the organisation in making improved risk management decisions, and the second most significant relationship is discovered in efficiently managing the organisation’s cash. For example, suppose artificial intelligence and machine learning allow decisions based on past relationships between the values of different assets. In that case, financial institutions will better manage these risks

[9]. Tools to reduce driving risks can be particularly beneficial for the entire system. [5]. In addition, artificial intelligence and machine learning can predict and detect the risk of fraud, suspicious transactions, late payments, and cyber-attacks, leading to better risk management. However, artificial intelligence and machine learning tools can also omit new types of dangers and events, as they can potentially “over-educate” previous events [10]. While artificial intelligence and machine learning tools can improve risk management, the latest developments in these strategies have not yet been tested to manage risks in changing economic conditions. This research article is organised as follows: Section 1 describes the introduction, and Section 2 describes the literature work. The methodology is described in Section 3. Section 4 summarises the outcomes and research findings, and Section 5 concludes with a conclusion and future scope. Using artificial intelligence and machine learning creates risk “black boxes” in decision-making that can cause complex problems, especially at the end of events. It can be challenging for financial users—and regulators in particular—to understand how decisions such as those relating to trade and investment were made. Artificial intelligence and machine learning are problematic not just because of the lack of clarity but also because of potential biases acquired by the techniques from human preconceptions and collecting artefacts buried in the training data, which may result in unfair or incorrect choices.

Artificial intelligence and machine learning can facilitate “more personal” and “more personal” financial services through big data analytics [12]. For example, artificial intelligence and machine learning can enable extensive data analysis, thereby clarifying the characteristics of individual consumers and investors and allowing companies to design well-targeted services. However, the use of consumer data can lead to privacy and information security issues. In addition, since analytical artificial intelligence and machine learning data can analyse the characteristics of individual customers through public data, it would be necessary to consider customer results. It must be protected while protecting the anonymity of individual consumers and facilitating the safe and efficient use of big data for better services [13]. Deep learning algorithms, in particular, offer benefits for organisational decision-making, such as supporting employees with information processing, augmenting their analytical capacities, and maybe assisting them in transitioning to more design output. In addition, to protect consumers and investors, it would be essential to establish well-designed governance structures for financial service providers using artificial intelligence and machine learning.

3.2. Financial Decision Model Approach

Order execution optimisation is a fundamental problem in algorithmic trading, which aims to complete a preset meta-order through a series of trading decisions, such as closing, opening, and positioning. In essence, the goal of order execution is twofold, not only requiring the completion of the entire order, but also pursuing a more economical execution strategy that maximizes gains or minimizes capital losses. For the sequential decision characteristics of order execution, machine learning methods can take advantage of capturing the microstructure of the market, so as to better execute orders.

But a simple, straightforward use of machine learning runs into a problem - there is a lot of noise and imperfect information in the raw order and market data. Noisy data may lead to low sample efficiency of reinforcement learning and reduce the effectiveness of learning order execution strategies. More importantly, when taking action, the only information available is historical market information, and there are no obvious clues to make accurate predictions about the future trend of market prices or trading activity.

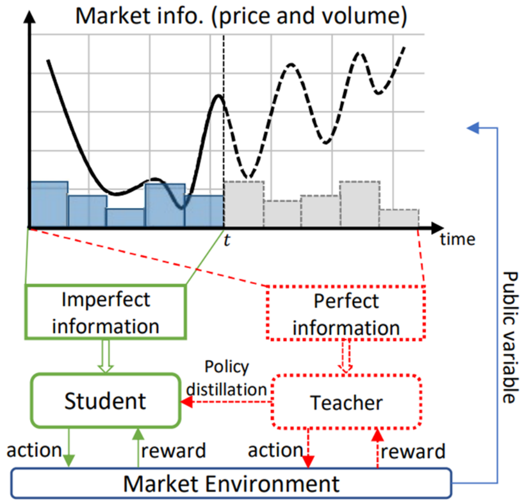

Figure 2. Schematic diagram of OPD prophetic strategy extraction realized by machine learning

To this end, the Qlib team proposed a generic optimization framework for order execution strategies and introduced a new strategy extraction method, OPD (Oracle Policy Distillation), to bridge the gap between noise and imperfect market information and optimal order execution strategies. The technique is a "teacher-student" learning paradigm, in which the "teacher" is trained to be a "prophet" who can find the best trading strategy in the case of perfect information. Then the "student" learns by imitating the best behaviour pattern of the "teacher". When the model training stage ends and enters the actual use stage, OPD will use the "student" strategy to plan the order execution without the "teacher" or future information. Moreover, different from the traditional reinforcement learning method, which trains a single model only for a single stock, the reinforcement learning algorithm proposed by the Qlib team can use the data of all stocks for joint training, thus significantly alleviating the overfitting problem in the learning process.

The experimental results show that the performance of OPD is significantly better than that of other methods, which proves the effectiveness of OPD and also confirms that traditional methods based on financial market assumptions are not applicable in real scenarios. In addition, other training-based data-driven approaches need to capture the market's microstructure well enough to adjust their strategies accordingly, resulting in weaker performance compared to OPD approaches.

Table 1. Experimental results of the OPD method for financial decision-making by machine learning

Category	Strategy	Reward($\times 10^{-2}$)	PA	GLR
financial model-based	TWAP (Bertsimas et al. 1998)	-0.42	0	0
	AC (Almgren et al. 2001)	-1.45	2.33	0.89
	VWAP (Kakade et al. 2004)	-0.30	0.32	0.88
learning-based	DDQN (Ning et al. 2018)	2.91	4.13	1.07
	PPO (Lin et al. 2020)	1.32	2.52	0.62
	OPD^S (pure student)	3.24	5.19	1.19
	OPD (our proposed)	**3.36***	**6.17***	**1.35**

3.3. I have Frequently Asked Questions About the Application of Machine Learning in Finance

1. When using machine learning in the financial field, users often need to connect with the financial reinforcement learning environment and integrate machine learning strategy algorithms by designing the Markov Decision Process (MDP). The whole process requires a lot of engineering work but also a lot of financial expertise and field experience, which is very time-consuming and laborious, and researchers cannot concentrate on the research problem itself. Qlib directly provides a complete technology stack covering the above issues, eliminating a lot of tedious reworks for researchers.

2. Machine learning optimises strategies by interacting with the environment through trial and error. However, there are often significant differences between the simulated environment and the actual market environment, which may lead to a large gap between the optimal solution of the simulated environment and the optimal solution of the natural environment, which is one of the difficulties of machine learning research. On the one hand, this gap comes from the fact that actual transactions contain a large number of cumbersome rules, which are often ignored by trading frameworks commonly used for academic research. On the other hand, actual trading is usually a combination of different levels of trading (such as daily frequency trading and high-frequency trading), ignoring this part of the interaction will also cause bias to the simulation. Qlib is designed with various rules in mind as much as possible, and the nested decision-making framework is used to simulate the interaction of different levels of trading strategies in actual trading, thus minimizing simulation errors.

3. Machine learning requires a lot of computing resources, involves interaction with the environment and trial and error, and may require multiple iterations to reach the optimal strategy. Especially under the complex rules of financial markets, these interactions can be very time-consuming and require a lot of memory and computation. In order to accelerate the research iteration of machine learning, optimizing the training and testing process is critical. Qlib provides simulators with different simulation degrees. Users can use simulators with different simulation degrees at different stages during training (for example, simulators with low simulation degree but high operation efficiency are used in the early stage of training, and simulators with high simulation and high resource cost are used in the later stage of training), so as to achieve the optimal strategy in a high simulation environment. Save computing resources and speed up training. In the test process, Qlib can flexibly schedule the training of machine learning agents and the test environment, so as to improve the parallelism of backtest and accelerate the evaluation of strategies.

4. Methodology

This paper aims to explore the significance of machine learning methods in supporting household financial decisions. The researchers selected private banks and financial institutions in India for the study and collected data from the respondents. Machine learning algorithms play a key role in the financial sector, including identifying fraud, streamlining transaction processes, and providing financial advice to clients. Machine learning is able to analyze large data sets in a short period of time to improve results.

4.1. Data Sets and Assumptions

The researchers used a descriptive research design because the use of machine learning in financial decision-making is becoming increasingly important in emerging economies. In addition, business leaders are looking to implement new technologies to effectively manage risk, optimize cash inflows and outflows, support securities pricing, and understand areas that generate better financial returns.

Data were collected through questionnaires using non-probabilistic sampling methods, and the researchers obtained 229 complete data from the sample population, all of which were used for analysis. The use of closed questionnaires enables researchers to obtain responses from the sample population effectively. To translate the overall response into quantitative aspects, Likert scale principles (1: strongly disagree, 5: strongly agree) were applied.

hypothesis

1. Ho: There is no significant correlation between the application of machine learning in risk management and effective financial decision making in an organization.

2. Ho: There is no significant correlation between the application of machine learning to analyze and improve financial performance and effective financial decision making in organizations.

3. Ho: There is no significant correlation between cash management and effective financial decision making in an organization.

4.2. Data Analyze

Table 2. Demographic analysis.

Demographic variables	Features	Frequency	Percent
Gender category	Male	197	86
	Female	32	14
Age category	Less than 30 years	66	28.8
	31–40 years	70	30.6
	41–50 years	30	13.1
	Above 50 years	63	27.5
Type of family currently living	Joint family	119	52
	Nuclear family	110	48
Nature of industry	Banking companies	141	61.6
	Financial and nonbanking companies	88	38.4
Management cadre	Lower-level management	62	27.1
	Middle level management	134	58.5
	Process head	33	14.4
Total experience	Less than 3 years of experience	60	26.2
	4–8 years	54	23.6
	8–12 years	32	

This section provides a detailed analysis based on the data collected by the authors; The main analysis includes percentage analysis, correlation analysis and structural equation model (SEM) analysis.

According to the analysis in Table 2, 86% of the sample population are male and the rest are female. 30.6% of the respondents were aged between 31-40, 28.8% were under 30, 27.5% were over 50, and the rest were between 41-50. 52%

of respondents live in joint households, 61.6% work in banking companies, and the remaining 38.4% work in financial and non-banking companies. 58.5% are in middle management positions, 27.10% are in junior management positions, and the rest are process leaders in the current organization; 26.2% of respondents had less than 3 years of experience, 23.6% had between 4 and 8 years of experience, and 14% had between 8 and 12 years of experience.

These detailed analysis results help to understand the characteristics of the sample population and lay the foundation for subsequent quantitative analysis, such as the application of structural equation modeling (SEM).

4.3. Machine Learning Possesses More Opportunities.

More opportunities	Frequency	Percent
Strongly disagree	12	5.2
Disagree	18	7.9
Neutral	31	13.5
Agree	73	31.9
Strongly agree	95	41.5
Total	229	100

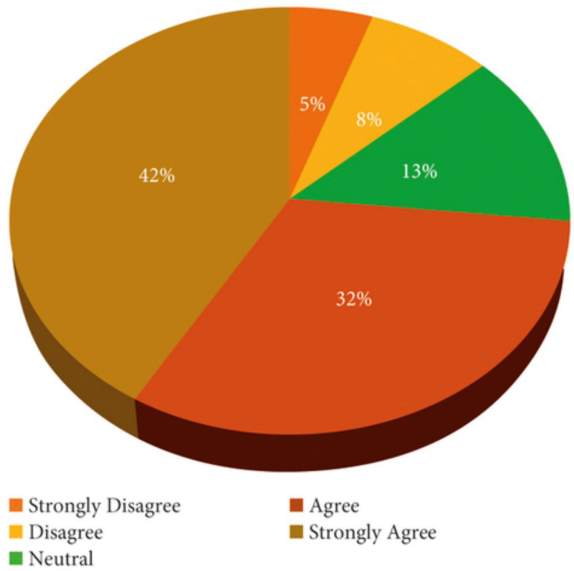

Figure 3. introduces a chart that represents the opportunities possessed by machine learning

According to the results of the data analysis in Table 3, 39.3% of respondents strongly agreed with the application of machine learning in managing total operating costs, and another 30.1% agreed. At the same time, 15.7% of respondents were neutral, 9.6% disagreed, and 5.2% strongly disagreed. Figure 2 shows the support of machine learning in managing cost-effectiveness based on feedback values from different respondents, including strongly disagree, disagree, neutral, agree, and strongly agree.

Correlation analysis is a valuable statistical tool that can be used to assess the overall relationship between variables. In this study, the researchers examined three key independent variables: risk management, areas of enhancing financial performance, and effective cash management, in relation to the dependent variable of improved financial decision-making.

5. Conclusion

According to the correlation analysis presented in Table 4, significant positive associations were observed among these variables, with correlation coefficients exceeding +0.700. Particularly noteworthy is the strong correlation between financial decision-making and risk management, indicating that machine learning (ML) greatly facilitates enhanced decision-making in risk management within organizations. Additionally, effective cash management showed the next highest correlation, highlighting ML's role in enabling swift and informed decisions concerning organizational cash flow optimization. Businesses can efficiently manage cash inflows from sales and other sources, thereby minimizing costs and maximizing profits with the support of machine learning technologies.

In the future, with the further popularization and development of mobile Internet technology, family investment decisions will be further intelligent and personalized. Future research is expected to focus more on how to leverage more accurate data models and deep learning algorithms to optimize portfolio allocation for greater return and risk control. In addition, with the continuous advancement of data security and privacy protection technology, it is foreseeable that home investors can enjoy the convenience and efficiency brought by the mobile Internet, but also more secure protection of personal financial information.

In summary, the mobile Internet has great potential for household investment decisions, but it also faces many technical and legal challenges. With the advancement of relevant technologies and policies, we are confident that in the future we will see the arrival of a more intelligent and secure home asset management environment, providing more investment options and optimized decision support for ordinary families.

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