Factors Influencing the Rollout of Robo-advisor in China Based on Potential Investors

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Abstract

This thesis investigates the impact of sociodemographic factors, behavioral factors, and financial and skilled behavioral factors on the intention to use robo-advisors (hereinafter “RAs”) among potential users in China. It comprises three main empirical chapters and one chapter dedicated to robustness analysis.

Chapter 1 provides an outline of, and introduction to, the thesis. Thereafter, Chapter 2 sets out the research background for the thesis, and Chapter 3 contains the literature review and hypotheses development. Chapter 4 outlines the editing and publishing process of the questionnaire used in this thesis, details the sample size of the collected data, and presents the main research methodologies employed for analysis, including logit regression and ordinary least squares (OLS). It also includes frequency analysis and preliminary analysis of the data.

Chapter 5 analyzes the effect of sociodemographic factors on the intention to use RAs based on 1,250 valid questionnaire responses. The sociodemographic factors considered in this thesis include age, gender, place of residence (urban or rural), marital status, number of financial dependents, employment status, monthly income, residential status, and educational background. Our analysis reveals that males exhibit a greater intention to use RAs compared to females. In addition, married respondents and those with a higher number of financial dependents are found to be more willing to try RAs in the future. Furthermore, both monthly income and educational background significantly and positively influence intention to use RAs.

Chapter 6 empirically analyzes the impact of behavioral factors on intention to use RAs. The behavioral factors in this thesis include risk aversion, risk perception, the better-than-average effect (BTAE), illusion of control (IOC), confidence, and trust. Our analysis shows that both risk aversion and risk perception significantly negatively

impact the intention to use RAs. Conversely, respondents with a higher degree of IOC and greater trust exhibit a stronger intention to utilize RAs.

Chapter 7 analyzes the impact of financial and skilled behavioral factors on the intention to use RAs among respondents, including financial literacy, financial confidence, perception of financial knowledge, experience of using traditional advisors, experience of using RAs, digital literacy, and numeracy skills. The analysis shows that potential users with higher levels of financial literacy are more likely to try out RAs in the future. Moreover, past investment experiences, whether with traditional advisors or RAs, significantly enhance the willingness of future RA usage among potential users. In addition, individuals with higher digital literacy, which indicates a greater acceptance of technology, also demonstrate a heightened intention to try using RAs.

Chapter 8 employs propensity score matching using one, three, and five nearest-neighbor matches per observation to conduct a robustness analysis of the main results mentioned in Chapters 5, 6, and 7. The robustness results are similar to our main empirical findings, except for financial confidence, perception of financial knowledge, and numeracy skills. The propensity score matching analysis reveals that potential users with higher levels of financial confidence and a more favorable perception of their own financial knowledge have a stronger intention to use RAs. Similarly, the intention to use RAs also increases with improvement in potential users' numeracy skills.

Chapter 9 summarizes the main findings, outlines the limitations encountered during the research process, and identifies audiences potentially audiences interested in this thesis. It also highlights potential avenues for future research.

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Declaration

I hereby declare that all material and results that are not original to this work have been fully cited and referenced. Except where explicit attribution is given to the work of others, this thesis is solely a product of my original outcome under the supervision of my supervisors and has not been proffered for any other degree at the University of Essex or any other institution.

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Content

Figure

Table

Appendix

Chapter 1 Introduction

China, as the world's second-largest economy, continues to play a pivotal role in the global. In the face of challenges such as trade disputes and the lingering effects of the COVID-19 pandemic, China's economy has demonstrated significant resilience. In 2023, the country maintained a year-on-year GDP growth rate of around 5%, driven by domestic consumption, technological advancements, and urbanization (UNCTAD, 2024). The Chinese government has focused on transitioning its economy from a heavy reliance on manufacturing and exports to a more balanced model placing a greater emphasis on services and innovation (Morgan Stanley, 2022). This economic transformation has been supported by government policies aimed at stabilizing growth while also addressing financial risks. Key areas of focus here include boosting domestic consumption, encouraging high-tech industries, and promoting green development as part of the broader goals set in China's 14th Five-Year Plan (UNCTAD, 2024).

The personal investment landscape in China has evolved significantly over the past decade as well. With increasing disposable income and a growing middle class, Chinese investors have shown a rising propensity to explore diverse investment options beyond traditional savings. The stock market, mutual funds, and real estate continue to be popular investment channels. However, there has been a noticeable shift towards more sophisticated financial products, including insurance and wealth management services (PWC, 2023). The rise of fintech has further revolutionized personal investment in China. Online investment platforms and mobile apps have made it easier for individuals to access a wide range of investment products, contributing to a more democratized investment environment. Younger investors, in particular, are increasingly turning to digital tools to serve their investment needs, reflecting a wider trend towards the digitization of financial services (Andrus, 2023).

In recent years, in order to better stimulate the development of China's economy and investment market, broader financial inclusion has been a central goal of China's economic reforms, particularly in extending financial services to underserved populations, such as rural residents and small businesses. The Chinese government has implemented a series of policy measures to promote the development of financial technology and financial inclusion, providing strong support for the advancement of RA services. For example, the State Council issued the 13th Five-Year Plan for National Science and Technology Innovation in 2016, explicitly proposing the promotion of innovation and development in financial technology and supporting the application of emerging technologies such as RA services (State Council, 2016). Additionally, the People's Bank of China (PBOC) emphasised in the ‘FinTech Development Plan (2019–2021)’ the need to strengthen the regulation of financial technology while encouraging innovation to enhance the inclusiveness and intelligence of financial services (PBOC, 2019). These policies provide a regulatory foundation for the development of RA services while also requiring RA platforms to meet higher standards of technological security and service quality.

Against this backdrop, China's RA services have gradually expanded from simple investment advice to more comprehensive asset management services. For instance, technology giants such as Ant Group and Tencent have launched RA services through their fintech platforms, leveraging big data and artificial intelligence to offer personalised investment recommendations to users (PWC, 2023). These innovations not only enhance the user experience of RA services but also provide Chinese investors with more diversified investment options. The development of more inclusive finance has been significantly bolstered by advances in digital technology. Mobile payments, internet banking, and microfinance have become vital tools in expanding access to financial services across China (PWC, 2023). Moreover, government policies have been instrumental in this progress, with initiatives designed to lower the barriers hindering access to financial products. The Chinese government has also partnered with fintech companies to create innovative solutions addressing the needs of those previously excluded from the traditional financial system. This has resulted in a significant increase in the availability of credit, insurance, and savings products in rural and low-income areas.

As an emerging technology that cannot be ignored in the pursuit of financial inclusivity, RAs, which use algorithms and artificial intelligence (AI) to offer automated financial advice, have rapidly gained traction in China. Since their introduction in the mid-2010s, these digital platforms have become increasingly popular, particularly among younger, tech-savvy investors. Unlike in Western countries where RAs often manage client assets directly, Chinese RAs have traditionally focused on providing portfolio recommendations due to regulatory constraints. However, the landscape is changing. The China Securities Regulatory Commission (CSRC) launched a pilot program in 2019 that allows RAs to offer more comprehensive services, including discretionary management of client portfolios. This regulatory shift has opened up new opportunities for RAs to expand their offerings and attract a broader customer base. Major Chinese tech companies, such as Ant Financial and Tencent, have also entered the market, further driving the growth and adoption of RA services.

The main contribution of this thesis lies in addressing a research gap regarding RA services in the Chinese market, particularly by exploring how potential users' sociodemographic factors, behavioural factors, and financial and skilled behavioural factors influence their willingness to use RA services. Unlike Western markets, RA services in China are still in the early stages of development, characterised by unique market acceptance, user demand, and regulatory environments. In recent years, the Chinese government has tightened regulations on the fintech industry, particularly in areas such as data security, compliance in investment advisory services, and algorithm transparency. For example, in 2019, the China Securities Regulatory Commission (CSRC) launched a pilot programme for RA services, allowing certain institutions to offer more comprehensive asset management services while imposing stricter compliance requirements on RA algorithms (CSRC, 2019). China's current policy context enhances the theoretical and practical value of this thesis research.

This study’s innovation is reflected in its integration of China’s unique socioeconomic context, a comprehensive analytical framework incorporating socioeconomic, behavioural, financial, and skilled factors, and advanced statistical methods such as propensity score matching (PSM) to ensure robust results.

Against this background, this thesis uses a survey method to collect data from 1,250 respondents in China. It empirically analyzes the relationships among respondents' sociodemographic factors, behavioral factors, and financial and skilled behavioral factors with their intention to use RAs in the future. The aim is to provide potential directions and insights to support the future development of RAs in China. Chapters 6 through 8 focus on the empirical analyses, each dedicated to examining how specific respondent characteristics influence their intention to use RAs. Chapter 6 explores the impact of sociodemographic factors, Chapter 7 examines the influence of behavioral factors, and Chapter 8 investigates the effects of financial and skilled behavioral factors on intention to use RAs. Finally, Chapter 9 comprises a robustness analysis using propensity score matching to validate the conclusions drawn from the empirical studies presented in the previous chapters.

Chapter 6 presents an empirical analysis of the factors influencing respondents' intentions to use RAs, focusing on sociodemographic variables. Specifically, this chapter includes variables such as age, gender, place of residence (urban or rural), marital status, number of financial dependents, employment status, monthly income, residential status, and educational background. Using a logit regression model, the analysis reveals that gender, marital status, number of financial dependents, monthly income, and educational background significantly influence intention to use RAs.

The results suggest that males have a higher propensity to use RAs in the future compared to females, potentially due to a greater acceptance of emerging technologies among men. In addition, married individuals are more likely to consider using RAs compared to single or divorced individuals, indicating that family responsibilities might drive the need for more structured financial management solutions.

Moreover, the intention to use RAs increases in line with the number of financial dependents, possibly indicating that greater financial pressure heightens the demand for efficient investment technologies. The analysis also shows that higher income levels are associated with a stronger likelihood of using RAs in the future. This may be due to higher-income individuals generally having a higher level of educational attainment, which enables them to understand and trust the mechanisms of RAs quickly. In addition, such individuals may have more opportunities to encounter and become familiar with RAs, thus increasing their willingness to adopt these tools. Furthermore, the study finds that a higher level of educational attainment also correlates with an increased intention to use RAs, as education enhances a person’s ability to comprehend and trust technology, leading to greater initial acceptance and usage intent.

Finally, the analysis using OLS yielded results that were consistent with those obtained from the logit regression. Specifically, both methods identified similar significant relationships between sociodemographic factors and the intention to use RAs. This consistency across different analytical approaches reinforces the robustness of the findings, confirming that gender, marital status, the number of financial dependents, monthly income, and educational background are significant predictors of the likelihood to adopt RAs in the future.

Chapter 7 shifts the empirical research focus onto the impact of behavioral factors on intention to use RAs. In this chapter, the influence of several key behavioral factors are explored, including risk aversion, risk perception, the BTAE, IOC, confidence, and trust. These factors are crucial in understanding the decision-making processes of potential users of RAs, particularly in the context of an emerging market like China.

Our results reveal that risk aversion, risk perception, IOC, and trust significantly impact upon the intention to use RAs in the future. Specifically, the findings indicate that respondents' intention to use RAs tends to increase as their level of risk aversion decreases. This suggests that individuals who are less risk-averse are more willing to adopt innovative financial technologies like RAs, possibly because they are more open to exploring new investment tools that potentially offer higher returns. Conversely, risk perception negatively affects intention to use RAs. This can be attributed to the fact that, currently, Chinese investors generally lack trust in RAs as financial products. As a result, they are hesitant to take the risk of relying on an automated system for investment decisions. This lack of trust acts as a significant barrier to the widespread adoption of RAs in the market. Perceived trust emerges here as a critical factor influencing investors' future intentions to use RAs. Our research confirms that as trust in RAs increases, so does the willingness to use them. This finding underscores the importance of building and maintaining trust in financial technologies to enhance their acceptance among potential users.

On the other hand, the level of illusion of control also plays a significant role in shaping respondents' intentions to use RAs. A high level of illusion of control leads individuals to overestimate their ability to influence investment outcomes. Consequently, they are more likely to believe that RAs can assist them in achieving their desired investment goals. This perceived ability to select and control the operations of RAs boosts their intention to use the technology. This observation aligns with Venkatesh et al.'s (2003) Unified Theory of Acceptance and Use of Technology (UTAUT), which posits that perceived ease of use is a key determinant of technology acceptance. In summary, this chapter highlights the complex interplay between behavioral factors and the intention to use RAs, providing valuable insights into the factors that drive or hinder the adoption of this emerging fintech.

Chapter 8 entails an empirical analysis of the impact of financial and skilled behavioral factors on the intention to use RAs. In this chapter, several key factors are examined, including financial literacy, financial confidence, perception of financial knowledge, digital literacy, traditional advisor experience, RA experience, and numeracy skills.

Our results show that, when considering all the factors involved in this study, financial literacy, digital literacy, traditional advisor experience, and RA experience have significant positive effects on the intention to use RAs. Specifically, higher financial literacy among potential users correlates with a greater likelihood of using RAs in the future. This is because higher financial literacy enables potential users to better understand how RAs function and fosters initial trust, which in turn makes them more willing to try this technology. In addition, individuals with higher financial literacy often seek more control over their investments, making the flexibility offered by RAs particularly appealing to this group.

Furthermore, our research finds that digital literacy also positively influences the future use of RAs. This finding partially supports the applicability of the UTAUT in the Chinese investment context, suggesting that digital competence is crucial to the adoption of fintech. The study also reveals that previous experience with traditional financial advisors encourages the future use of RA products. This is because past experiences provide potential users with a foundational understanding of investment processes, allowing them to grasp the mechanisms of RAs more quickly and thus perceive them as easier to use. On the other hand, prior experience with RAs helps users to build a certain level of trust, making them more inclined to continue using RA products for their investments in the future.

In summary, Chapter 8 highlights the significant role that financial literacy, digital literacy, and prior experience of both traditional advisors and RAs play in shaping the intention to use RAs, offering valuable insights into the factors facilitating the adoption of this financial technology.

In Chapter 9, propensity score matching analysis is employed to further strengthen the analysis of all factors discussed in the previous chapters. To ensure the robustness of our results, this study conducted the analysis using one match per observation, three matches per observation, and five matches per observation. The findings from this analysis are consistent with the conclusions drawn in Chapters 6, 7, and 8, reinforcing the validity of our earlier results.

Overall, this dissertation is dedicated to an in-depth empirical study of the factors influencing the intention of potential users in China to adopt RAs. By examining the impact of sociodemographic factors, behavioral factors, and financial and skilled behavioral factors on intention to use RAs, the research seeks to identify potential future directions for the development of RAs in China. In addition, the findings offer valuable insights for RA platforms and relevant regulatory bodies, providing strategic guidance for future development. This study also contributes to existing literature by supplementing our understanding of the factors that may drive or inhibit the adoption of this emerging financial technology.

Chapter 2 Motivation for Selecting China as a Case Study

2.1 China's economy situation

China is one of the world's largest economies and has consistently maintained a relatively high GDP growth rate since the introduction of its reform and opening-up policy in the 1970s. Over the past few decades, China's economic development has been marked by significant milestones, including rapid industrialization, urbanization, and technological advancement. These transformations have propelled China to become a global economic powerhouse and shaped its unique growth trajectory. The following analysis delves into the key trends and drivers of China's GDP growth since 2000, highlighting the factors that have influenced its economic performance and the challenges it has faced.

***INSERT FIGURE 2.1 HERE ***

Figure 2.1 illustrates the overall trend of China's gross domestic product (GDP) and its growth rate from 2000 to 2024. As shown in the figure, China's GDP per capita exhibits a significant upward trend since 2000, particularly between 2000 and 2007, when GDP experienced rapid growth. This can be primarily attributed to the development of an export-oriented economy following China's accession to the World Trade Organization (WTO) (Li, Liu and Zhou, 2023), as well as large-scale infrastructure construction and urbanisation (Lin, 2011). The government's proactive fiscal and accommodative monetary policies also supported economic growth (Zhang & Wan, 2007).

However, from 2007 to 2024, although total GDP continued to increase, its growth rate gradually slowed. This deceleration may be associated with multiple factors, including the global financial crisis (2007–2009), economic structural transformation, population ageing, increasing environmental pressures, and rising global economic uncertainties (Cai & Lu, 2013). Notably, the global financial crisis particularly impacted China's economy, leading to a sharp decline in GDP growth between 2007 and 2009 (Huang & Tao, 2010). More recently, the COVID-19 pandemic severely impacted the global economy, including China. However, through effective pandemic control measures and policy support, the Chinese economy has gradually recovered since 2020 (Group W.B, 2021). Furthermore, the Chinese government has emphasised high-quality development and innovation-driven growth in its 14th Five-Year Plan, which is expected to further optimise the country's economic structure and promote sustainable growth in the coming years (OECD, 2022).

Over the past 24 years, China's GDP has consistently grown, albeit at a slower pace. As a result, China's per capita disposable income has undergone significant increases. Therefore, after analyzing the performance of China's GDP and its growth rate, this thesis further examines the changes in per capita disposable income. This indicator not only reflects the outcomes of economic growth but also reveals improvements in residents' living standards and the transformation of the economic structure. Although its growth rate has mirrored the slowdown observed in GDP, per capita disposable income has continued to rise. Figure 2.2 (National Bureau of Statistics), based on data gleaned from the National Bureau of Statistics, illustrates the growth of per capita disposable income in China since 2000.

*** INSERT FIGURE 2.2 HERE ***

Figure 2.2 illustrates the overall trend of China's per capita disposable income and its growth rate from 2000 to 2024. The figure shows that per capita disposable income has grown significantly over this period, with the growth rate accelerating particularly after 2010. This growth trend is closely linked to China's rapid economic development, especially as industrialisation and urbanisation accelerated under the impetus of the reform and opening-up policy, leading to a substantial increase in residents' income levels (Zhang & Wan, 2006). Additionally, changes in the global economic environment and adjustments in China's internal economic structure have also positively impacted income growth (Lin, 2011). Research indicates that China's rapid economic expansion has primarily been driven by improvements in labour productivity and increased capital accumulation (Perkins & Rawski, 2008).

Despite the continued increase in per capita disposable income, its growth rate has decreased in recent years. This slowdown may be related to the shift in China's economic growth model, population ageing, and rising global economic uncertainties (Dollar et al., 2020). Studies suggest that China's economic growth has transitioned from a period of high-speed growth to medium-to-high-speed growth, naturally affecting the pace of income growth (Li & Gibson, 2013). Moreover, income inequality may also have exerted a certain restraining effect on overall income growth (Kanbur & Zhang, 2005).

In this context, in addition to the growth rate of per capita income, another closely related economic indicator is China's per capita savings rate. As income levels rise and the economic environment evolves, saving behaviors are also continuously adjusting. In particular, amid fluctuations in income growth and increasing economic uncertainty, the public's willingness to save and their saving patterns may undergo significant changes. To analyzing China's savings rate, data from the National Bureau of Statistics of China are used to fill out Figure 2.3 (World bank). The analysis of per capita disposable income not only reflects residents' living standards to a certain extent, but also provides a means through which to study the investment intentions of the populace further.

*** INSERT FIGURE 2.3 HERE ***

Figure 2.3 illustrates the trend of China's savings rate from 2000 to 2023. As shown in the figure, China's savings rate remained at a relatively high level during this period, reaching its peak in 2008. This high savings rate is closely related to Chinese residents' traditional saving habits, the underdeveloped social security system, and the increase in income driven by rapid economic growth (Modigliani & Cao, 2004). To some extent, the high savings rate reflects precautionary savings in response to future uncertainties, particularly regarding expenditures on education, healthcare, and retirement (Chamon & Prasad, 2010).

The savings rate has fluctuated in recent years and has shown a downward trend. This decline may be associated with China's economic structural transformation, the gradual improvement of the social security system, and changes in consumption patterns (Wei & Zhang, 2011). As China's economy continues to develop, residents' consumption levels have gradually increased, and the growing prevalence of consumer credit has reduced the need for savings (Wen, 2010). Additionally, government policies aimed at boosting domestic demand has also promoted consumption to some extent, thereby influencing changes in the savings rate (Wei & Zhang, 2011).

This section has elucidated the recent changes in China's economy, as illustrated by Figures 2.1, 2.2, and 2.3. The dynamics of the savings rate are influenced by multiple factors, including economic growth and inflation rates, and may also affect individuals' capital planning and investment willingness. Thus, data from the National Bureau of Statistics of China were used to construct these line graphs and a thorough analysis was conducted to establish a foundation for subsequent investigations into the Chinese public's investment intentions through RA. This foundational analysis is crucial to understanding how broader economic factors shape individual financial decisions and future investment trends.

2.2 China's current investment situation

Undoubtedly, the relationship between China's personal savings rates and investment behaviors is intricate, as a high savings rate plays a pivotal role in the development of the Chinese market and the expansion of investments. As noted earlier, China boasts one of the highest savings rates globally, creating a substantial pool of capital that can be channeled into financial markets and serve as a crucial source of funding for China's investment sector. Conversely, when the savings rate is excessively high, banks may be inclined to lower interest rates to alleviate the burden of paying interest. This scenario can lead savers to struggle in securing reasonable returns on their savings in the short term, prompting them to channel their savings into relatively risky investments such as stocks and bonds in pursuit of higher returns. While such a shift can indeed enhance capital inflow into financial markets (China Securities Regulatory Commission, 2021) and potentially yield higher returns for individual investors, it also exposes them to increased risk. This dynamic underscores the delicate balance between encouraging savings to foster investment while managing the investment risks that individuals face in financial markets.

In recent years, China's economic expansion has forged significant opportunities and favorable conditions for individual investors. The rise in personal income and wealth accumulation has fueled demand for various investment products and related services. According to the CSRC, the number of individual investors in China surged to 191 million in 2020, encompassing diverse investment avenues such as stocks, funds, and futures—up from just 8.8 million in 2000. Furthermore, a 2019 report from the China Securities Investment Fund Association highlighted that the size of public funds in China reached $1.87 trillion 7(¥13.7 trillion), with individual investors representing 76.5% of this figure. The China Banking and Insurance Regulatory Commission also noted in its 2020 report that the total size of insurance funds in China had reached $2.61 trillion (¥19.1 trillion) by the end of June 2020, with $0.63 trillion (¥4.6 trillion) in individual insurance accounts. The investment landscape in China offers individual investors a vast array of options, including stocks, bonds, mutual funds, and other financial portfolio products. This diversity has been bolstered by nearly three decades of market development. Particularly noteworthy here is the growth of China’s financial sector, with the Shanghai Stock Exchange and Shenzhen Stock Exchange ranking among the largest stock exchanges globally. In addition, the Beijing Stock Exchange, which officially launched around September 2021, has also shown rapid growth. To stimulate investment further, the Chinese government has implemented various supportive measures, such as tax incentives for individual investors and the introduction of policies aimed at enhancing investor protection. The increased availability of investment products and services, combined with strong government support, has notably contributed to the heightened willingness among individuals to invest, marking a dynamic shift in China's financial landscape.

Indeed, while the expansion of China's economy and the proliferation of investment opportunities have been largely beneficial, they also present considerable risks, particularly to individual investors who may lack experience or access to reliable financial information. Despite rapid advancements, China's financial market is relatively young, and the frameworks of laws and regulations governing it still require significant refinement. Consequently, concerns about corporate governance quality and the accuracy of financial reporting are prevalent among individual investors. Economic fluctuations in China can also induce volatility in financial markets, exposing individual investors to significant risks. A poignant example came in 2015 when the Chinese stock market experienced a sharp transition from a robust rally to a precipitous decline, with the Shanghai Composite Index plummeting by almost 50% in just a few months (Zhao et al., 2019). This crash resulted in substantial financial losses for many, affecting their subsequent investment decisions and perspectives. Overall, while China's economic growth is generally viewed as a positive force that creates substantial opportunities for individual investors, it also introduces risks, especially for those who are new to investing or lack the necessary expertise. As China continues to progress and its financial market evolves towards greater sophistication and maturity, the enthusiasm of individual investors to engage in therein is expected to grow. However, it is essential that this enthusiasm is matched with improved financial literacy and enhanced regulatory frameworks to safeguard and empower investors.

In the current landscape of China's financial market, individual investors are presented with a variety of investment options, including stocks, bonds, mutual funds, and real estate. For those looking to engage in the stock market, the primary platforms include the Shanghai Stock Exchange (SSE), the Shenzhen Stock Exchange (SZSE), and the newly established Beijing Stock Exchange (BSE). However, navigating these exchanges can be particularly risky for inexperienced investors with limited access to pertinent information. Such investors may face substantial losses due to sudden market fluctuations (Wen et al., 2019). An alternative for individual investors is to invest in mutual funds. These are professionally managed portfolios that aggregate capital from multiple investors to invest in a diverse array of securities. This method is inherently less risky than investing directly in individual stocks due to the diversification of investments (Ben-David et al., 2019). Mutual funds can mitigate the risks associated with the volatility of individual stock investments; a strategy known as risk diversification. In recent years, online investment platforms have gained hereinafter in the Chinese market, appealing to some individual investors by offering a convenient, rapid, and efficient means of engaging with financial markets (You et al., 2023). These platforms enable users to trade stocks, mutual funds, and bonds, while also providing access to financial news and investment advisory services. According to a 2021 report by the Association of Securities and Investment Funds of China (AMAC), over 60% of investors possess less than $69,000 (¥500,000) in financial assets. Investment decisions among these individuals tend to focus more on return rates and risk levels. The data also indicate that only 21% of investors are inclined to pay for relatively expensive investment advisory services. With the ongoing development of China's financial market, there is an increasing trend towards seeking professional investment advice. Thus, an online investment adviser that offers low-cost, accessible investment advice could potentially attract a substantial number of users. Overall, Chinese individual investors face several challenges and risks in the financial market, including a lack of financial literacy, insufficient investment knowledge and experience, and relatively limited and often expensive access to quality financial advice. As the market continues to evolve, providing educational resources and affordable advisory services could play a critical role in helping investors to navigate these complexities more effectively.

In light of the recent instability in the economic environment, which contributes to significant stock market volatility and potential government interventions, investors face challenges when it comes to making informed decisions. In the current financial market, individuals aiming to invest typically follow these steps.

Research the Market and Industry: Initially, investors need a thorough understanding of the financial market and the target industry to identify potential investment opportunities and associated risks. This involves careful analysis of past market data, industry trends, company financials, and competitive dynamics, which helps to pinpoint viable investment areas.

Determining Investment Objectives and Strategies: With insights into the market and its segments, investors must then define their investment goals and strategies. Options here might include long-term investments, short-term speculations, value investing, growth investing, or pension-focused investing, depending on their future plans and financial capacity. This step is crucial in crafting a tailored investment plan as follows: (1) After establishing their investment objectives, investors can choose appropriate investment products such as stocks, bonds, mutual funds, futures, or foreign exchange, aligning with their expectations and strategies. In the current Chinese financial market, a variety of investment tools and platforms are available, including the investment advisory services of banks and financial institutions, as well as emerging online trading platforms; (2) Investors execute buy-or-sell orders for chosen investment products through brokers or online trading platforms. During this process, they must consider factors like price, volatility, liquidity, and the transaction costs of the investment products to ensure they do not exceed their capacity for loss; (3) Postinvestment, it is essential for investors to regularly monitor and manage their portfolios. This includes assessing investment risks and returns and making necessary adjustments. This step is often supported by real-time data monitoring tools like the portfolio's seven-day annualized rate of return and portfolio optimization features provided by the investment platform; and (4) Regular evaluation of investment performance is vital. Investors can use various metrics and tools, such as returns, Sharpe ratios, and benchmark indices to gauge their performance. Professional investment platforms or institutions typically offer these performance indicators in a visual format, along with brief explanations to aid less financially literate investors in understanding their significance and the performance of their portfolios.

To facilitate easier, faster, and safer investment operations for individual investors and further promote the financial market in China, the country has been focusing on developing and popularizing inclusive finance in recent years. Such efforts have aimed to democratize access to financial services and ensure that a broader segment of the population can participate in, and benefit from, the financial market's growth.

2.3 Financial Inclusivity in China

Financial inclusion is about ensuring that all members of an economy, particularly the underserved and marginalized, have access to, and can effectively use, the formal financial system (Sarma and Pais, 2011). This concept specifically targets the provision of financial services to low-income groups, the poor, and marginalized populations, as well as micro-groups such as SMEs that are often underserved by traditional financial institutions. As defined by Demirguc-Kunt et al. (2017), financial inclusion is a policy that leverages financial innovation to promote equitable, inclusive, and sustainable financial services to meet the basic financial needs of the general public broadly. In simpler terms, at its core, financial inclusion is about ensuring access and equality in financial services. Traditional financial services typically cater to high-income individuals and large corporations. In contrast, inclusive finance seeks to fill this gap by enabling low-income groups and SMEs to access financial services more readily. This can take on various forms, including microfinance, mobile payments, and digital finance, among others. Financial inclusion has increasingly become a policy priority for numerous countries (Sarma and Pais, 2011), with China beginning its implementation thereof in the early 21st century. Initially, the Chinese government encouraged financial institutions to extend their services to micro, small, and medium-sized enterprises (MSMEs) and rural residents. Accordingly, banks and credit unions started pilot projects in inclusive finance. In 2014, the Chinese government launched a "3-year action plan for inclusive finance," which mandated banks and financial institutions to develop inclusive finance vigorously over a three-year period. Under this initiative, the requirements for the supervision and assessment of inclusive finance were standardized, compelling financial institutions to enhance the management of their inclusive finance practices and continuously improve the services offered.

Inclusive finance in China has since transitioned into a phase of standardized development, marked by expanding service coverage and the introduction of innovative service methods, contributing positively to the financial sector's growth (Fungáčová and Weill, 2015). According to the People's Bank of China, by the end of 2020, the number of inclusive financial service providers in the country had reached 13,000. These services cater to SMEs, individual entrepreneurs, rural residents, and low-income individuals. The total balance of inclusive financial loans amounted to \$2.26 trillion (¥16.4 trillion), covering 98% of counties and cities nationwide. Furthermore, the integration of technology has facilitated the digitization of inclusive finance. Prominent

Chinese internet finance companies, such as those behind Alipay's Ant Credit and WeChat's financial services, have begun to offer small loans and consumer credit through their online platforms (Hua and Huang, 2020), significantly broadening access to financial services. The primary aim of inclusive finance is to provide more individuals and businesses with the financial services necessary to enhance their income opportunities and, consequently, their quality of life—thereby giving economic development more vitality. Currently, financial inclusion encompasses the following several key services and initiatives (Garg and Agarwal, 2014): (1) financial services of non-traditional institutions including credit unions, microfinance companies, and community banks; (2) services for underserved demographics, targeting people with low incomes, farmers, migrants, and others not typically served by traditional financial institutions; (3) universal access to financial tools and technologies such as mobile payments, digital finance, and internet finance; and (4) enhancing financial literacy to improve the public's understanding and effective use of financial services.

*** INSERT FIGURE 2.4 HERE ***

Figure 2.4 (CNNIC, 2025) illustrates a significant increase in both the number of mobile payment users and the usage rate in China. Although the growth rate slowed down after 2020, the overall trend remains robust, with the number of users expected to approach or exceed 1 billion by 2024. Figure 2.4 also represents the mobile payment usage rate, which exhibits slight fluctuations but generally trends upward, with the rate projected to reach nearly 90% by 2024.

This growth reflects China's remarkable progress in promoting inclusive finance, particularly in expanding financial services and enhancing financial accessibility. One of the core objectives of inclusive finance is to ensure that all members of society, especially low-income and marginalised groups, have equal access to financial services (Corrado and Corrado, 2017). China's mobile payment systems, particularly platforms like Alipay and WeChat Pay, have become key enablers of this goal (Hasan, Yajuan and Khan, 2020). Through mobile payments, more people in rural areas, low-income groups, and small businesses can easily access financial services, overcoming the limitations of the uneven distribution of traditional bank branches and financial resources (Patel, Rao and Radhakrishnan, 2023).

In advancing inclusive finance, mobile payments have emerged as an effective means of reducing costs and improving the efficiency of financial services (Bezhovski, 2016). In China, technological innovations such as QR code payments and digital wallets, coupled with supportive government policies, have driven the rapid adoption of mobile payments (Ye, Chen and Fortunati, 2021). This is particularly evident in rural areas, where many people can access convenient financial services through mobile payments. This has facilitated broader economic participation, improved quality of life, and enhanced overall financial inclusion in society (Hasan, Le and Hoque, 2021).

*** INSERT FIGURE 2.5 HERE ***

In addition to mobile payments, digital banking also represents a product of financial inclusion. Figure 2.5 (Statistic, 2024) reveals a significant upward trend in deposits and loans in China's digital banks since 2017, with the growth rate of loan value far surpassing that of deposit value. This indicates that digital banks have performed better in providing loans than deposit services.

This trend underscores the crucial role of digital banks in advancing inclusive finance in China. Digital banks, particularly those leveraging internet and mobile platforms, offer advantages such as high efficiency and low costs, enabling financial services to reach populations that traditional banks have struggled to serve effectively, especially low-income groups and small businesses (Wewege, Lee and Thomsett, 2020). These groups often face barriers such as high thresholds and cumbersome approval processes when seeking loans from traditional financial institutions (Giraldo et al., 2024). In contrast, digital banks provide more convenient and flexible financial services through technological innovation, thereby driving the development of inclusive finance (Du, Wang and Zhou, 2023).

The growth in digital banks' loan business, particularly in small business and personal loans, highlights how financial technology promotes financial inclusion (Liu et al., 2021). With the application of technologies such as artificial intelligence, big data analytics, and blockchain, digital banks can conduct more precise credit assessments, reducing loan risks and expanding access to credit services (Sadok, Sakka and El Maknouzi, 2022). Additionally, these technologies enable digital banks to offer loans to more marginalised groups, lowering barriers to entry into the financial market (Ozili, 2020). Within the framework of inclusive finance, the rapid development of digital banks has not only facilitated the widespread availability of financial services but has also contributed to socially inclusive economic growth (Hasan, Yajuan and Khan, 2020).

The significance of financial inclusion lies in its ability to balance social equity, promote economic inclusivity, and foster sustainable development. Furthermore, it plays a crucial role in alleviating poverty and reducing inequality, contributing to economic growth and the increasing prosperity of the financial sector (Garg and

Agarwal, 2014). Financial inclusion not only bolsters the economy by broadening access to financial services—thus increasing employment opportunities and economic dynamism (Fungáčová and Weill, 2015)—but it also aids the impoverished in gaining financial services and support. This contributes to narrowing the wealth gap and promoting social equity. Furthermore, inclusive finance enhances the development of financial markets by improving their inclusiveness and stability and also drives innovation in financial products to meet diverse customer needs.

The development of inclusive finance, while bringing substantial benefits, also has to overcome significant challenges to ensure its sustainability and effectiveness. One major issue here is the necessity to enhance the precision of financial products and services designed to achieve inclusivity. Moreover, the high cost of capital and the complexities associated with risk management pose considerable obstacles too. Inclusive finance typically targets low-income and high-risk groups, making risk management challenging and necessitating robust control mechanisms. Furthermore, the focus on serving low-income and economically disadvantaged groups often results in lower profitability for financial institutions providing these services. Credit risk is also heightened since the clientele often includes individuals and businesses with limited or poor credit histories. The policy drive towards inclusivity and the broadening of the market base have intensified competition within China's inclusive finance sector, prompting a need for increased innovation and effective marketing strategies among actors to capture and grow their market share. For individual investors, the Chinese government’s vigorous promotion of inclusive finance has impacted upon their future investment decisions. The expansion of financial institutions into inclusive products offers more opportunities for individual investors. However, it is crucial to recognize that inclusive finance predominantly supports micro, small, and medium-sized enterprises (MSMEs) and low-income individuals, groups that typically pose higher financial risks (Abel et al., 2018). Therefore, when investing in inclusive finance products, individual investors must conduct thorough financial risk assessments and opt for investments offering a high level of credit quality and a stable cash flow to safeguard their returns and capital. In addition, individual investors also need a deep understanding of market conditions and the specific risk characteristics associated with inclusive financial products to make informed and cautious investment choices. In sum, inclusive finance serves as a crucial mechanism in providing financial services to underrepresented groups, such as MSMEs and low-income populations, addressing significant barriers they face in accessing financial support. Although the development of inclusive finance presents certain risks and challenges, its potential to narrow the wealth gap, foster social stability, and propel economic growth is undeniable. Thus, it represents a pivotal force in advancing economic inclusivity and development.

Indeed, the challenges presented by serving customers who are high risk and have low credit ratings in inclusive finance necessitate more precise and nuanced financial services. Specifically, these services must be supported by innovative financial tools and technologies, a demand that aligns perfectly with the burgeoning fintech field. Fintech aims to enhance and optimize financial services through technological advancements, reshaping the structure of the industry and making financial services more accessible and cost-effective. The integration of digitization within financial services, facilitated by fintech, provides users with easier access to necessary services (You et al., 2023), significantly reducing the cost and complexity associated with delivering inclusive financial services. Mobile payments and e-banking, for instance, enable individuals to conduct financial transactions seamlessly without the need to visit a bank. Furthermore, fintech's capabilities in data analytics allow for the efficient collection and analysis of customer information, ensuring that the most appropriate product information and services are delivered promptly. At the core of fintech is the utilization of big data, AI, and machine learning technologies, which are instrumental in assessing a customer's credit risk. This assessment helps financial institutions to determine the most suitable products to recommend, enhancing the precision of their service delivery. The adoption of fintech enables inclusive financial institutions to better manage risk, circumvent the challenges previously mentioned, and enhance the sustainability of their financial offerings. The synergy between financial inclusion and fintech is profound, with both fields working together to extend financial services to a wider audience. As fintech continues to evolve and expand across various financial segments, RAs are gaining prominence as innovative financial tools (Anshari et al., 2022). These advisors, powered by AI and big data, offer customized portfolio solutions tailored to individual investors based on their risk tolerance and investment objectives (Abraham et al., 2019). One significant advantage of RAs is their ability to automate investment processes, which helps investors to avoid the pitfalls of emotional and cognitive biases, thereby enhancing investment returns and improving risk management. Overall, the integration of fintech innovations into inclusive finance not only addresses the immediate needs of underserved populations but also propels the financial sector towards more sustainable and equitable growth. This integration is essential in broadening the reach and impact of financial services, ensuring that they are both accessible and beneficial to all segments of society.

Consequently, the ongoing evolution of inclusive finance in China has significantly contributed to the growth of RAs, in turn enhancing development and innovation within China’s financial market. Through automated investment decisions, RAs offer users more precise and varied financial services, thereby facilitating the achievement of their development objectives more effectively. It would be plausible to assert that the expansion of RAs will become a prominent trend within the financial industry; one that cannot be overlooked.

2.4 Current situation regarding RAs

In Europe and the United States, using RAs has become an important topic in investment and is increasingly favored by investors. After decades of development, RAs have significantly progressed and yielded positive results. According to recent surveys, RAs occupy a considerable share of the investment market in Europe and the United States (Todd & Seay, 2021). Furthermore, the application of RAs is continuously expanding, covering independent investment institutions, financial services organizations, banks, and insurance companies, all of which have incorporated RAs into their business operations.

Countries in Europe and North America generally adopt a more open attitude toward RAs, believing they can provide more efficient, intelligent, and cost-effective investment services. This model is beneficial in enhancing individual investors' investment efficiency and risk management capabilities. After years of development, the regulatory frameworks in Europe and the United States have also gradually improved the standards and requirements for RAs. For example, the U.S. Securities and Exchange Commission (SEC) mandates that RAs must clearly disclose their investment strategies, associated risks, and expected returns to investors and that their algorithms must be transparently disclosed (USE, 2017). Similarly, European regulators require RAs to ensure full risk disclosure, transparency, and compliance and to undergo regular monitoring and evaluation. Meanwhile, the United Kingdom has also promoted the development of RAs through the innovative regulatory sandbox approach (Lee et al., 2018). The widespread acceptance of RAs in Europe and the United States has significantly increased their popularity among investors, especially younger generations, who are more inclined to choose these technology-based investment solutions.

With the continuous expansion of China's financial market, the diversity of investment options is constantly increasing, and the amount of information is growing exponentially (Pilbeam, 2018). Traditional investment service models are becoming inadequate (Zhao et al., 2023). As an emerging investment service model, RA is expected to accelerate the transformation of the investment market (Guo, 2020). By providing investment institutions with more accurate market analysis and predictions, RA will drive the evolution of the market (Gomber et al., 2017). As the investment market matures, the compliance of investment services becomes increasingly important. As a relatively new model, RA requires strict regulation and standardization. Researching the factors influencing RA's popularization in China can provide important insights and guidance for standardized practices, which will not only promote the standardization of the investment market but also increase RA's adoption rate and popularity in China, ensuring that it meets the market's ever-changing demands responsibly and effectively (Jung et al., 2018).

By 2024, RA services in China had rapidly entered a new phase, receiving increasing attention from institutions and investors. With the continuous advancement of technologies such as artificial intelligence, big data, and blockchain, the applications of RA platforms in China are becoming more intelligent and personalised (Ge et al., 2021). For example, Ant Group's Ant Wealth platform uses AI algorithms to provide professional investment advice and incorporates blockchain technology to enhance data verification and transparency (Sironi, 2016). These technological innovations have strengthened the competitiveness of RA platforms, attracting more investors. Meanwhile, China's regulatory environment is also gradually loosening (Chorzempa and Huang, 2022). Although RA platforms still cannot directly manage user funds, the CSRC has released new policy documents to strengthen the regulation of internet investment advisors (Guo, 2020), requiring platforms to implement strict risk disclosure and transparency standards, providing clear guidance for the development of platforms, and increasing investor confidence (Dong and Wang, 2024).

In terms of market competition, besides Ant Wealth and Huatai Securities, platforms such as JD Finance and Baidu Finance have also launched their own RA products, promoting the diversification of RA services (Lee and Shin, 2018). These platforms have expanded the application scenarios of RAs and formed in-depth collaborations with traditional financial service companies, creating an integrated online and offline service model that further enhances market appeal. Although the popularisation of RAs in China still faces challenges, particularly in user education and trust-building (Xia et al., 2023), the promotion of digital financial education has improved users' financial literacy through online courses and intelligent customer service, helping them understand the operational mechanisms and investment strategies of RA platforms (Han et al., 2024), thus increasing user engagement.

Additionally, many RA platforms have begun integrating with traditional financial products, offering investment advice for products such as quantitative funds and index funds, helping investors optimise their portfolios within a controllable risk range (Yan, 2023). This cross-sector cooperation not only expands the application scope of RA products but also helps more traditional investors gradually adapt to intelligent investment. Overall, driven by technological innovation, policy support, and market competition, RA services in China present highly promising prospects for future development (Huang, 2021a) and are expected to play an increasingly significant role among younger generations (Dollar and Huang, 2022) and investors with a higher acceptance of fintech (Luo et al., 2024).

In the subsequent chapters of this thesis, a detailed literature review concerning RAs is first provided, briefly summarizing the existing body of research on RAs, setting the stage for a deeper exploration of the topic. The primary hypothesis of this study is then introduced in Chapter 3, which is formulated based on the insights gleaned from the current literature and the specific research goal of this thesis. Given that this research focuses on Chinese individuals, a structured questionnaire was utilized to gather data in a comprehensive manner. Chapter 4 of this thesis provides details on the design process of the questionnaire, including its pilot testing and the eventual deployment. This methodological approach ensures that the data collected are robust and reflective of the real-world context. Following the data collection phase, an analysis and discussion are undertaken based on the results obtained. This chapter aims to interpret the data in the context of the established research framework and explores the implications of the findings in relation to the initial hypotheses and broader research questions. The thesis concludes with a final chapter that synthesizes the key findings, discusses the implications for both theory and practice, and provides recommendations for future research. This concluding chapter aims to encapsulate the contributions of the study to the field of fintech and investment, particularly in the context of the Chinese market's dynamics and characteristics.

Figure for the economic situation in China

Figure 2.1 GDP and its growth in China

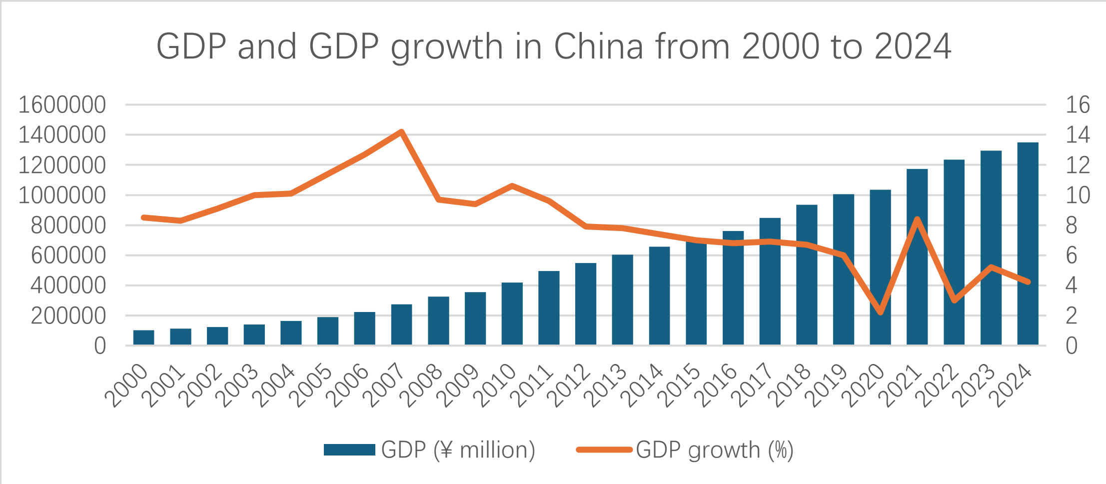

Figure 2.1 shows the change in China's GDP and GDP growth rate from 2000 to 2024.

Figure 2.2 Growth rate of disposable income per capita

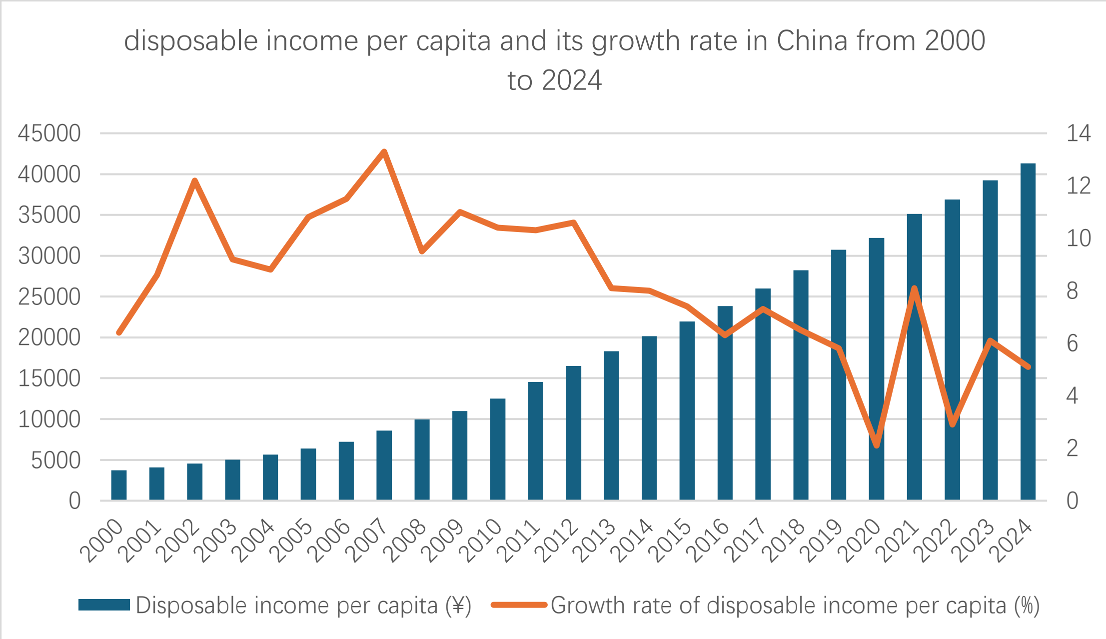

Figure 2.2 shows the change in per capita monthly income and its growth rate in China from 2000 to 2024.

Figure 2.3 Saving rate per capita

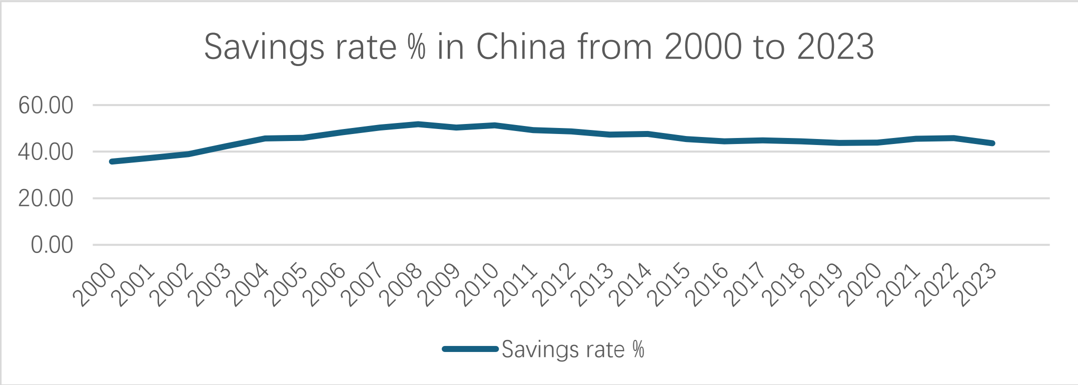

Figure 2.3 shows the trend in China's per capita savings rate from 2000 to 2023.

Figure 2.4 Mobile payment in China 2016-2024

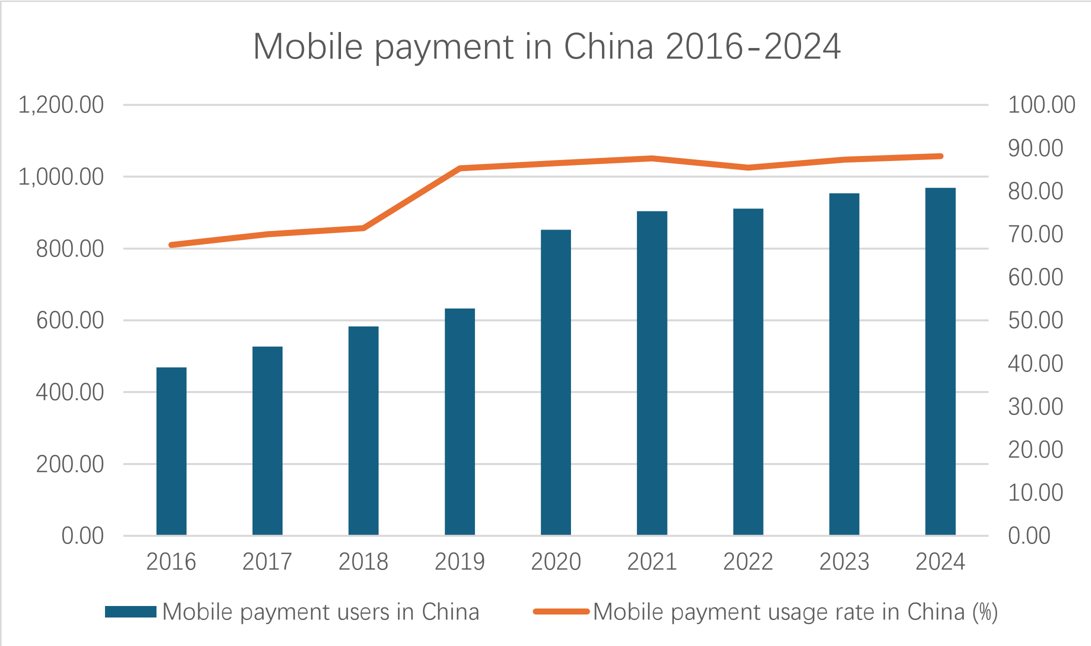

Figure 2.4 shows the trend of mobile payment and usage rate in China from 2016 to 2024.

Figure 2.5 Deposit value and Loan value of digital banks in China 2017-2023

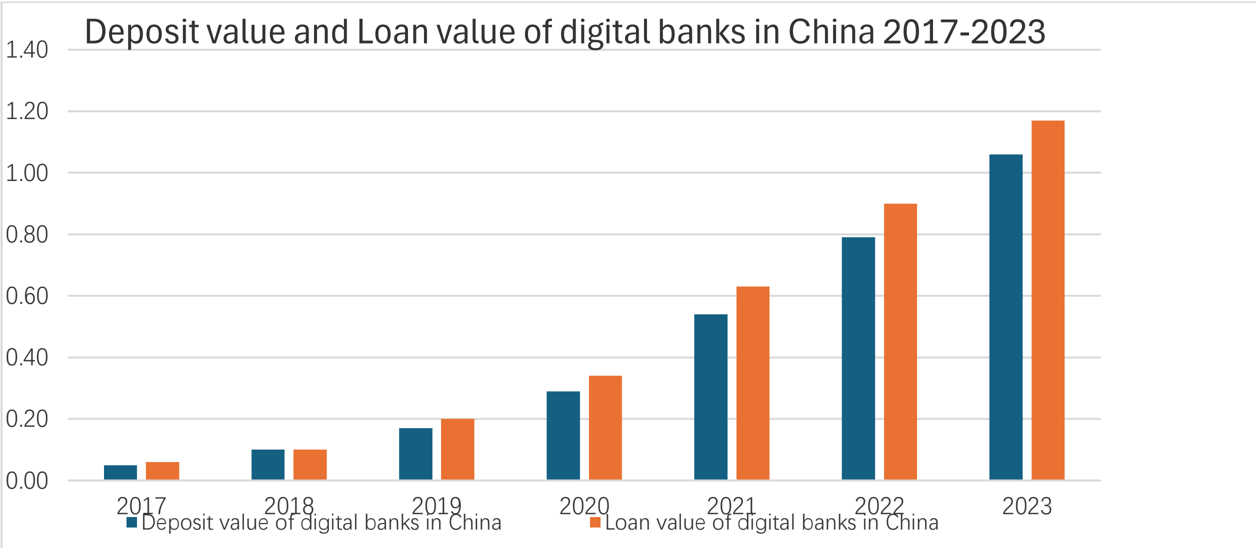

Figure 2.5 shows the deposit value and loan value of digital banks in Chins from 2017 to 2023

Chapter 3 Literature Review and Hypothesis development

3.1 Origin and development of RA

Investing, though sometimes daunting, has become an increasingly popular and lucrative activity. The rise in living standards over the last few decades has led consumer demand for investment and financial management services to soar. However, the unpredictability of financial markets has created a complex investment environment, particularly in the retail market, the intricacy of which has grown with the development of various types of investments (Fisch et al., 2019). Consequently, investors with limited financial knowledge, are at risk of making poor investment decisions (Fisch et al., 2016), creating the need for professional investment advisors. Despite the expertise possessed by human investment advisors, their ability to customize advice effectively for each client—considering their diverse backgrounds and conditions—can be highly time-consuming and may still yield suboptimal results. Simply put, computers are proficient in processing large volumes of data swiftly and can, in many cases, manage investment assets more efficiently and effectively than humans. This has led to the emergence and development of RAs, which use sophisticated back-office data analysis and AI to replace the traditional functions of human investment advisors. These systems analyze and predict future economic trends and provide personalized investment advice, effectively translating traditional investment methods into an online platform. In this regard, Paolo Sironi provided a clear definition in 2016, stating that a RA initially analyzes an investor's self-assessment through automated decision-making and trading algorithms. A RA’s analysis is based on responses to an online questionnaire filled out by the client (Fein, 2015), according to which investment solutions tailored to suit the investor's objectives are crafted.

RAs first emerged in 2008 in Europe and the United States, offering online investment advice and management services for a fee. By 2010, Betterment, an independent RA, was founded with the mission of "helping customers manage their wealth so they can pursue a better life," and it has since become the largest independent RA in the world (Stein, 2022). At this point, the concept of RAs began to gain traction globally. In China, the RA was first introduced in 2014, but its development has faced unique challenges due to cultural and cognitive differences between China and Western countries, as well as differing economic systems. From 2014 to 2017, the Chinese RA market experienced a period of "wild growth" during which many internet companies, financial institutions, and startups entered the market. Despite the initial enthusiasm, these firms soon encountered a familiar problem: difficulty in attracting and retaining customers. That very challenge also confronted Betterment when it was first established. This issue remains unresolved in the Chinese market and continues to be a common problem within the global RA industry. Data from 2020 show that the combined assets under management (AUM) of global RAs amounted to just US$1.07 trillion—a modest figure when compared to the assets managed by major asset managers such as BlackRock (US$8.7 trillion), Pioneer (US$7.2 trillion), and State Street ($3.5 trillion) (Oehler et al., 2021). This stark contrast highlights that RAs are used significantly less than traditional human investment advisors. For RAs to expand further, one of the primary challenges to be addressed is increasing investor usage. Therefore, it is crucial to understand both the strengths and weaknesses of RAs to enable a thorough analysis of the factors influencing Chinese investors' adoption of RAs, and to promote their growth within China. Maximizing their advantages and mitigating their disadvantages will be essential in enhancing their development and acceptance in the Chinese market.

Since 2020, the RA market has undergone significant changes in both technology and market acceptance. Recent advancements in artificial intelligence and big data analytics have greatly enhanced the ability of RAs to optimise investment strategies, enabling more accurate market trend predictions and dynamic portfolio adjustments based on real-time data (Beketov et al., 2018). Leading RA firms have begun integrating advanced AI and natural language processing (NLP) technologies to improve client interaction experiences, thereby increasing customer trust and investor retention (D'Acunto et al., 2019). Additionally, the hybrid RA model, which combines AI-driven automation with human advisor expertise, has gained traction in recent years. This model balances risk management and personalised investment needs, offering a more tailored approach to wealth management (Brenner & Meyll, 2020). In China, local fintech companies such as Ant Group, Tencent Wealth, and JD Finance have incorporated RA technologies into their wealth management platforms. These firms leverage social media data for precision marketing, significantly enhancing user engagement (Yang and Zhang, 2022).

Despite these advancements, the RA industry still faces several challenges. Investor trust remains a critical issue, particularly during periods of high market volatility, when many investors prefer traditional human advisors for more contextualised advice (Jung et al., 2019). Furthermore, data privacy and regulatory compliance have become increasingly pertinent issues, with governments worldwide tightening regulatory frameworks to ensure algorithmic transparency and fairness (Arner et al., 2015). In China, regulatory authorities have imposed stricter qualification requirements on RA products and limited the use of high-risk investment strategies to protect the interests of retail investors (Huang et al., 2021).

In summary, the future development of RAs will focus on further optimizing AI technologies to enhance the adaptability and intelligence of investment strategies, strengthening user trust mechanisms, and exploring more personalized investment solutions within regulatory frameworks. To promote the adoption of RAs in the Chinese market, it is essential to leverage their technological advantages while addressing challenges related to investor trust, regulatory compliance, and market penetration strategies, thereby fostering the long-term sustainable development of RAs in the wealth management industry.

3.2 RA's strengths and threats

First, the operational mechanism of RA makes them more cost-effective than human advisors. RA leverages advanced backend computing power to analyze customer data and efficiently match investment opportunities, saving a significant amount of time compared to human advisors. Additionally, the analysis process of RA is automated, requiring minimal additional labor costs, which results in much lower costs than human advisors (Oehler et al., 2021; Milani, 2019). Besides the cost advantage, RA offers greater flexibility. Human advisors are constrained by working hours and need to pause services during statutory breaks, limiting the possibility for investors to obtain investment advice during these periods.

In contrast, RA can operate around the clock, often providing 24/7 service. As long as the system functions properly, RA can offer advice whenever the customer needs it, providing unparalleled convenience to investors (Oehler et al., 2021). This round-the-clock accessibility not only enhances the convenience of the service but also meets modern investors' expectations for instant and on-demand financial services.

Secondly, RA is known for its relatively low and transparent fee structure (Oehler et al., 2021), and the quality of its advice is also easier to audit and evaluate (Fisch et al., 2019). Using RA significantly reduces the costs associated with information searching and processing that are typically involved in investment decision-making. In contrast, traditional human models have higher costs due to the cumbersome and complex process of gathering and processing information. Regarding fees, RA adopts a transparent system, with fixed and clearly listed fees on its website, allowing investors to calculate the actual investment cost quickly. Furthermore, as RA operates based on predefined algorithms, with a relatively fixed format and process, it greatly simplifies the investment planning process. This standardization makes the entire investment advisory process more transparent and direct than traditional human advisory services. RA typically communicates investment advice to investors via regular channels such as email and SMS. Over time, both investors and RA platforms can carefully evaluate the quality of the advice provided. This evaluation is crucial for further optimizing the system and adjusting parameters. For investors, the quality of the advice directly impacts their trust in RA and the likelihood of continuing to use the service. According to Milani (2019), when RA services are recommended by close or trusted individuals, people are more likely to adopt the service, and the quality of advice plays a significant role in whether investors recommend the technology to others. Therefore, simplifying the evaluation of advice quality not only helps optimize the advisory service but also enhances the recognition of RA.

Thirdly, the advice dispensed by RAs is generally perceived to be unbiased, and the investment recommendations provided to customers can be regarded as wholly rational. The utility theory axioms proposed by Von Neumann and Morgenstern (1944) suggest that investors should remain rational and make complex decisions to optimize risk aversion and wealth maximization. However, it is almost impossible for ordinary investors to maintain absolute rationality. Factors such as social experience, personal emotions, investment experience, and information sources may lead to irrational decisions. Similarly, this bias can also affect human investment advisors. Although their expertise can improve the rationality of decisions, their judgments may sometimes be influenced by traditional beliefs and past experiences, leading to imprudent decisions.

In contrast, RA uses advanced technology and automated portfolio management functions to provide low-cost, emotionally unbiased investment decisions (PWC). RA is generally considered to be free from behavioral biases (D'Acunto et al., 2019). Since its algorithms are scientific, fixed, continuously optimized, and upgraded, RA does not exhibit subjectivity, thereby mainly eliminating irrationality, provided that the algorithms are accurate and reasonable. In China, RA's impartiality ensures that investors from different social classes are treated equally, encouraging more people to participate in investment.

Fourth, the rise of RA can significantly diversify investments and enhance the investor experience. Due to limited capabilities, investors typically focus only on individual stocks or projects of interest (Jinfang et al., 2020), which may lead to missing a comprehensive perspective and lagging behind information. RA can fill this gap: it can quickly process large amounts of information, assist the decision-making process, and provide timely investment advice, even for niche investment strategies. Investment diversification allows investors to hedge risks and manage exposure. Moreover, the development of RA has also diversified the investor base. Traditional human advisors typically serve wealthier clients, meaning that investors with limited financial knowledge and smaller amounts of capital often cannot receive tailored advice. Conversely, RA has a broader customer base and higher accessibility, allowing smaller investors to access appropriate investment solutions without paying high advisory fees (Fisch et al., 2016). In addition, RA can manage a broader range of tasks than human advisors (Day et al., 2018), such as investment selection and retirement planning. RA can quickly generate multiple feasible investment solutions while effectively controlling risks, time, and financial costs.

Furthermore, RA promotes financial inclusion in China, enabling more retail investors to use complex investment tools. By setting different parameters based on investors' risk tolerance, RA can adjust the sensitivity of risk detection, thereby reducing errors and increasing safety. This approach allows RA to allocate customized investment plans for investors with different preferences, making these financial services more democratic.

Despite the numerous advantages of RA, it also faces some challenges. First, data security is a critical issue that must be addressed for RA to succeed in China. Pertinently, recent incidents of online fraud and information leaks have heightened public concern about personal data security (Al-Harrasi et al., 2023). These incidents have not only led to the leakage of large amounts of personal information but also triggered deep concerns about data security. For example, a survey conducted in August 2023 showed that 104 victims who purchased encrypted asset storage devices were generally harassed by spam, scams, and phishing emails after data leakage, and some even faced new forms of attacks, such as device tampering (Abramova & Böhme, 2023). RA relies heavily on big data and complex algorithms, requiring the collection of user data to operate effectively. Therefore, the security of this data significantly impacts investors' acceptance and adoption of RA technology. When investors are unsure of when and how their data is being used, it can severely undermine their trust. Therefore, ensuring strong data protection and safeguarding customer privacy is crucial for building trust in RA services (Huang et al., 2022). Ultimately, when clients trust the security and confidentiality of their personal information, they are more likely to use the service.

Second, regulatory and technical limitations make many investors hesitant to use RA. According to Fein (2015), RA cannot always guarantee that its investment recommendations fully align with the client's best interests, avoid conflicts of interest, or minimize investment costs. A key issue is that RA operates based on fixed backend programs, which may not fully meet the specific needs of certain retail clients, such as expected expenditures. Therefore, despite the standardized calculations of RA, the individual circumstances of retail clients may vary considerably, which could lead to a mismatch in service delivery. Additionally, the algorithms on which RA relies are not flawless. Although there has been some regulatory progress for financial technologies like RAs following the COVID-19 pandemic, significant gaps remain, particularly in China, where the technology is still in its developmental stages. Addressing these technical and regulatory challenges is crucial for ensuring the widespread adoption and effectiveness of RAs in the Chinese market. According to Huang et al. (2021), the rapid growth of fintech in China has outpaced the development of a comprehensive regulatory framework, leading to uncertainties in areas such as algorithmic transparency and investor protection. Similarly, Arner et al. (2015) emphasise that while fintech innovations have accelerated globally, regulatory harmonisation and technological maturity remain critical barriers to their full potential. In the context of RAs, the integration of advanced technologies like AI and big data analytics requires robust regulatory oversight to build investor trust and ensure market stability (Yang and Zhang, 2022).

Third, investor acceptance of RA may vary significantly across age groups. Woodyard and Grable (2018) noted that RA is more likely to attract younger, tech-savvy consumers. Furthermore, recent studies suggest that RA users tend to be younger, have higher risk tolerance, and have less patience (Fan & Chatterjee, 2020). Younger individuals are generally more willing to adopt new technologies and innovations, so they are more inclined to try RA and similar financial tools. In addition, younger investors often have limited time and struggle to balance investment decisions with their work and personal life.

In contrast, middle-aged investors may prefer the stability and familiarity of traditional human investment advisors. For elderly investors, cognitive decline may require them to rely on professional services or tools to make investment decisions.

However, there is still controversy over whether older individuals can effectively learn to use RA and whether they can use these tools appropriately and wisely.

3.3 Hypothesis development

Unlike the relatively mature advisory industries in Europe and the United States, the RA user base in China exhibits distinct characteristics. For instance, Chinese investors typically demonstrate strong tendencies towards long-term investment and strategic asset allocation (Huang, 2021). As such, RA services represent a burgeoning sector in China, fraught with both opportunities and risks, where different investors exhibit varying levels of interest and acceptance criteria. Although recent substantial developments in digital infrastructure and the implementation of policies favoring new technologies have established a solid foundation for fintech adoption in China, the assimilation of such technologies varies significantly across different socioeconomic groups, with some pronounced disparities (Niu et al., 2020). Therefore, understanding the factors influencing individuals' decisions to use RAs is crucial to advancing the RA market in China. Historically, investors have sought wealth accumulation through traditional investment avenues such as stocks and funds. However, with the swift evolution of AI and the expansion of internet-based finance, an increasing number of investors are experimenting with RAs. Studies indicate that factors influencing the adoption of RAs among Chinese individuals include personal financial management capabilities, familiarity with financial products, and risk tolerance. Given the diversity of influencing factors, this thesis initially focuses on analyzing the determinants that affect retail investors' use of RAs, starting with an exploration of user characteristics.

Adoption of RAs is significantly influenced by age, as younger individuals are more likely to embrace new technologies than older generations. Generally, having grown up in the digital age, Millennials and Generation Z demonstrate greater familiarity with AI-driven technologies and are, therefore, more inclined to trust and adopt RA services (Seongsu et al., 2019). Additionally, the technology adoption lifecycle highlights that younger individuals, often categorised as ‘early adopters,’ are more open to experimenting with innovative solutions. In comparison, older individuals tend to be ‘late adopters’ or ‘laggards‘ due to resistance to change and lower technological literacy (Rogers, 2003). In China, younger investors, accustomed to digital tools from an early age, are more likely to view RAs as a convenient and cost-effective investment option, especially given their lower barriers to entry and flexibility (Todd & Seay, 2020).

Conversely, older individuals, particularly those in middle or late adulthood, are less likely to adopt RAs due to differing financial priorities and technological challenges. Middle-aged investors often seek stable, high-yield investments aligned with their long-term financial goals, which they perceive as better served by human advisors offering personalised solutions (Chen et al., 2023). Older individuals, facing declining pension reserves and policy changes like delayed retirement, may prioritise security and familiarity over innovation (Chee, 2024). Furthermore, cognitive aging theory suggests that older adults may experience difficulties in learning and adopting new technologies, leading to lower trust in digital financial tools (Czaja et al., 2006). This reluctance is compounded by a preference for traditional financial advisory services, which align with their established financial behaviours and comfort levels. Therefore, as Chen et al. (2023) put forth, adoption of fintech, including RAs, declines with age, reflecting a clear generational divide in technology acceptance.

H1: The lower the individual’s age, the greater their intention to use a RA in the future.

Gender plays a significant role in shaping individuals' willingness to adopt RAs, as men and women exhibit distinct risk preferences and attitudes toward financial technologies. According to gender differences in risk-taking theory, women tend to be more risk-averse than men, particularly in financial decision-making (Croson & Gneezy, 2009; Charness & Gneezy, 2012). This risk aversion is reflected in their preference for stable, low-risk investments and their reluctance to adopt innovative financial products like RAs, which may be perceived as less transparent or reliable (D'Acunto et al., 2019). Additionally, women often express greater concerns about privacy and data security, which can further deter them from using technology-driven financial services (Chen et al., 2023). These factors align with the technology acceptance model (TAM), which suggests that perceived risk and trust are critical determinants of technology adoption (Davis, 1989). For women, the perceived risks of RAs may outweigh their potential benefits, leading to lower adoption rates.

In contrast, men are generally more risk-tolerant and proactive in experimenting with new technologies, making them more likely to adopt RAs. Research by Powell and Ansic (1997) highlights that men are more inclined to take financial risks and explore innovative investment tools, as they prioritise potential returns over asset preservation. This aligns with gender differences in risk-taking theory, which posits that men are more likely to engage in behaviours that involve uncertainty and novelty (Harris & Jenkins, 2023). Furthermore, men's greater comfort with technology and lower sensitivity to privacy concerns may make RAs more appealing (Chen et al., 2023). These gender-based differences in risk tolerance and technology acceptance suggest that men are more likely than women to embrace RAs as part of their investment strategy.

H2: Males have a greater intention to use a RA than females.

Fintech services, including RAs, have gained significant popularity globally; however, their adoption rates vary considerably across different populations and regions (Lashitew et al., 2019; Frost, 2020). In China, this variability is particularly pronounced due to the country's vast geographical and socioeconomic diversity. Economic development is uneven, with coastal regions generally experiencing faster growth than inland areas, leading to a socioeconomic divide (Murendo et al., 2018). This divide is further exacerbated by disparities in digital infrastructure and internet penetration, which are critical for the accessibility and adoption of fintech services (Niu et al., 2020).

The concept of 'smart cities,' which leverage advanced technologies to enhance urban living, has been instrumental in narrowing the digital divide within urban areas. Smart cities are characterised by robust digital infrastructure, high internet penetration, and widespread access to digital services, all of which contribute to higher levels of digital literacy among urban residents (Anthopoulos, 2019). Digital literacy, defined as the ability to effectively and critically navigate, evaluate, and create information using digital technologies, is a key determinant of fintech adoption (Van Deursen & Van Dijk, 2014). Urban residents benefiting from the technological advancements and government initiatives associated with smart cities are more likely to be exposed to and familiar with new technologies, including RAs (Nam & Pardo, 2011).

In contrast, rural areas often lag in digital infrastructure development and internet accessibility, resulting in lower levels of digital literacy and slower adoption of fintech services (Townsend et al., 2013). The lack of exposure to digital technologies and limited access to fintech products in rural regions further widens the gap in adoption rates between urban and rural populations (Niu et al., 2020). Consequently, urban residents, with their higher digital literacy and greater motivation to experiment with new technologies, are more likely to adopt RAs than their rural counterparts.

H3: People living in urban areas are more willing to use a RA than those who live in rural areas.

Research indicates that marital status may influence individuals' investment decision-making behaviour. Married individuals typically bear greater responsibility for household financial planning and need to manage family assets and liabilities carefully. Therefore, compared to unmarried individuals, they may need RAs to assist in constructing and managing investment portfolios, enabling more effective asset allocation and risk control. This perspective is supported by the study of Hohenberger, Lee, and Coughlin (2019). Additionally, through the research of family financial responsibilities, it was found that that married individuals, due to their increased financial responsibilities, tend to seek more stable and automated investment tools (Bodie & Merton,1998). In contrast, unmarried individuals often have more free time and disposable income and may focus more on maximizing both short-term and long-term investment returns. Barber & Odean (2001) also showed that unmarried individuals may be more inclined to rely on their judgment for investment decisions rather than on automated tool. However, unmarried individuals—including divorced individuals or those cohabiting with a partner—may also adopt a more cautious attitude toward emerging technologies. The technology acceptance model suggests that individuals' acceptance of new technology is influenced by perceived ease of use and perceived usefulness (Davis, 1989). As a result, unmarried individuals may take advantage of their additional free time to thoroughly understand new technology before deciding whether to adopt it.

Overall, it is reasonable to infer that married individuals are more likely than single individuals to use RA. This difference may be attributed to the impact of marital status on financial responsibility and lifestyle choices, which, in turn, affect their openness to and demand for automated investment services.

H4: People who are married may be more willing to use a RA than those who are single, divorced, or living with a partner.

Financial dependence is one of the key factors influencing an individual's willingness to use RA. Financial dependence includes children, parents, grandparents, and even friends who require financial support. This financial pressure significantly impacts an individual's investment decisions. According to life-cycle theory, an individual's financial needs and risk tolerance vary at different stages of life (Modigliani & Brumberg, 1954). Individuals with a higher level of financial dependence generally need to manage household assets more cautiously to meet various expenditure and consumption needs. Such individuals are more likely to choose traditional, familiar, and perceived-as-safer investment advice methods rather than emerging technologies such as RA, which are still under development. This preference often stems from concerns about the safety of current liquid assets and an aversion to the higher risks associated with unfamiliar investment methods (Grable & Lytton, 1999). Furthermore, individuals with higher household expenditures typically have limited disposable income, which may further decrease their willingness to try new investment methods like RA. Financial constraints not only limit their investment capacity but also make them reluctant to experiment with financial tools that require learning and may introduce additional risks.

In contrast, individuals with less financial dependence usually encounter less financial pressure. According to behavioral finance theory, individuals with lower financial pressure are more likely to embrace new opportunities and take risks (Kahneman & Tversky, 1979). These individuals generally have more disposable income and do not face urgent liquidity needs, thus they are more willing to invest excess funds. The lower level of financial pressure and the lack of immediate financial demands make them more likely to try new investment technologies such as RA. The availability of innovative tools and their potential for high returns are particularly attractive to this group (Gomber et al., 2017). In recent years, research has further indicated that individuals with less financial dependence are more inclined to adopt digital financial tools, as they place greater emphasis on convenience and efficiency in financial decision-making (D'Acunto et al., 2019). Additionally, younger generations of investors (who typically have less financial dependence) are more receptive to technology, which has also contributed to the overall widespread adoption of RA (Fan & Chatterjee, 2020).

Therefore, it is reasonable to assume that individuals with less financial pressure and financial dependence are more likely to use RA. Their financial flexibility allows them to explore and adopt new investment technologies without facing significant financial obligations.

H5: People with fewer financial dependents have a greater intention to use a RA compared to those who have more financial dependents.

Employment status is becoming an important factor influencing investment behaviour, as it significantly affects individuals' financial stability and their ability to use various investment tools, including RAs. Changes in employment status, combined with shifts in marital status, age, and financial dependents, create a complex matrix that shapes investment decisions. First, for investors with lower or unstable incomes, the inclusivity and low-cost threshold of RAs make them an attractive choice. RAs are known for their affordability and relatively low fees (McCaffrey & Schiff, 2017), making them particularly attractive to this group. Additionally, these investors often prioritize investment security and liquidity and require more customized portfolio options for cautious risk management.

Meanwhile, stable employment and higher income levels typically provide individuals with more disposable income, increasing their ability and willingness to adopt new investment methods and technologies, including RAs. According to the Financial Confidence Theory, stable employment not only enhances individuals' financial confidence but also improves their risk tolerance, making them more willing to explore new investment technologies (Grable & Joo, 2004). This correlation suggests that individuals with stable jobs and stable income are more likely to appreciate the potential benefits of RAs and feel secure enough to experiment with new investment platforms (Yeh et al., 2022).

However, unstable employment or fluctuating income may reduce individuals' willingness to invest (Bloom, 2014), as they face more significant financial uncertainty and need to prioritize stable cash flow and income sources over investments. According to the Precautionary Saving Theory, in situations of income instability, individuals prioritize meeting their current financial needs and consider investments—especially those perceived as high-risk or unfamiliar—as secondary concerns (Leland, 1968, Cherif et al., 2018).

H6: People who have a full-time job are more likely to use a RA in the future.

H7: Having a higher monthly income may increase a person's intention to use a RA in the future.

Today's generation increasingly views housing not only as a basic necessity but also as a significant investment. Residential status – whether an individual rents, owns with a mortgage, or owns outright – plays a critical role in shaping financial behaviour and the intention to use RAs. This relationship can be understood through the behavioral life-cycle theory, which suggests that individuals categorise wealth into mental accounts – such as housing, savings, and investments – and make financial decisions based on perceived stability and liquidity (Shefrin & Thaler, 1988). Renters and mortgage holders often face more significant financial pressures, such as monthly payments, which increase their risk aversion and reduce their willingness to adopt new technologies like RAs. This aligns with the housing wealth effect, which posits that housing-related financial obligations lead to more conservative financial behaviour (Case et al., 2005). The technology acceptance model also highlights that perceived risks and benefits influence technology adoption (Davis, 1989). For renters and mortgage holders affected by financial pressures, the perceived risks of RAs may outweigh their benefits, leading to lower adoption rates (Cairney and Boyle, 2004).

Conversely, homeowners without mortgages are generally under less financial pressure, which may increase their openness to innovative investment tools (Gerardi, Rosen, and Willen, 2010). The housing wealth effect suggests that outright homeowners perceive their housing wealth as stable, freeing up mental and financial resources to explore new technologies (Ciarlone, 2011). Furthermore, the diffusion of innovations theory (Rogers, 2003) explains that individuals with greater financial stability are more likely to adopt new technologies. Having achieved financial security, homeowners without mortgages may view RAs as a tool to diversify and enhance their investment portfolios. In contrast, renters and mortgage holders may prioritise security and risk management, making them more cautious about adopting RAs (Cheng et al., 2019).

H8: Homeowners without a mortgage will be more willing to use a RA in the future.

Educational attainment is a key factor influencing individuals' interaction with financial technology, including RAs. Well-educated individuals generally achieve better outcomes, including financial decision-making, as they demonstrate greater competence to process complex information (Oreopoulos & Salvanes, 2011). Furthermore, according to the Human Capital Theory, education not only enhances individuals' knowledge and skills but also increases their willingness to acquire new knowledge and engage with high-tech products (Becker, 1964). In the field of financial technology, understanding a product or service is a prerequisite for adoption, which requires investors to have a certain level of education and cognitive ability. Educated investors are typically more adept at processing information, a critical skill for using financial technology solutions such as RAs (Lusardi & Mitchell, 2014). Besides, due to their algorithmic nature, RAs can minimize the subjective biases of human advisors, offering more consistent and objective investment recommendations. This view is supported by Bhattacharya et al. (2012), who pointed out that automated investment tools can effectively reduce behavioural biases, thereby improving the quality of investment decisions.

On the other hand, potential investors with lower education levels may find it challenging to understand and effectively use RAs. While these individuals can benefit significantly from such technology, their lack of familiarity with digital platforms may pose a significant obstacle. For example, according to technology acceptance model theory, perceived usefulness may be affected by lower educational attainment, leading to the possibility that this group may not be able to trust RA initially (Veena Parboteeah et al., 2014). Addressing this issue may require targeted interventions to help these potential investors overcome barriers to using modern financial services (Hilgert et al., 2003). In China, the expansion of undergraduate and master's education in recent years (Jiang and Ke, 2021) suggests that younger generations are more educated than their predecessors (Roberts, 2012) and are, therefore, more inclined to experiment with new products, including financial technology solutions (Mehra et al., 2020). This generational shift may influence the nationwide adoption and effective use of new technologies such as RAs.

H9: The higher a person's level of educational attainment, the more willing they will be to use a RA.

In the field of investment, individuals with different characteristics exhibit differences in their risk attitude, risk tolerance, and ultimately their investment behaviour (Grable, 2000; Hallahan et al., 2004; Schooley & Worden, 1996). In this thesis, I use risk aversion and perception to measure individuals' risk attitudes.

Firstly, risk aversion refers to an individual's tendency to avoid taking risks or to minimise risk exposure as much as possible (Morin & Suarez, 1983). According to prospect theory, individuals tend to exhibit risk aversion when faced with potential losses, preferring safer options (Kahneman & Tversky, 1979). Although RA can help users minimise risks and prevent investment losses through data-driven investment advice, RA is still in its early stages of development in China and has not yet established sufficient trust. Therefore, highly risk-averse individuals may currently have a lower preference for using RA (D'Acunto et al., 2019).

Secondly, risk perception refers to an individual's subjective assessment of risk, which may differ from statistical estimates, common opinions, or reality (Slovic, 1987). According to risk perception theory, individuals with higher risk perception are more sensitive to the risks associated with investment behaviour and related new technologies, such as RA (Weber et al., 2002). Such individuals tend to be more cautious in their investment decisions, making them less likely to try RA.

According to risk perception theory, an individual's attitude and perception of risk significantly influence their behaviour (Slovic, 1987). In other words, risk attitude, to some extent, shapes an individual's investment behaviour, especially when facing emerging technologies like RA, where the impact of risk attitude is particularly pronounced.

Understanding these dimensions of risk attitude is crucial for exploring how different investors adopt RA. These insights can help tailor RA platforms to better meet the needs of potential users, particularly in effectively communicating the level of risk and control these systems provide.

H10: A higher level of risk aversion is associated with a lower propensity to use a RA.

H11: Higher risk perception is associated with a lower propensity to use RA.

Confidence is a key factor influencing financial decision-making (Ward et al., 2022). When individual investors have high confidence in their abilities, they are less likely to rely on RAs because they rely on their judgment (Ge et al., 2021). Investors who have an accurate understanding of their financial situation and exhibit high confidence can make reasonable investment decisions without the assistance of RAs. Additionally, according to self-efficacy theory, an individual's level of confidence directly influences their behavioural decisions and performance (Bandura, 1977). Therefore, highly confident investors are more inclined to manage the entire investment decision-making process independently and are less likely to seek advice from either human or robotic advisors.

Conversely, lacking confidence can complicate investment decision-making, leading to hesitation and lost investment opportunities (Sudhir, 2012). Overconfidence, on the other hand, represents an extreme form of confidence. Studies suggest that overconfidence significantly reduces an individual's willingness to seek investment advice, which can negatively impact their long-term financial well-being (Lewis, 2018). According to Overconfidence Theory, overconfident individuals tend to overestimate their abilities, causing them to disregard external advice in decision-making (Moore & Healy, 2008).

One manifestation of overconfidence is the Better-Than-Average Effect (BTAE), where individuals tend to believe that their abilities, traits, and personality are above average (Svenson, 1981). According to Zell et al. (2020), BTAE may lead individuals to overestimate their investment capabilities, thereby reducing their perceived need for RAs. However, not all individuals who exhibit BTAE possess above-average abilities (Heck & Krueger, 2015). Those who have higher capabilities may perceive limited benefits from using RAs. Conversely, individuals exhibiting the Worse-Than-Average

Effect (WTAE) tend to believe their abilities are below average, making them more likely to rely on automated investment tools like RAs to compensate for their perceived shortcomings.

Another form of overconfidence is the Illusion of Control, where individuals mistakenly believe they can control outcomes that are, in reality, beyond their control (Langer, 1975). According to Yarritu et al. (2014), the illusion of control can lead individuals to overestimate their influence on investment outcomes, thereby reducing their reliance on tools like RAs. In contrast, those who recognize that they cannot fully control investment results are more likely to adopt RAs, believing that their algorithms and artificial intelligence capabilities can help them achieve better investment outcomes.

In summary, confidence levels, the Better-Than-Average Effect, and the Illusion of Control are important factors influencing individuals' willingness to use RAs. Understanding these psychological traits can help improve the design of RA platforms to meet the needs of different users better.

H12: The higher the investors' confidence level, the greater their intention to use a RA in the future.

H13: People with the worse-than-average effect (WTAE) are more inclined to use a RA in the future.

H14: The greater a person's illusion of control, the less likely it is that they will use a RA.

Trust is a critical factor in decision-making, particularly in financial investments and the adoption of new technologies. Rousseau et al. (1998) define trust as 'a state of mind that involves the acceptance of a vulnerable intention based on a positive expectation of another person's intentions or behavior.' This concept is fundamental in everyday investment decisions, as investors need to trust the industries and projects they choose to invest in. In fintech, trust is paramount for the successful diffusion and acceptance of new technologies. If consumers trust a fintech platform, they are less likely to be sceptical about its products and features, thus facilitating broader adoption (Roh et al., 2022). Trust encompasses multiple dimensions, including trust in the industry, relevant laws and regulations, and the credibility of sources such as referrals. Jøsang (2007) describes trust as the 'subjective probability that one individual (A) expects another (B) to perform a particular action upon which their welfare depends,' often referred to as 'reliability trust.' This form of trust grows as the perceived trustworthiness of a person or platform increases.

In the RA industry, trust is particularly crucial due to the reliance on algorithms and automated systems to manage investments. However, the industry has faced significant challenges recently, particularly during 2022-2023, when increased governmental scrutiny and high-profile scandals eroded consumer confidence (Moussa & McMurray, 2025). Regulatory actions and scandals involving mismanagement of funds, misleading marketing practices, and consumer data breaches have highlighted vulnerabilities in the RA ecosystem, leading to heightened scepticism among potential users (Zetzsche et al., 2020). Despite these challenges, trust remains a decisive factor in adopting RAs. When a trusted source recommends a product or service, its perceived trustworthiness increases, significantly enhancing the likelihood of adoption (Roh et al., 2022). Therefore, rebuilding trust through transparency, regulatory compliance, and ethical practices is essential for the future growth of the RA industry. Individuals with a higher general tendency to trust the outside world may still be more open to experimenting with RAs, provided their concerns about reliability and security are adequately addressed.

H15: A person with a higher level of trust in the outside world may have an increased probability of using a RA.

Numeracy skills are key factors influencing an individual's willingness and ability to use RAs. According to Lusardi & Mitchell (2014), numeracy is an important component of financial literacy and directly affects an individual's ability to understand and use complex financial tools. Individuals with stronger numeracy skills can better comprehend the investment advice provided by RAs because they can interpret the mathematical logic behind RA algorithms and effectively analyse the data and statistical information presented by RAs (Hastings et al., 2015). This ability allows them to make more informed investment decisions and increases their willingness to adopt RA technology.

In contrast, individuals with weaker numeracy skills may be sceptical about RA technology. According to the technology acceptance model, an individual's acceptance of new technology depends on their perceived ease of use and perceived usefulness (Davis, 1989). For individuals with weaker numeracy skills, the data-driven nature of RAs may seem complex and difficult to understand, reducing their perceived ease of use. Moreover, they may doubt the reliability of the advice provided by RAs, further weakening their perceived usefulness. This discomfort with digital data may lead to lower acceptance of RA technology.

Additionally, educational background and work experience also influence an individual's numeracy skills. Studies have shown that individuals with higher levels of education or those working in fields related to mathematics or statistics typically possess stronger numeracy skills (Cokely et al., 2018). These individuals are more likely to understand RAs' data-driven approach and perceive it as more credible.

Therefore, numeracy skills seem to be an important factor that affects the adoption and effective use of RA technology in China. As the financial market continues to develop and grow more complex, the ability to understand and apply numerical data will play a key role in the interaction between individuals and RA technology. This also suggests that educational initiatives aimed at improving financial literacy and numeracy skills may be crucial for expanding the acceptance and usage of RA services.

H16: Investors with greater numerical abilities are more likely to use a RA.

RAs, as a modern investment advisory service, leverage high-intensity computer-based analytical calculations to optimize investment portfolios. Therefore, an individual's digital literacy—their ability to understand and use digital technologies—is a key factor influencing their acceptance of RAs. According to the technology acceptance model, an individual's acceptance of new technology depends on perceived ease of use and perceived usefulness (Davis, 1989). Individuals with higher digital literacy can better understand and effectively use RA technology. Their familiarity with digital data and technology enhances their comprehension and trust in RAs, making them more willing to rely on these tools for investment advice. Such individuals are more likely to appreciate the capabilities of RAs and recognize their potential in providing insightful investment guidance and optimizing financial decision-making.

Conversely, individuals with lower digital literacy may feel overwhelmed or sceptical about RA technology. The complexity of digital tools and a lack of understanding can lead to confusion and distrust, making these individuals less likely to adopt such technologies for their investment needs. According to the Diffusion of Innovations Theory, early adopters are typically individuals who have a higher acceptance of new technology and are willing to take risks (Rogers, 2003). With continuous technological advancements, the financial technology industry, including RAs, is driving the integration of technology and finance, fostering innovation and creating new opportunities (Cheng et al., 2019). Therefore, improving the digital literacy of potential investors is crucial for the widespread adoption and effective use of RAs. As individuals become more familiar and proficient with digital tools, their likelihood of accepting and benefiting from financial technology innovations such as RAs will also increase.

H17: Individuals with higher digital literacy (i.e. those who are more receptive to new technology) may have stronger willingness to use a RA.

When exploring the factors influencing Chinese investors' intention to use RAs, it is essential to consider both objective and subjective factors that affect individual investment decisions. China's investment environment has undergone significant changes over the past two decades, with an increasing number of people regularly participating in investment activities (Su et al., 2021). These changes significantly influenced the acceptance and use of RAs. According to Barberis et al. (1998), an individual's past investment experiences significantly influence their future investment decisions. Those who have achieved positive returns in past investments are more likely to develop an interest in investment and related technologies, such as RAs. Successful investment experiences enhance individuals' confidence in their investment abilities, making them more willing to use advanced tools to improve decision-making efficiency and potential returns (Davis, 1989). For these individuals, the automation and artificial intelligence features of RAs are particularly appealing, as they can efficiently replicate past successful experiences to some extent (Venkatesh & Davis, 2000). Research shows that when individuals perceive that new technologies can enhance their performance (perceived usefulness) and are easy to use, they are more inclined to accept such technologies (Gefen et al., 2003).

On the other hand, individuals who have suffered losses or negative experiences in past investments may approach new investment decisions with greater caution and skepticism, and this cautious attitude may extend to the intention to use RAs. According to McKnight et al. (2002), an individual's level of trust in new technologies directly influences their willingness to accept them. These individuals may worry that automated systems cannot provide personalized investment advice tailored to their specific needs and circumstances, thereby hindering their use of RAs (Gefen et al., 2003). In particular, negative experiences may lead to a lack of trust in new investment methods and technologies, making them less likely to adopt RAs (McKnight et al., 2002). For individuals with positive experiences, transitioning to RAs may be a natural and beneficial step. However, for those with negative experiences, additional assurances may be needed to ensure the safety, reliability, and personalization of RAs (Rogers, 2003). For example, increasing transparency, demonstrating the reliability of algorithms, and offering customized services can enhance these individuals' trust and acceptance of RAs (Venkatesh & Davis, 2000).

H18: People with experience of using traditional human advisors or RAs in the past may be more inclined to use RAs in the future.

There is generally a positive correlation between education and financial literacy; individuals with higher education levels tend to have higher financial literacy (Niu et al., 2020; Karakurum-Ozdemir et al., 2018) and are therefore more inclined to use RAs. According to Financial Literacy Theory, investors with higher financial literacy can better understand the investment environment and use the rational advice RAs provides, enabling them to make wiser investment decisions (Lusardi & Mitchell, 2014). Additionally, these investors often have a "practical mindset," actively applying their financial knowledge in real investment scenarios to gain experience and enhance their skills. The complexity of financial decision-making further highlights the importance of financial literacy, as it helps individuals effectively gather and process financial information (Niu et al., 2020).

An investor's level of financial literacy significantly influences their choice of investment advisors. While Seongsu David et al. (2019) suggested that individuals with lower financial literacy are more likely to use RAs because they are likely to make poor financial decisions when acting independently (Fisch et al., 2016), Todd and Seay (2020) presented an opposing view. They argued that RA users are typically individuals with high confidence in their financial knowledge who seek control over their financial decisions. Furthermore, Todd and Seay (2020) noted that RA users generally have higher financial literacy than those who do not use such services. This trend can be partially attributed to the limitations of traditional human investment advisors, who may not fully consider clients' actual preferences and needs (D'Acunto et al. 2019), instead providing advice based on their own perspectives. This sometimes results in discrepancies between the recommendations and clients' expectations. In contrast, RAs are not influenced by cognitive biases and rely solely on algorithms and user-provided information to generate investment recommendations (Buenaventura, 2024). This approach offers users enhanced decision-making autonomy and flexibility, making the investment process more personalized and controllable.

In summary, the decision to use RAs is influenced by users' level of financial literacy and confidence in managing financial matters. Individuals with higher financial literacy value the autonomy and customization provided by RAs and are thus more likely to adopt these technologies to optimize their investment strategies.

According to the Confidence Theory in behavioural finance, financial confidence can enhance financial decision-making and outcomes, as rational financial choices often require certain confidence (Hung et al., 2009). When potential investors possess adequate financial confidence, they may feel more capable of making independent investment decisions, which either increase or decrease their willingness to use RAs, depending on their belief in technology's ability to optimize financial outcomes. Existing research suggests a strong correlation between financial confidence and financial literacy; individuals with higher financial literacy are generally more likely to adopt and utilize financial technology solutions, including RAs (Hastings et al., 2013). Investors with high financial confidence tend to trust their financial knowledge and may prefer leveraging technology-based solutions like RAs because they believe in their decision-making abilities. These individuals are often more willing to use advanced tools to optimize their investment strategies, viewing such technologies as enablers that enhance their ability to achieve better financial outcomes.

H19: People who are more financially literate are more likely to use a RA.

H20: People with greater financial confidence are more likely to use a RA.

An individual's perception of their financial knowledge is crucial in determining how they participate in financial decision-making and use tools such as RAs. As previously discussed, sufficient financial knowledge enables individuals to make more informed and more rational investment decisions (Sharma et al., 2025), while a lack of financial knowledge may lead to poor investment outcomes and increased financial risk (Sobaih and Elshaer, 2023). In China, individuals' perception of their financial knowledge should also significantly influence their willingness to use RAs. According to Self-Efficacy Theory, an individual's belief in their own abilities directly affects their behavioural choices and performance (Bandura, 1977). The study by Xiao and O'Neill (2016) found that individuals who perceive themselves as having a high level of financial understanding are more likely to use RAs. They rely on their ability to fully comprehend and effectively utilize the services provided by these tools, making them more willing to adopt such technological solutions to optimize their investment strategies and overall financial management.

Furthermore, the technology acceptance model and Social Cognitive Theory (SCT) provide theoretical frameworks for understanding how perceived financial literacy influences individuals' adoption of financial technology solutions. According to these models, individuals who believe they possess high financial knowledge are more likely to perceive RAs as easy to use and effective. This perception increases the likelihood of adopting such technologies, as they view RAs as effective tools that help them achieve their financial goals (Venkatesh & Bala, 2008).

H21: Individuals with a higher perception of their financial knowledge are more likely to use a RA.

Chapter 4 Research Methodology

4.1 Research Philosophy

The research philosophy of this study is grounded in positivism, which emphasises acquiring knowledge through observation and experimentation and relies on data and statistical analysis to test hypotheses (Bryman & Bell, 2015). The core of positivism lies in revealing objective facts through quantifiable data, while the research results should be replicable, meaning that other researchers can verify the findings using the same or similar methods (Saunders et al., 2019). This philosophical stance aligns well with the objectives of this study, as it aims to explore the potential factors influencing ordinary individuals in China to use RAs in the future and to understand the direction of RA development in China. By adopting a positivist approach, this study can conduct rigorous hypothesis testing based on a large dataset, thereby deriving generalisable conclusions.

An important characteristic of positivism is its emphasis on objectivity and replicability in research. This study ensures the reliability and validity of its findings by designing a rigorous research methodology and defining clear variables, as described in Chapter 3. Furthermore, the positivist research approach requires that sample selection be representative to reduce bias and enhance the overall reliability of the study (Bryman & Bell, 2015). However, positivism also has certain limitations, particularly regarding potential biases in data collection and analysis. For instance, the research findings may be affected if data errors or sample selection biases exist. Additionally, including response options such as ‘Prefer not to answer’ and ‘Do not know’ in the questionnaire may lead to incomplete data, which could impact the reliability of the study. Nonetheless, positivism is an appropriate theoretical foundation given this study’s reliance on data and statistical analysis.

The research methodology of this study follows a deductive approach, which involves reasoning from the general to the specific. The researcher first proposes theoretical hypotheses and then tests them through data collection and analysis (Saunders et al., 2019). In Chapter 3, this study presents multiple hypotheses, which are tested through quantitative analysis methods. The advantage of the deductive approach lies in its logical rigour, allowing for the verification of theoretical correctness through data, thereby drawing conclusions of universal significance.

The quantitative analysis method employed in this study relies on large-scale data collection, which is used to test the hypotheses proposed in Chapter 3. Through measurement and quantification, quantitative analysis provides more objective and precise results, thereby enhancing the reliability and validity of the research findings (Bryman & Bell, 2015). By employing quantitative analysis, this study not only verifies the accuracy of the hypotheses but also identifies significant relationships or differences among variables, thereby reducing subjective bias in data analysis and improving the overall credibility of the research.

However, quantitative analysis also has certain limitations. Firstly, it depends on the accuracy and completeness of the data; if errors or biases exist in the data, the analysis results may be affected. Secondly, quantitative analysis typically assumes linear relationships between variables, which may fail to capture complex nonlinear relationships (Bryman & Bell, 2015). Nevertheless, this study minimises these limitations by implementing strict sample selection and data collection procedures. By utilising quantitative analysis methods, this study derives objective conclusions based on data, providing valuable insights into the future development of RAs in China.

4.2 Research Ethics

Regarding research ethics, this study strictly adheres to internationally recognised ethical guidelines while paying special attention to sensitivity issues and ethical challenges within the Chinese cultural context. First, during the questionnaire design phase, the research team carefully considered culturally sensitive issues in China, such as the privacy protection of personal financial information, trust in authority, and the acceptance of new technologies. To ensure respondents' privacy and data security, the questionnaire included a 'Prefer not to answer' option, particularly for questions related to financial information, allowing respondents to choose not to disclose specific details (Bryman & Bell, 2015). Additionally, the questionnaire underwent multiple rounds of pre-testing before its official release to ensure that the wording of the questions would not cause cultural misunderstandings or awkwardness.

During the data collection process, this study paid particular attention to the sensitivity of privacy and trust in the Chinese cultural context. For example, Chinese society generally adopts a cautious attitude toward the public disclosure of personal financial information. Therefore, instead of directly asking respondents about their exact income or asset details, the questionnaire collected relevant information through indirect questions, such as income ranges (Hofstede, 2011). Furthermore, to enhance respondents' trust, the questionnaire explicitly stated the scope of data usage and confidentiality measures at the beginning. A detailed informed consent form (Appendix 4.1) was also provided to ensure that participants voluntarily participated in the study with full awareness (Saunders et al., 2019).

To further ensure ethical compliance, this study signed strict confidentiality agreements with third-party questionnaire distribution platforms to prevent collected data from being disclosed or used for non-research purposes. Additionally, before its official release, the questionnaire was reviewed and approved by the University of Essex Ethics Approval Committee to ensure compliance with international research ethics standards (University of Essex Ethics Approval Committee, 2022). Through these measures, this study not only adheres to international ethical norms but also fully considers the specific needs within the Chinese cultural context, ensuring both ethical compliance and cultural adaptability.

4.3 Questionnaire design

The development of RA in China has been influenced by several potential factors. Therefore, the questionnaire was customized and distributed across mainland China to address these factors.

The main body of the questionnaire consisted of three parts. The first part concerned the main demographic characteristics of the respondents, and the second contains questions gleaning insights on respondents' financial literacy, financial confidence, illusion of control, better-than-average effect, confidence level, trust level, risk attitude, acceptance of new technology, and investment experience. The third part of the questionnaire sought to measure the respondents' intention to use RA. The information collected in the first and second parts of the questionnaire provided the independent variables for this study, while the information gleaned from the third part contributed the dependent variable. In order to ensure the validity of the questionnaire and the overall quality of the data collected, the sources of the questions were strictly controlled and adjusted appropriately.

In the rest of this section, the questions in each part of the questionnaire are briefly described and explained.

4.3.1 Demographics

In the first section of the questionnaire, we designed a series of demographic questions to collect basic information about respondents, including age, gender, place of residence (urban or rural), marital status, number of economic dependents, employment status, housing situation, and educational background (see Appendix 4.2). The selection of these variables helps outline the respondents' fundamental characteristics and provides crucial background information for subsequent analysis. This enables a deeper understanding of how these factors influence respondents' willingness to use RAs in the future.

Age is a key factor affecting financial behaviour and technology adoption willingness. Individuals of different age groups may exhibit significant differences in financial decision-making, risk tolerance, and acceptance of emerging financial technologies. For example, younger individuals tend to have a higher level of technology acceptance and are, therefore, more likely to adopt RAs, whereas older individuals may rely more on traditional financial advisors (Lusardi & Mitchell, 2011). Collecting age-related data helps analyze the acceptance of RAs across different age groups and further explores the potential influencing factors. Gender is also a critical variable, as financial decision-making, risk preferences, and investment behaviour may vary by gender. Studies have shown that men are generally more inclined to take risks in investment decisions, whereas women tend to be more risk-averse (Barber & Odean, 2001). These gender differences may influence the willingness to use RAs, making it necessary to include gender in the study to identify potential target markets for RA adoption.

Place of residence (urban or rural) affects individuals' access to financial services and their acceptance of technology. Urban residents, who have greater exposure to emerging financial technologies and generally higher income levels, are more likely to use RAs. In contrast, rural residents may rely more on traditional financial advice due to lower technology acceptance or insufficient financial knowledge (Hodge et al., 2017). Similarly, marital status may influence financial decision-making and risk attitudes. Married individuals often need to plan long-term financial strategies for their families, making them more inclined to use RAs for financial optimization. In contrast, unmarried individuals may focus more on personal financial goals (Hira & Loibl, 2005). Additionally, the number of economic dependents reflects a respondent's financial responsibilities. Individuals with heavier family burdens are typically more concerned with optimizing financial planning to manage household expenses more effectively, which may increase their interest in using RAs (Lusardi & Mitchell, 2011).

Employment status is another crucial factor influencing financial decision-making. Full-time employees typically have a stable source of income and are, therefore, more likely to consider using RAs for wealth management. In contrast, due to financial instability, part-time workers or unemployed individuals may have a lower willingness to adopt RAs (Hira & Loibl, 2005). Housing status (such as homeownership versus renting) may also impact financial decision-making. Homeowners generally enjoy greater financial stability and are more likely to engage in long-term financial planning (Herbert and Belsky, 2008), whereas renters may focus more on short-term financial arrangements.

Finally, educational background plays a critical role in financial decision-making and the acceptance of RAs. Research has shown that individuals with higher education levels typically possess more potent financial literacy and are more likely to understand and adopt new financial technologies (Lusardi & Mitchell, 2011). Therefore, this study collects respondents' educational background data to analyze the impact of financial literacy on RA adoption willingness.

In summary, by collecting and analyzing these demographic variables, this study provides a more comprehensive understanding of respondents' background characteristics and their potential influence on RA adoption willingness. These variables not only serve as foundational data for subsequent quantitative analysis but also help identify the acceptance levels of RAs across different socio-economic groups, offering valuable insights for the promotion of RAs in the Chinese market.

4.3.2 Questions gleaning insights from respondents in the questionnaire

The second part of the questionnaire aims to collect data on respondents' psychological and behavioural characteristics, including financial literacy, financial confidence, illusion of control (IOC), better-than-average effect (BTAE), confidence level, trust level, risk attitude, digital literacy, numeracy skills, experience with traditional advisors, and experience with RA (see Appendix 4.3). These variables not only help us understand respondents' psychological and behavioural characteristics but also provide important data support for subsequent analysis to better understand how these factors influence respondents' willingness to use RA in the future.

First, risk aversion and risk perception are important factors affecting individuals' financial decisions. This study measures respondents' risk aversion levels through the question, "Are you willing to take financial risks?" (Question 11 in Appendix 4.3). A higher score indicates a more substantial risk tolerance and lower risk aversion, making respondents more likely to consider using RA (Chak et al., 2022). Meanwhile, risk perception is measured using four adapted statement-based questions from Forsythe and Shi (2003) (Questions 30 to 33 in Appendix 4.3). A higher score indicates a higher level of risk perception, thus reducing the likelihood of using RA (Hypothesis 11). Additionally, confidence level is a key factor influencing individuals' financial decisions. This study measures respondents' confidence levels using questions from Siegrist, Keller, and Kiers (2005) (Questions 24 to 26 in Appendix 4.3). A higher score indicates a higher confidence level, making respondents more likely to use RA (Hypothesis 12).

The better-than-average effect (BTAE) refers to individuals' tendency to overestimate their abilities. This study assesses BTAE by asking respondents to evaluate their financial confidence (Question 13 in Appendix 4.3) and financial literacy (Questions 14 to 16 in Appendix 4.3) and compare their self-assessment with public evaluations. A positive score indicates that respondents perceive themselves as above average, while a negative score suggests they perceive themselves as below average. A higher score indicates a stronger BTAE, meaning respondents are more likely to overestimate their abilities (Hypothesis 13). The illusion of control (IOC) refers to individuals' tendency to overestimate their control over situations. This study measures IOC levels using four statement-based questions from Billieux et al. (2011) and Raylu & Oei (2004) (Questions 20 to 23 in Appendix 4.3). A higher score indicates a lower tendency to overestimate control, thereby reducing the likelihood of using RA (Hypothesis 14).

Trust level is another important factor influencing individuals' willingness to use RA. This study measures respondents' trust levels using questions from Dohmen et al. (2008) (Questions 27 to 29 in Appendix 4.3). A higher score indicates a higher level of trust in others, making respondents more likely to use RA (Hypothesis 15). Additionally, numeracy skills play a significant role in financial decision-making. This study measures respondents' numeracy skills using a question from Chak et al. (2022)

(Question 12 in Appendix 4.3). A higher score indicates stronger numeracy skills (Hypothesis 16). Digital literacy is also an important factor influencing individuals' acceptance of new technologies. This study measures digital literacy using three statement-based questions from Ye, Zheng, and Yi (2020) (Questions 34 to 36 in Appendix 4.3). A higher score indicates higher digital literacy, making respondents more likely to use RA (Hypothesis 17).

Investment experience is another key factor influencing individuals' willingness to use RA. This study measures respondents' investment experience using questions from Oehler et al. (2021) (Questions 37 and 38 in Appendix 4.3). A higher score indicates greater investment experience, making respondents more likely to use RA (Hypothesis 18). Financial literacy and financial confidence are also critical factors affecting financial decision-making. This study measures financial literacy using three multiple-choice questions from Lusardi and Mitchell (2008) (Questions 14 to 16 in Appendix 4.3). A higher score indicates higher financial literacy (Hypothesis 19). Meanwhile, financial confidence is measured using a question from Chak et al. (2022) (Question 13 in Appendix 4.3), with a higher score indicating stronger financial confidence (Hypothesis 20). Finally, perceived financial knowledge is another key factor influencing financial decision-making. This study measures respondents' perceived financial knowledge using a question from Lusardi and Mitchell (2011) (Question 19 in Appendix 4.3). A higher score indicates greater satisfaction with their financial knowledge (Hypothesis 21).

By collecting and analyzing these psychological and behavioural characteristic variables, we can better understand respondents' psychological and behavioural traits and their potential impact on the willingness to use RA. These variables not only provide fundamental data for subsequent quantitative analysis but also help identify different psychological and behavioural groups' acceptance of RA, thereby offering valuable insights for the market expansion of RA in China.

4.3.3 Intention-to-use-RA questions in questionnaire

The third section of the questionnaire investigated the respondents' willingness to try RA. Given the possibility of some respondents not knowing about RA, this section started by presenting a preliminary outline of RA. A brief introduction to RA's basic concepts and working principles was thus given (Appendix 4.4). Subsequently, a question from Venkatesh et al. (2003) (all questions for this part are in Appendix 4.5), asking respondents about the degree of their willingness to use RA in the future, and this represents the dependent variable in this paper. An endogenous question (Question 42 in Appendix 4.5) was also included to enhance the accuracy of the questionnaire data. Here, a five-point Likert scale was used to measure the respondents' intention to use RA in the future. Question 42 in Appendix 4.5 is reverse scored, whereby "strongly disagree" was given a score of 5 and "strongly agree" was given a score of 1. The higher the score, the more likely the respondent would be to use RA in the future.

4.4 Pilot Testing, Calibration and Data Collection

The questionnaire's design and data collection process underwent multiple rounds of pre-testing and calibration to ensure its validity and reliability. The questionnaire was initially written in English and then translated into Chinese, followed by four rounds of pre-testing before its official release. The first round of pre-testing was conducted after the completion of the English version, with participants including PhD students, lecturers from the Essex Business School (EBS), and both Chinese and British students studying in the UK. Through face-to-face or online communication, we recorded the time required for respondents to complete the questionnaire and gathered feedback on their overall experience (Teijlingen & Hundley, 2001). Based on the first round of feedback, we adjusted the layout and structure of the questionnaire, such as consolidating all five-point Likert scale questions into a single table to improve respondents' understanding. Additionally, we optimised the wording of the questionnaire, particularly in the RA introduction section, using more accessible language and removing redundant options (e.g., replacing the 'Other' option with 'Prefer not to say') (Presser & Blair, 1994).

The second round of pre-testing further refined the language and wording of the questionnaire. Based on the feedback, we replaced currency symbols with the Chinese yuan (¥) and added commas to numbers with four or more digits (e.g., 5,000 and 10,000) to align with Chinese writing conventions. Additionally, we adjusted the singular and plural forms of certain words to ensure linguistic accuracy. The third round of pre-testing focused on the Chinese version of the questionnaire, revealing inconsistencies in layout compared to the English version. Consequently, we reviewed the Chinese version again to ensure consistency between the two versions. For example, we added the term 'province' after all provincial names and 'city' after all municipality names, and we standardised the translations of certain technical terms to avoid confusion. (Brislin, 1986). The fourth round of pre-testing further refined the translation of the RA introduction to make it more natural and fluent. Additionally, we improved the translation of questions related to 'confidence', 'trust', and 'risk aversion' to enhance clarity and comprehension.

Based on feedback from the pretesting, we made several adjustments to the questionnaire. For instance, we removed some "Do not know" and "Prefer not to say" options to minimize data loss. For privacy-sensitive questions (e.g., income, living conditions, and financial dependents), we retained the "Prefer not to say" option to respect respondents" privacy. However, for simpler questions, we removed this option. These adjustments increased the retention rate of valid data from 48% to over 70% (Dillman, 2007). Additionally, we explicitly defined the geographic and age distribution requirements for questionnaire distribution to ensure the sample's representativeness.

The questionnaire was distributed and collected online via a third-party platform (https://www.wjx.cn/). Before selecting this platform, we conducted a thorough review and consulted relevant literature (e.g., Peng et al., 2019) to ensure data authenticity and high quality. Before formal distribution, we signed a confidentiality agreement with the platform to ensure that the data would be used solely for research purposes. The questionnaire distribution adopted a quota sampling method, dividing the target population into 40 subgroups based on age, gender, and income, with at least 30 respondents per group, resulting in a total sample size of 1,200 participants (see Table 4.1). This approach allowed us to more accurately define the study population's characteristics and enhance the data's authenticity and reliability (Groves et al., 2009).

*** INSERT TABLE 4.1 HERE***

We filtered out questionnaires with excessively long or short response times during data collection to ensure data quality. Additionally, the platform employed intelligent analysis to eliminate careless responses, such as those with identical selections throughout or those exhibiting cyclical patterns. Ultimately, we collected 1,277 valid questionnaires within 12 working days. After a second round of screening, in which responses containing the "Prefer not to say" option were excluded, 1,250 valid datasets were retained for further analysis (see Table 4.2). Data analysis indicated that the final sample was evenly distributed in terms of age, gender, region, and monthly income, meeting the requirements of the sampling framework (Groves et al., 2009).

*** INSERT TABLE 4.2 HERE***

However, potential response bias or non-response bias may exist in sample selection. For example, some respondents may have chosen not to participate due to privacy concerns or a lack of interest in RA, which could affect the sample's representativeness (Dillman, 2007). Furthermore, although quota sampling is controlled for age, gender, and income distribution, unobserved biases may still exist, such as variations in respondents' financial knowledge levels or technological acceptance (Groves et al., 2009). To mitigate the impact of these biases, we simplified the questionnaire design as much as possible and provided a clear, informed consent form to enhance respondents' trust and willingness to participate.

Through rigorous pre-testing and calibration during the data collection process, we ensured the validity and reliability of the questionnaire and the data. These steps not only helped optimise the questionnaire design but also provided high-quality data support for subsequent quantitative analysis, offering valuable insights for promoting RA in the Chinese market.

4.5 Preliminary Analysis

4.5.1 Validity and Correlation Analysis

Before performing the regression analysis, I first conducted a validity analysis and correlation test on the data. Firstly, the Kaiser-Meyer-Olkin (KMO) and Bartlett tests were used to determine the feasibility of the data. The KMO values ranged from 0 to 1, reflecting whether or not the data were suitable for further analysis. If the KMO value was equal to or greater than 0.5, it indicated that the data were suitable for further analysis (Kaiser, 1974). The Bartlett test was applied to check whether the correlation matrix was a unit matrix, thereby confirming whether or not the variables were independent. It was based on the correlation coefficient matrix of the variables and involved a hypothesis in which H_0 meant that the data were not sufficient for further analysis. When the significance level in the analysis result was greater than 0.05, H_0 was accepted. In contrast, when the significance was less than 0.05, it meant H0 was rejected (Napitupulu et al., 2017), meaning these variables may provide some information independently and was thus suitable for further analysis of the variables. Table 4.3 shows the results of the KMO and Bartlett tests. The KMO value for sociodemographic factors was 0.73, and the significance level was 0.00; therefore, H_0 was rejected, meaning that the data were suitable for further analysis because they met the previously mentioned requirement of a KMO value being greater than 0.5 and having a significance level less than 0.05.

*** INSERT TABLE 4.3 HERE ***

Besides, I also carried out correlation analysis between variables. Correlation analysis measures the strength and direction of the linear relationship between two variables (Hendry and Morgan, 1997). Here, the correlation coefficients ranged from -1 to 1, where 0 indicated no correlation, 1 indicated perfect correlation, and -1 indicated inverse correlation (Akoglu, 2018). The larger the absolute value of the correlation, the more obvious the correlation between the variables. If the value was too large, that may reveal a problem of collinearity, which meant the predictor (independent) variables in the regression model were highly correlated. This correlation implies that variables share a significant amount of information with each other, making it difficult to assess the individual impact of each predictor on the dependent variable (Leamer, 1973).

*** INSERT TABLE 4.4 HERE ***

Table 4.4 shows the results of the correlation analysis between the independent variables covered in this thesis, with the values in the table representing the correlation coefficients between factors. Based on Table 4.4, the correlation coefficients between factors were relatively small. Therefore, these factors could be used for analysis without significant concern about bias in the results caused by multicollinearity problems which occur where independent variables in a regression model are highly correlated (Thompson, 1978). To sum up, this proves that the data corresponding to the factors in this section had good usability and could be used for the subsequent regression analysis.

4.5.2 Description of the dependent variable: intention to use RA

I first measured the dependent variable "intention to use RA" as a continuous variable where I sum the values for each question to get a total score for each respondent. For the logit regressions, the dependent variable was measured using the respondents' answers to the statement "I intend to use RA in the future" and constructing a dummy variable that takes the value of 1 if the respondent chose either "agree" or "strongly agree" and the value of 0 for the other options. Moreover, for the OLS regression, I gave the respondents four options, namely "I intend to use RA," "I expect to use RA," "I will use RA," and "I would prefer not to use RA." In order to measure the dependent variable, for each question I assigned a value of 1 if the respondent chose the option "strongly disagree," the value of 2 if the respondent chose the option "disagree," the value of 3 if the respondent chose "neutral," the value of 4 if the respondent chose "agree," and the value of 5 if the respondent chose "strongly agree".

*** INSERT TABLE 4.5 HERE ***

Table 4.5 shows the responses to Questions 39 to 42. These questions were asked to investigate respondents' intention to use RA. The mean for the statement "I intend to use RA in the future" was 3.88 ((1) in Table 4.5). Besides, the statistics indicated that 75% of the respondents selected "agree" or "strongly agree" in response to the statement "I intend to use RA in the future" (Question 39). In comparison, 87% of the respondents chose "agree" or "strongly agree" in response to the statement "I predict I would use the RA in the future" (Question 40), and the average score for this question was 4.24 ((2) in Table 4.5). Furthermore, the average score for the statement "I will use RA in the future" was 3.87 ((3) in Table 4.5), with 68% of respondents choosing "agree" or "strongly agree" when asked if they would use RA in the future. However, in the reverse question (Question 42), the average score was only 3.09 ((4) in Table 4.5), which means the proportion of respondents who thought they would not use RA in the future was lower than those who thought they would use RA in the future. Only 33% of respondents responded with "agree" or "strongly agree" when asked if they would prefer to use an investment method they are familiar with rather than RA.

Besides, (5) and (6) in Table 4.5 describe the dependent variable for OLS and logit regression. According to the statistics, the mean score for intention to use RA among all respondents was 14.33 and 75% of the respondents explicitly stated their intention to use RA in the future. Based on these statistics, there is evidence to suggest that potential users in China have a high level of intention to use RA in the future. Therefore, it is important to conduct an in-depth analysis of the factors that influence intention to use RA.

4.5.3 Preliminary analysis of the impact of sociodemographic variables on intention to use RA

In this section, we preliminarily analysed the impact of sociodemographic variables on the willingness to use RA using descriptive statistics and t-tests. First, Table 4.6 shows the frequency distribution of the sociodemographic variables included in the questionnaire. As can be seen from the table, the age distribution of the sample is relatively even, with the proportions of respondents aged 18-27, 28-37, 38-47, and 48-60 being 24.08%, 24.88%, 25.68%, and 25.36%, respectively. In terms of gender, 51.36% of respondents are male, while 48.64% are female. Most respondents live in urban areas (87.84%), and the proportion of married respondents is relatively high (79.04%). Additionally, most respondents are in full-time employment (83.52%), with a relatively balanced income distribution; more than half of the respondents are homeowners without a mortgage (51.36%). Regarding education, most respondents have a bachelor's degree or higher (82.64%).

*** INSERT TABLE 4.6 HERE ***

Table 4.7 describes the sociodemographic factors examined in this thesis. For the *age* factor, I set up four age groups and assigned a value of 1 if the respondent’s age was between 18 and 27 years, a value of 2 if the respondent’s age was between 28 and 37 years, a value 3 if the respondent’s age was between 38 and 47 years, and a value of

4 if the respondent's age was between 48 and 60 years. Accordingly, the age groups of the respondents ranged from 1 to 4, and the average age of the respondents was between 28 and 37. *Female gender* was set as a dummy variable where the value "1" denotes female respondents and the value "0" denoted male respondents. The mean value for the female gender was 0.49, which means males exceeded females by two percentage points in the sample of this thesis, and thus the numbers of male and female respondents were almost the same. I then set the place of residence as a dummy variable; respondents living in an urban area were assigned the value "1" and respondents living in rural areas were assigned the value "2." Statistics from Table 4.7 show that 88% of the respondents lived in urban areas, and only a small number of respondents lived in rural areas. Marital status was also set as a dummy variable, with value of 1 meaning the respondents were married and 0 meaning they were not, as mentioned in Question 5, and it was found that 79% of the respondents in our analysis were married.

*** INSERT TABLE 4.7 HERE ***

I then measured the variable of *financial dependents* and assigned the value of 1 if the respondent did not have financial dependents, and the value of 2 if the respondent had one financial dependent, the value of 3 if the respondent had two financial dependents, and the value of 4 if the respondent had three or more financial dependents. Based on the statistics in Table 5.2, the average value for financial dependents was 2.73, which means that the average number of financial dependents for respondents was around one. Regarding employment status, I measured the dummy variable as 1 if the respondent was "full-time employed" and 0 for others, and it was found that 84% of respondents in our analysis were in full-time employment. Besides, with regard to *monthly income*, I also assigned the value of 1 if the respondent's monthly income was below ¥5,000, the value of 2 if the respondent's monthly income was between ¥5,001 and ¥10,000, the value of 3 if the respondent's monthly income was between ¥10,001 and ¥15,000, the value of 4 if the respondent's monthly income was between ¥15,001 and ¥20,000, and the value of 5 if the respondent's monthly income was above ¥20,001. For our respondents, the average score for the monthly income factor was 2.98, meaning the average range for monthly income was between ¥5,001 and ¥15,000. I then measured the residential status of respondents by constructing a dummy variable where a value of 1 was assigned if the respondent was a *homeowner without a mortgage,* and 0 otherwise. After setting the dummy variable, I found that the proportion of respondents classed as "homeowner without mortgage" was basically the same as that of those classed as "otherwise."

Finally, for the respondent's educational background, I assigned a value of 1 if the respondent's level of educational attainment was high school or below, the value of 2 if the respondent's level of educational attainment was college, the value of 3 if the respondent's level of educational attainment was undergraduate, the value of 4 if the respondent's level of educational attainment was postgraduate, and the value of 5 if the respondent's level of educational attainment was PhD or above. Therefore, the value range for educational background was 1 to 5, and in our sample the average score was 2.89, meaning that the average level for the respondents was between college and undergraduate.

Table 4.8 shows the t-test results of the sociodemographic variables included in this thesis, which are used to preliminarily assess the impact of different sociodemographic factors on the intention to use RA. The results indicate that age has no significant impact on the willingness to use RA, suggesting that there is no significant difference in the intention to use RA among respondents of different age groups. This finding is consistent with some studies, which suggest that age may not be a key factor influencing the willingness to use fintech products (Venkatesh et al., 2012).

The results indicate that gender affects the intention to use RA at the 10% significance level, with male respondents demonstrating a slightly higher willingness to use RA than females. This result aligns with previous research, which indicates that males may have a slightly higher acceptance of fintech products compared to females (Gefen & Straub, 1997). Additionally, urban respondents show a slightly higher willingness to use RA than rural respondents; however, this difference is only marginally significant at the 10% significance level, possibly reflecting a greater acceptance of emerging technologies among urban residents (Rogers, 2003).

Marital status significantly impacts the willingness to use RA, with married respondents showing a considerably higher intention to use RA than those who are single, divorced, or living with partners. This may be related to the increased demand for financial planning and investment among married individuals (Xiao & Anderson, 1997). Respondents with financial dependents also exhibit a significantly higher willingness to use RA than those without financial dependents, suggesting that financial burdens may prompt individuals to prefer automated financial tools (Hilgert et al., 2003). Full-time workers demonstrate a significantly higher intention to use RA than respondents with other employment statuses, which may be linked to the higher demand for time efficiency and financial management among full-time workers (Lusardi & Mitchell, 2014). In terms of educational background, respondents with a bachelor's degree or higher show a significantly greater willingness to use RA than those with lower educational qualifications, consistent with previous research indicating that individuals with higher education levels are more inclined to adopt new technologies (Riquelme & Rios, 2010).

*** INSERT TABLE 4.8 HERE ***

In summary, the preliminary analysis reveals that marital status, financial dependency, employment status, and educational background are significant sociodemographic factors influencing respondents' willingness to use RA. Additionally, gender and the urban–rural distinction also influence respondents' intentions to use RA. These findings provide a foundation for subsequent regression analysis and guide further exploration of the mechanisms through which these variables influence the willingness to use RA.

4.5.4 Preliminary analysis of the impact of behavioural variables on intention to use RA

In this section, we present the frequency of behavioural factors, descriptive statistics, and t-tests from the study sample, offering a preliminary analysis of the impact of the included behavioural variables on the willingness to use RA. Firstly, according to the frequency analysis (Table 4.9), most respondents exhibited a strong tendency towards risk aversion, particularly in financial decision-making, preferring more conservative strategies. In terms of risk perception, respondents demonstrated low trust in financial security, especially concerning credit card information and personal privacy protection. Additionally, the frequency analysis revealed that respondents generally had a strong illusion of control. Furthermore, respondents displayed a relatively high level of confidence overall. Similarly, regarding trust, respondents showed a comparatively high level of trust in others. These distribution characteristics provide a foundation for the subsequent analysis of behavioural variables.

*** INSERT TABLE 4.9 HERE ***

Next, I conducted a descriptive statistical analysis of the data (Table 4.10) which describes the behavioral factors in our analysis, including *risk aversion, risk perception, BTAE, IOC, confidence,* and *trust*. I used Question 11 in the questionnaire to measure the risk aversion factor. The options for this question ranged from 1 to 10, where 1 meant the highest level of risk aversion, and 10 meant the lowest level. The average score for respondents was 6.72. Then, I used fourother questions to determine whether the respondents were better or worse than average. Two of them (Questions 13 and 17) were used to evaluate respondents themselves and the other two questions (Questions 13-1 and 18) were used to allow respondents to evaluate the average level for the general public. I then subtracted the respondent's score for self-assessment from the score for their assessment of the general public average. The BTAE ranged from -5 to 8, with an average score of 1.27. I then assigned the value of 1 if the respondent’s score was positive, and 0 otherwise.

*** INSERT TABLE 4.10 HERE ***

For *IOC* (Questions 20 to 23), *confidence* (Questions 24 to 26), *trust* (Questions 27 to 29), and *risk perception* (Questions 30 to 33). These variables are measured using five-level Likert scale. For each of these questions, I assigned the value of 1 if a respondent chose “strongly disagree,” the value of 2 if a respondent chose “disagree,” the value of 3 if a respondent chose “neutral,” the value of 4 if a respondent choose “agree,” and the value of 5 if the respondent chose “strongly agree.” I then added the scores together for each question to get the respondent’s final score for each factor. The range of values varied here because the number of questions used to measure each behavioral factor differed.

Furthermore, this thesis conducted a preliminary analysis of the behavioural variables through t-tests (Table 4.11), aiming to explore the potential impact of these variables on the willingness to use RA. The results of the t-tests show that there are significant differences in risk aversion, risk perception, illusion of control, and trust among different groups, indicating that these variables may significantly impact the willingness to use RA. Firstly, the significant difference in risk aversion suggests that risk-averse individuals may have a lower intention to use RA. This result is consistent with existing research, as risk-averse individuals are usually cautious about emerging technologies and automated tools, especially in financial decision-making (Gerrans et al., 2014). RA, as an algorithm-dependent investment tool, may lack transparency in its decision-making process, which could exacerbate the concerns of risk-averse individuals, thereby reducing their willingness to use it. Secondly, the significant difference in risk perception suggests that individuals with a high level of risk perception may be more inclined to use RA. This finding aligns with the research results of Belanche et al. (2019), as individuals with a high risk perception often place greater emphasis on financial security, and the transparency and automated management offered by RA may satisfy their need for both security and efficiency. Therefore, individuals with higher risk perception may be more inclined to use RA as an investment tool. Additionally, the significant difference in the illusion of control suggests that individuals with a stronger illusion of control may be more willing to use

RA. This is consistent with the illusion of control theory proposed by Langer (1975), as individuals with a stronger illusion of control tend to increase their sense of control over outcomes through specific behaviours or rituals. These individuals may view RA as an automated decision-making process that enhances their sense of control, thereby increasing their intention to use it. Finally, the significant difference in trust suggests that individuals with higher trust may be more inclined to use RA. This result aligns with the research of Gefen et al. (2003), as trust is one of the key factors in user acceptance of new technologies. As an algorithm-dependent financial service, RA largely relies on user trust in technology for its success. Therefore, individuals with a high level of trust may be more willing to accept RA as their investment tool.

*** INSERT TABLE 4.11 HERE ***

Overall, these preliminary analysis results suggest that behavioural variables may significantly impact the willingness to use RA. Risk-averse individuals and those with high risk perception may be cautious about RA, while individuals with a high illusion of control and high trust may be more willing to accept this emerging financial service. These findings provide important directions for further in-depth research, especially on how to enhance user trust by improving the transparency and security of RA, and how to meet the needs of users with different risk preferences through personalised services.

4.5.5 Preliminary analysis of the impact of financial and skilled behavioural variables on intention to use RA

In this section, we conduct a preliminary analysis of the impact of the financial and skilled behavioural variables included in this thesis on the intention to use RA by presenting frequency reports, descriptive statistics, and t-tests of the financial and skilled behavioural factors.

Firstly, Table 4.12 displays the frequency distribution of variables such as financial literacy, financial confidence, perceived financial knowledge, digital literacy, traditional advisor usage, RA usage, and numeracy skills. Table 1 indicates that most respondents performed well on financial literacy questions, particularly in calculating savings account interest. However, some respondents demonstrated a lack of understanding in relation to questions about inflation and stock investment.

The distribution of financial confidence and perceived financial knowledge suggests that respondents have a high level of confidence in managing their finances and hold a positive evaluation of their financial knowledge. Regarding digital literacy, respondents generally exhibit a strong interest and initiative in adopting new technologies. The usage rates of traditional advisors and RAs are 76.64% and 62.32%, respectively, indicating a notable level of popularity for these financial services among respondents.

*** INSERT TABLE 4.12 HERE ***

Table 4.13 describes financial and skilled behavioral factors. Firstly, financial literacy was measured using three multiple-choice questions (Questions 14 to 16), each with one correct answer option. Respondents received one point for each correct answer, resulting in a range of financial literacy scores from 0 to 3. The average score of 2.36 indicated a relatively high level of financial literacy among respondents. I then used a 10-point Likert-type scale to measure financial confidence (Question 13) and numeracy (Question 12). Respondents' scores for each question ranged from 1 to 10, with higher scores indicating greater financial confidence or numeracy skills. According to the statistics obtained, the respondents' average score for financial confidence was 8.04, and for numeracy it was 7.72. This indicates that the respondents had relatively strong financial confidence and numeracy skills. In addition, I used a seven-point Likert-type scale to measure the respondents' perception of financial knowledge (Question 19). The respondents' scores ranged from 1 to 7, with higher scores indicating a greater perception of their own financial knowledge.

*** INSERT TABLE 4.12 HERE ***

I also included *digital literacy* (Questions 34 to 36) as a variable, which was measured using a five-point Likert scale. For each of these questions, I assigned the value of 1 if a respondent chose “strongly disagree,” a value of 2 if a respondent chose “disagree,” a value of 3 if a respondent chose “neutral,” a value of 4 if a respondent chose “agree,” and a value of 5 if respondents chose “strongly agree.” I then added the scores for the questions under this variable to attain the respondent’s final score for digital literacy.

At the same time, I also examined the investment experience of respondents, including whether they had had experience of using traditional advisors when investing and whether they had had experience of using RA (Oehler et al., 2021). For each of these two questions, I set dummy variables where I assigned the value of 1 if a respondent chose “yes” and the value of 0 if a respondent chose “no.” The statistics showed that 76% of the respondents had had experience of using traditional advisors in the past two years, and 62% of the respondents had had experience of using RA.

Next, I conducted a preliminary analysis of the impact of behavioural variables on the intention to use RA through t-tests (Table 4.13). Based on the t-test results in Table 4.13, we can preliminarily analyse the impact of financial and skilled behavioural variables on the intention to use RA. The mean value of the high financial literacy group is significantly higher than that of the low financial literacy group at the 1% significance level, indicating that respondents with higher financial literacy are more likely to use RA. This result is consistent with the findings of Lusardi and Mitchell (2014), who found that individuals with higher financial literacy are more inclined to use complex financial tools, such as investment advisers or automated investment platforms. Similarly, the mean value of the high financial confidence group is significantly higher than that of the low financial confidence group at the 1% significance level, indicating that respondents with a higher level of confidence in their financial management abilities are more inclined to use RA. This finding aligns with the research of Goyal and Kumar (2021), who pointed out that individuals with higher financial confidence are more willing to try technology-driven financial services.

*** INSERT TABLE 4.13 HERE ***

The mean value of the high perceived financial knowledge group is significantly higher than that of the low perceived financial knowledge group at the 1% significance level, indicating that respondents who evaluate their financial knowledge more positively are more likely to use RA. This result is consistent with the research of Hilgert et al. (2003), who found that individuals with higher perceived financial knowledge are more inclined to engage in complex financial decision-making. The mean value of the high digital literacy group is significantly higher than that of the low digital literacy group at the 1% significance level, indicating that respondents with a stronger acceptance of new technologies are more likely to use RA. This finding aligns with the technology acceptance model (TAM) proposed by Venkatesh et al. (2003), which posits that digital literacy is a key factor influencing individuals' acceptance of new technologies.

The mean value of respondents with traditional advisor usage experience is significantly higher than that of those without such experience at the 1% significance level, indicating that individuals who have used traditional financial advisers are more likely to switch to using RA. This result is consistent with the research of D'Acunto et al. (2019), who found that users of traditional financial services are more likely to adopt automated investment tools. The mean value of respondents with RA usage experience is significantly higher than that of respondents without such experience at the 1% significance level, indicating that individuals who have used RA are more likely to continue using or recommending it. This finding aligns with the research of Bhattacharya et al. (2008), who pointed out that user experience is a key factor influencing the intention to continue using RA. The mean value of the high numeracy skills group is significantly higher than that of the low numeracy skills group at the 1% significance level, indicating that respondents with stronger numeracy skills are more likely to use RA. This result is consistent with the research of Lusardi and Tufano (2015), who found that individuals with higher numeracy skills are more inclined to use digital financial services.

Through the preliminary analysis of the frequency distribution, descriptive statistics, and t-tests of financial and skilled behavioural variables, this study finds that financial literacy, financial confidence, perceived financial knowledge, digital literacy, traditional advisor usage experience, RA usage experience, and numeracy skills all have a significant impact on the intention to use RA. These variables show significant differences at the 1% significance level, indicating that they play an important role in driving respondents to use RA. These findings are consistent with existing literature and provide a theoretical foundation for further regression analysis and in-depth research.

4.6 Logit analysis and average marginal effects

Logit regression is a statistical technique commonly used to model binary outcome variables. When the dependent variable is a dummy variable (e.g. yes/no or success/failure), traditional linear regression models may not be appropriate because they can predict values outside the 0-1 range. Logit regression addresses this issue by using a logistic (or sigmoid) function to transform the output of a linear model into a probability that lies between 0 and 1 (Hosmer et al., 2013).

Therefore, based on the approach taken in the article by Oehle et al., (2021), this part deploys the logit regression approach for data analysis. According to Pohlmann and Leitner, logit regression can help to produce more accurate estimates of the probability of belonging to a causal category. While this study focuses on the factors that influence the effect of behavioral variables on the future use of RA, and the dependent variable is categorical comprising two levels, logit regression is more applicable to obtain more accurate estimates and results (Zarrouk et al., 2021). In a logit regression model, the focus is on the change in the log odds of the occurrence of the value of the dependent variable to bring about a one-unit change in the independent variables (Hilbe, 2009). The model is typically expressed as:

$$\ln\left(\frac{P(y)}{1-P(y)}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k \qquad (4.1)$$

and,

$$P(y) = \frac{e^{\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k}}{1 + e^{\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k}} \tag{4.2}$$

where $\ln\left(\frac{P(y)}{1-P(y)}\right)$ is the log of the outcomes, $\beta_1, \beta_2, \ldots \beta_k$ are the regression coefficients, and β_0 is the intercept. In equation (4.2), the logit regression model directly relates the probability of the dependent variable to the independent variables. The goal of logit regression is to estimate the $k + 1$ unknown parameters β in equation (4.2) through maximum likelihood estimation, which involves finding the set of parameters with the highest probability for the observed data. Each coefficient β indicates the amount of change I expected in the response variable if the predictor variable changed by one unit (Boateng and Abaye, 2019).

In order to more accurately reflect the influence of the independent variables on the dependent variable, this study used the average marginal effect (AME) (Baetschmann et al., 2014). The AME reflects the direction and extent of change in the dependent variable when the independent variables increase by one unit. It was estimated according to the dependent variable's coefficient value in the logit analysis results. Then, the partial effect of the independent variable on the dependent variable was estimated as the average of this partial effect (Bounthavong, 2018). The following formula expresses it:

$$AME = \frac{1}{N}\sum_{i=1}^{N} \frac{\partial E[y_i | x_i, w_i]}{\partial_x} \beta_k \tag{4.3}$$

AME analysis shows the changes in the probability of a result occurring when a factor changes by one unit while keeping other variables unchanged. When the probability of the outcome is close to 0 or 1, the marginal effect is small, while when the probability is close to 0.5, the marginal effect is relatively significant. Moreover, since the values of other independent variables change the predictive probability, the marginal effect of any independent variable in the model depends on the values of other independent variables to some extent (Norton et al., 2019). Therefore, in this study, AME analysis was conducted several times in both univariate and multivariate analysis to better clarify the potential influence of independent variables on the intention to use RA.

4.7 Ordinary least squares (OLS)

Following Larrabee et al., (2014), this study applied the OLS method for analysis, using the continuous dependent variable of the intention to use RA as mentioned in Chapter4.6. OLS regression is considered a statistical technique that can be used to analyze survey data, especially when used to estimate the relationship between multiple independent variables and a single dependent variable. The core purpose of OLS is to minimize the sum of squared errors, thereby finding the best-fit linear model (Wooldridge, 2016), and clearly explaining how each independent variable is associated with the dependent variable. The choice of OLS was based on its wide application in social sciences and economic research, and its robustness and reliability when interpreting survey data (Wooldridge, 2016). Its simplicity and interpretability make OLS the preferred method for analyzing linear relationships in empirical research (Gujarati and Porter, 2010). Mathematically, OLS tries to minimize the sum of the squares of the residuals (the difference between the actual observations and the predicted values) by choosing the coefficient (beta). The general form of a linear regression model is represented as:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} + \varepsilon_i \tag{4.4}$$

where y_i is the dependent variable, which here was the intention to use RA, β are the coefficients to be estimated, x_{ik} are the independent variables, ε_i and is the error term. OLS aims to find estimates of the coefficients so that the sum of squared errors is minimized. This is accomplished by taking the derivative of the following equation and setting it to zero; solving this equation yields an estimate of β (Hill et al., 2018).

$$S = \sum_{i=1}^{n} \varepsilon_i^2 = \sum_{i=1}^{n} (y_i - \beta_0 - \beta_1 x_{i1} - \beta_2 x_{i2} - \cdots - \beta_k x_{ik})^2 \tag{4.5}$$

Table for the research methodology

Table 4.1 Target sample boxes

Gender by	**Females**				**Male**			
Age by income	**18 - 27**	**28 - 37**	**28 - 47**	**48 - 60**	**18 - 27**	**28 - 37**	**28 - 47**	**48 - 60**
Below ¥5000	30	30	30	30	30	30	30	30
¥5001 - ¥10,000	30	30	30	30	30	30	30	30
¥10,001 - ¥10,500	30	30	30	30	30	30	30	30
¥10,501 - ¥20,000	30	30	30	30	30	30	30	30
Above ¥20,001	30	30	30	30	30	30	30	30

Table 4.1 shows the sample box that set up before the questionnaire published. Number of respondents per sub-group across the interlocked quotas for age, gender and income (after removing non-completes and non-serious attempts).

Table 4.2 Final sample box

Gender by	**Females**				**Males**			
Age by income	**18-27**	**28-37**	**28-47**	**48-60**	**18-27**	**28-37**	**28-47**	**48-60**
Below ¥5000	31	31	31	32	29	30	33	30
¥5001 - ¥10,000	32	33	30	29	33	31	34	36
¥10,001 - ¥10,500	28	29	30	30	31	32	35	40
¥10,501 -¥20,000	29	31	30	29	29	31	38	31

Table 4.2 shows the sample box of the available samples collected in the questionnaire. Number of respondents per sub-group across the interlocked quotas for age, gender and income (after removing non-completes and non-serious attempts).

Table 4.3 Validity analysis

Determinant of the correlation matrix	=	0.05
Bartlett test of sphericity		
Chi-square	=	3683.29
Degrees of freedom	=	253
p-value	=	0.000
H_0: variables are not intercorrelated		
Kaiser-Meyer-Olkin Measure of sampling adequacy		
KMO	=	0.73

This tables reflects the results include all factors in our thesis. The results are carried out by Bartlett test and Kaiser-Meyer-Olkin Measure.

Table 4.4 Correlation between variables

Factors	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) Age	1.00														
(2) Financial dependent	0.01	1.00													
(3) Monthly income	-0.00	0.07	1.00												
(4) Educational background	-0.10	0.07	0.30	1.00											
(5) Risk aversion	0.04	0.04	0.17	0.12	1.00										
(6) Risk perception	-0.05	-0.02	-0.09	-0.07	-0.08	1.00									
(7) Better than average effect	-0.01	0.01	-0.01	0.01	-0.00	-0.04	1.00								
(8) Illusion of control	-0.01	0.14	0.08	0.07	0.15	0.13	-0.07	1.00							
(9) Confidence	-0.05	0.00	0.02	0.04	0.00	0.29	-0.03	0.12	1.00						
(10) Trust	0.06	0.14	-0.01	0.01	-0.01	0.18	0.02	0.08	0.13	1.00					
(11) Financial literacy	0.03	0.07	0.06	0.16	0.02	-0.19	0.11	-0.16	0.03	-0.01	1.00				
(12) Financial confidence	0.07	0.05	0.12	0.07	0.24	-0.07	0.41	0.05	-0.06	0.12	0.06	1.00			
(13) Perception of financial knowledge	0.16	0.07	0.22	0.15	0.43	-0.13	0.05	0.19	-0.07	0.05	0.09	0.33	1.00		
(14) Digital literacy	-0.00	0.07	0.13	0.16	0.32	-0.14	0.05	0.07	-0.00	0.09	0.09	0.21	0.31	1.00	
(15) Numeracy	0.05	0.03	0.18	0.14	0.41	-0.14	0.12	0.04	0.02	0.10	0.17	0.46	0.43	0.32	1.00

Table 5.2 presents the correlation results including independent factors in our thesis without dummy independent factors.

Table 4.5 Description of dependent variable

	Description	Obs	Mean	Std. Dev	Min	Max
(1) Intention to use RA	Answer the question "I intention to use RA in the future"	1250	3.88	0.79	1	5
Strong disagree	Choose "strong disagree" in question "I intention to use RA in the future"	1250	0.01	0.07	0	1
Disagree	Choose "disagree" in question "I intention to use RA in the future"	1250	0.05	0.21	0	1
Neutral	Choose "neutral" in question "I intention to use RA in the future"	1250	0.20	0.40	0	1
Agree	Choose "agree" in question "I intention to use RA in the future"	1250	0.56	0.50	0	1
Strong agree	Choose "strong agree" in question "I intention to use RA in the future"	1250	0.19	0.39	0	1
(2) Predict to use RA	Answer the question "I predict I would use the RA in the future."	1250	4.24	0.81	1	5
Strong disagree	Choose "strong disagree" in question "I predict I would use the RA in the future."	1250	0.01	0.11	0	1
Disagree	Choose "disagree" in question "I predict I would use the RA in the future."	1250	0.03	0.16	0	1
Neutral	Choose "neutral" in question "I predict I would use the RA in the future."	1250	0.09	0.29	0	1
Agree	Choose "agree" in question "I predict I would use the RA in the future."	1250	0.45	0.50	0	1
Strong agree	Choose "strong agree" in question "I predict I would use the RA in the future."	1250	0.42	0.49	0	1
(3) Will use RA	Answer the question "I will use RA in the future."	1250	3.87	0.94	1	5
Strong disagree	Choose "strong disagree" in question "I will use RA in the future."	1250	0.01	0.12	0	1
Disagree	Choose "disagree" in question "I will use RA in the future."	1250	0.06	0.24	0	1
Neutral	Choose "neutral" in question "I will use RA in the future."	1250	0.25	0.43	0	1
Agree	Choose "agree" in question "I will use RA in the future."	1250	0.40	0.49	0	1

Strong agree	Choose "strong agree" in question "I will use RA in the future."	1250	0.28	0.45	0	1
(4) Prefer not to use RA	Answer the question "I prefer to use the investment method I am familiar with rather than RA"	1250	3.09	1.07	1	5
Strong disagree	Choose "strong disagree" in question "I prefer to use the investment method I am familiar with rather than RA"	1250	0.04	0.20	0	1
Disagree	Choose "disagree" in question "I prefer to use the investment method I am familiar with rather than RA"	1250	0.28	0.45	0	1
Neutral	Choose "neutral" in question "I prefer to use the investment method I am familiar with rather than RA"	1250	0.34	0.48	0	1
Agree	Choose "agree" in question "I prefer to use the investment method I am familiar with rather than RA"	1250	0.21	0.41	0	1
Strong agree	Choose "strong agree" in question "I prefer to use the investment method I am familiar with rather than RA"	1250	0.12	0.33	0	1
(5) Intention_dummy	Binary dummy: 1 if respondent is "agree" or "strong agree" in (1), 0 otherwise	1250	0.75	0.43	0	1
(6) Intention_continuous	Continuous variable. Sum of responses in the "intention to use RA", "Predict to use RA", "Will use RA" and "Prefer not to use RA"	1250	14.33	2.31	4	20

Table 6.1 describes the dependent variables used in the thesis. (1) (2) (3) (4) describe each of the four questions in the questionnaire related to the dependent variable. (5) and (6) describe the data for the dependent variables using the logit regression and OLS individually.

Table 4.6 Frequency of sociodemographic variables

Characteristics		Frequency	Percentage (%)
(1) Age		1250	
	18-27	301	24.08
	28-37	311	24.88
	38-47	321	25.68
	48-60	317	25.36
(2) Female		1250	
	Male	642	51.36
	Female	608	48.64
(3) Urban		1250	
	Urban	1098	87.84
	Rural	152	12.16
(4) Married		1250	
	Single	206	16.48
	Married	988	79.04
	Divorce	12	0.96
	Living with partner	44	3.52
(5) Financial dependent		1250	
	0	100	8
	1	403	32.24
	2	472	37.76
	3 or more	275	22
(6) Employed status		1250	
	Employed (full time)	1044	83.52
	Employed (part time)	33	2.64
	Self employed	68	5.44
	Unemployed	5	0.4
	Student	61	4.88
	Homemaker	11	0.88
	Retired	28	2.24
(7) Income		1250	
	Below ¥5,000	247	19.76
	¥5,001 – ¥10,000	258	20.64
	¥10,001 - ¥15,000	255	20.4
	¥15,001 – ¥20,000	248	19.84
	Above ¥20,001	241	19.28
(8) Homeowner without mortgage		1250	
	Homeowner without mortgage	642	51.36
	Homeowner with mortgage	266	21.28
	Private renting	176	14.08
	Social renting	33	2.64

Living with parents/ friends/ relatives (no rent to pay)	106	8.48
Living with others and need to pay the rent together	27	2.16
(9) Education background	1250	
High school or below	73	5.84
College (associate's degree; vocational or trade school after high school)	162	12.96
Undergraduate	860	68.8
Postgraduate	164	13.12
PhD or above	9	0.72

Table 4.6 presents the frequency and percentage distribution of responses for various behavioral variables. Each question within the variables was answered by a total of 1,250 respondents (N=1250). The table categorizes responses into different options or scales, providing insights into the distribution of opinions across the sample. The percentages indicate the proportion of respondents selecting each option, offering a detailed view of the sample's behavioral tendencies and perceptions.

Table 4.7 Description of sociodemographic variables

Factors	Description	Obs	Mean	Std. dev	Min	Max
Age	Ordinal dummy: 1: “18-27”, 2: “28-37”, 3: “38-47”, 4: “48-60”	1250	2.52	1.11	1	4
Female	Binary dummy: 0 for Male, 1 for Female	1250	0.49	0.5	0	1
Urban	Binary dummy: 1 if living in urban, 0 if living in rural	1250	0.88	0.33	0	1
Married	Binary dummy: 1 if respondent is married, 0 otherwise	1250	0.79	0.41	0	1
Financial dependent	Ordinal dummy: 1: “0”, 2: “1”, 3: “2”, 4: “3” or more,	1250	2.73	0.89	1	4
Employed status	Binary dummy: 1 if respondent is full time employed, 0 otherwise	1250	0.84	0.37	0	1
Income	Ordinal dummy: 1: “<￥5,000”, 2: “￥5,001-￥10,000”, 3: “￥10,00-￥15,000”, 4: “￥15,001-￥20,000”, 5: “>￥20,001”	1250	2.98	1.40	1	5
Homeowner without mortgage	Binary dummy: 1 if respondent is the homeowner without mortgage, 0 otherwise	1250	0.51	0.50	0	1
Education background	Nominal variable: 1: “High school or below”, 2: “College (associate’s degree; vocational or trade school after high school)”, 3: “Undergraduate”, 4: “Postgraduate”, 5: “PhD or above”	1250	2.89	0.70	1	5

Table 6.2 describes the sociodemographic variables used in this thesis, including the type of variable (continuous variable, nominal variable or dummy variable), the subjective, mean, standard deviation, and maximum and minimum values of the data.

Table 4.8 Significance testing of sociodemographic variables

Variable		Mean	P-Value
Age	Age (18-37)	0.75	0.8171
	Age (38-60)	0.75	
Gender	Male	0.77	0.0958*
	Female	0.73	
Urban & Rural	Urban	0.76	0.0533*
	Rural	0.68	
Marital status	Married	0.78	0.0000***
	Not-married	0.63	
Financial dependents	Without dependents	0.58	0.0000***
	With dependents	0.76	
Employed status	Full-time employed	0.77	0.0000***
	Other work status	0.64	
Residential status	Homeowner without mortgage	0.77	0.1247
	Other residential status	0.73	
Educational background	Undergraduate or above	0.79	0.0000***
	College or below	0.56	

Note: This table presents the mean values and corresponding p-values from a t-test analysis comparing different demographic groups. The mean values represent the average scores or proportions for each category within the specified variables. The p-values indicate the statistical significance of the differences between the groups. In this table, *** p<0.01, ** p<0.05, * p<0.1. A p-value less than 0.1 suggests a statistically significant difference between the groups. For example, a mean of 0.78 for married individuals compared to 0.63 for non-married individuals, with a p-value of 0.0000, indicates a significant difference in the measured variable between these two marital status groups. Specifically, the married group show a higher intention to use RA, while the not-married group have lower intention to use RA.

Table 4.9 Frequency of behavioural variables

Characteristic	Question	Options	Frequency	Percentage (%)
Risk aversion	Are you a person that takes risks with finances?	1	30	2.40%
		2	32	2.56%
		3	77	6.16%
		4	71	5.68%
		5	90	7.20%
		6	175	14.00%
		7	257	20.56%
		8	270	21.60%
		9	148	11.84%
		10	100	8.00%
Risk perception	I do not trust that my credit card number will be secure	Strongly disagree	86	6.88%
		Disagree	314	25.12%
		Neutral	381	30.48%
		Agree	320	25.60%
		Strongly agree	149	11.92%
	It is difficult for me to judge quality of a product/service	Strongly disagree	139	11.12%
		Disagree	464	37.12%
		Neutral	332	26.56%
		Agree	248	19.84%
		Strongly agree	67	5.36%
	I do not trust that my personal information will be kept private	Strongly disagree	105	8.40%
		Disagree	267	21.36%
		Neutral	324	25.92%
		Agree	374	29.92%
		Strongly agree	15.20%	15.20%
	It is faster/ easier to purchase locally	Strongly disagree	71	5.68%
		Disagree	200	16.00%
		Neutral	304	24.32%
		Agree	435	34.80%
		Strongly agree	240	19.20%
Better than average effect	How confident do you think the public is in being able to manage their money?	1	0	0.00%
		2	3	0.24%
		3	14	1.12%
		4	44	3.52%
		5	115	9.20%
		6	254	20.32%
		7	306	24.48%
		8	282	22.56%
		9	167	13.36%

		10	65	5.20%
	How many points do you think you scored in the previous four questions (Question 14 to 16)?	0	5	0.40%
		1	124	9.92%
		2	524	41.92%
		3	597	47.76%
	How many marks do you think other people could have gained for their answers to the previous three questions (Question 14 to 16)?	0	6	0.48%
		1	198	15.84%
		2	793	63.44%
		3	253	20.24%
Illusion of control	Prayer helps me win when have to play gambling games	Strongly disagree	339	27.12%
		Disagree	447	35.76%
		Neutral	194	15.52%
		Agree	207	16.56%
		Strongly agree	63	5.04%
	When having to play gambling games, specific numbers and colours can help increase my chances of winning	Strongly disagree	236	18.88%
		Disagree	350	28.00%
		Neutral	337	26.96%
		Agree	262	20.96%
		Strongly agree	65	5.20%
	When have to play a gambling game, I collect specific items that help increase my chances of winning before start	Strongly disagree	188	15.04%
		Disagree	344	27.52%
		Neutral	256	20.48%
		Agree	353	28.24%
		Strongly agree	109	8.72%
	When having to play gambling games, I have specific rituals and behaviours to increase my chances of winning	Strongly disagree	309	24.72%
		Disagree	404	32.32%
		Neutral	247	19.76%
		Agree	220	17.60%
		Strongly agree	70	5.60%
Confidence	There will be more accidents and catastrophes in the future than we had in the past	Strongly disagree	90	7.20%
		Disagree	228	18.24%
		Neutral	389	31.12%
		Agree	415	33.20%
		Strongly agree	128	10.24%
	Nowadays, things seem to be getting more and more out of control.	Strongly disagree	72	5.76%
		Disagree	215	17.20%
		Neutral	280	22.40%
		Agree	496	39.68%
		Strongly agree	187	14.96%
		Strongly disagree	10	0.80%

	A person can never have too much insurance to protect against the inevitable disasters in life.	Disagree	30	2.40%
		Neutral	88	7.04%
		Agree	505	40.40%
		Strongly agree	617	49.36%
Trust	In general, one can trust people	Strongly disagree	19	1.52%
		Disagree	141	11.28%
		Neutral	412	32.96%
		Agree	539	43.12%
		Strongly agree	139	11.12%
	These days you cannot rely anybody else	Strongly disagree	45	3.60%
		Disagree	225	18.00%
		Neutral	247	19.76%
		Agree	481	38.48%
		Strongly agree	252	20.16%
	When dealing with strangers, it is better to be careful before you trust them.	Strongly disagree	6	0.48%
		Disagree	26	2.08%
		Neutral	93	7.44%
		Agree	561	44.88%
		Strongly agree	564	45.12%

Table 4.9 presents the frequency and percentage distribution of responses for various behavioral variables. Each question within the variables was answered by a total of 1,250 respondents (N=1250). The table categorizes responses into different options or scales, providing insights into the distribution of opinions or behaviors across the sample. The percentages indicate the proportion of respondents selecting each option, offering a detailed view of the sample's behavioral tendencies and perceptions.

Table 4.10 Description of behavioural variables

Factors	Description	Obs	Mean	Std. dev	Min	Max
Risk aversion	Continuous variable. Answer the question “Are you a person that takes risks with finances?”	1250	6.72	2.18	1	10
Risk perception	Continuous variable. Sum of responses in the risk perception questions	1250	12.49	2.93	4	19
Better than average effect	Continuous variable. Sum of responses’ self-score minus sum of responses’ evaluate for public.	1250	1.27	1.89	-5	8
Illusion of control	Continuous variable. Sum of responses in the illusion of control questions	1250	10.38	3.80	4	19
Confidence	Continuous variable. Sum of responses in the confidence questions	1250	10.97	2.19	3	15
Trust	Continuous variable. Sum of responses in the trust questions	1250	11.37	1.50	5	15

Table 7.1 describes the behavioural variables used in this thesis, including the type of variable (continuous variable, nominal variable or dummy variable), the subjective, mean, standard deviation, and maximum and minimum values of the data.

Table 4.11 Significance testing of behavioural variables

Variable		Mean	P-Value
Risk aversion	Risk averse	0.68	0.0000***
	Risk seeker	0.85	
Risk perception	High risk perception	0.77	0.0161**
	Low risk perception	0.71	
Better than average effect	Better than average	0.74	0.7530
	Worth than average	0.75	
Illusion of control	High illusion of control	0.81	0.0000***
	Low illusion of control	0.69	
Confidence	High confidence	0.74	0.7821
	Low confidence	0.75	
Trust	High trust	0.79	0.0006***
	Low trust	0.71	

Note: This table presents the mean values and corresponding p-values from a t-test analysis comparing different demographic groups. The mean values represent the average scores or proportions for each category within the specified variables. The p-values indicate the statistical significance of the differences between the groups. In this table, *** p<0.01, ** p<0.05, * p<0.1. A p-value less than 0.1 suggests a statistically significant difference between the groups. For example, a mean of 0.85 for individuals who are risk seeker compared to 0.68 for those who are risk aversion, with a p-value of 0.0000, indicates a significant difference in the measured variable between these two groups. Specifically, people who are risk seekers show a higher intention to use RA, while those who are risk aversion have lower intention to use RA.

Table 4.12 Frequency of financial and skilled behavioural variables

Characteristic	Question	Options	Frequency	Percentage (%)
Financial literacy	Support you had ￥100 in a saving account and the interest rate was 2% per year. After 5 years how much do you think you would have in the account if you left the money to grow?	more than ￥102	1098	87.84%
		exactly ￥102	56	4.48%
		less than ￥102	61	4.88%
		Do not know	27	2.16%
		Refuse to answer	2	0.16%
	Imagine that the interest rate on your saving account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in the account?	more than today	155	12.40%
		exactly the same	54	4.32%
		less than today	990	79.20%
		Do not know	47	3.76%
		Refuse to answer	4	0.32%
	Please tell me whether this statement is true or false. 'Buying a single company's stock usually provides a safer return than a stock mutual fund'	TRUE	169	13.52%
		FALSE	864	69.12%
		Do not know	210	16.80%
		Refuse to answer	7	0.56%
Financial confidence	How confident do you feel managing your money?	1	1	0.08%
		2	4	0.32%
		3	10	0.80%
		4	26	2.08%
		5	58	4.64%
		6	124	9.92%
		7	266	21.28%
		8	365	29.20%
		9	266	21.28%
		10	130	10.40%
Perception of financial knowledge	How would you assess your overall financial knowledge?	1	7	0.56%
		2	32	2.56%
		3	120	9.60%
		4	254	20.32%
		5	479	38.32%
		6	293	23.44%
		7	65	5.20%
Digital literacy	I am curious about new things	Strongly disagree	11	0.88%
		Disagree	49	3.92%
		Neutral	153	12.24%
		Agree	550	44.00%
		Strongly agree	487	38.96%

	I usually take the lead in trying new technologies compare to people around me	Strongly disagree	33	2.64%
		Disagree	109	8.72%
		Neutral	257	20.56%
		Agree	568	45.44%
		Strongly agree	283	22.64%
	I think it is very interesting to try out the new technology	Strongly disagree	7	0.56%
		Disagree	31	2.48%
		Neutral	158	12.64%
		Agree	602	48.16%
		Strongly agree	452	36.16%
Traditional advisor	Have you consulted a personal financial advisor (including via phone or internet) at a bank or saving bank or a financial advisor on fee basis during the last two years?	Yes	958	76.64%
		No	292	23.36%
RA	Have you used a RA during the last two years?	Yes	779	62.32%
		No	471	37.68%
Numeracy skill	How confidence do you feel working with numbers when you need to in everyday life?	1	1	0.08%
		2	3	0.24%
		3	4	0.32%
		4	17	1.36%
		5	50	4.00%
		6	105	8.40%
		7	216	17.28%
		8	330	26.40%
		9	313	25.04%
		10	211	16.88%

Table 4.12 presents the frequency and percentage distribution of responses for various behavioral variables. Each question within the variables was answered by a total of 1,250 respondents (N=1250). The table categorizes responses into different options or scales, providing insights into the distribution of opinions or behaviors across the sample. The percentages indicate the proportion of respondents selecting each option, offering a detailed view of the sample's behavioral tendencies and perceptions.

Table 4.13 Description of financial and skilled behavioural variables

Factors	Description	Obs	Mean	Std. dev	Min	Max
Financial literacy	Continuous variables. Sum of the score in three financial literacy questions.	1250	2.36	0.83	0	3
Financial confidence	Continuous variables. Answer the question "How confident do you feel managing your money?"	1250	8.04	1.49	1	10
Perception of financial knowledge	Continuous variables. Answer the question "How would you assess your overall financial knowledge?"	1250	4.84	1.15	1	7
Digital literacy	Continuous variable. Sum of responses in the digital literacy questions	1250	12.10	2.00	4	15
Traditional advisor	Binary dummy: 0 for No, 1 for Yes	1250	0.76	0.43	0	1
RA	Binary dummy: 0 for No, 1 for Yes	1250	0.62	0.49	0	1
Numeracy	Continuous variables. Answer the question "How confidence do you feel working with numbers when you need to in everyday life?"	1250	7.72	1.51	1	10

Table 8.1 describes the financial variables used in this paper, including the type of variable (continuous variable, nominal variable or dummy variable), the subjective, mean, standard deviation, and maximum and minimum values of the data.

Table 4.14 Significance testing of financial and skilled behavioural variables

Variable		Mean	P-Value
Financial literacy	High financial literacy	0.81	0.0000^{***}
	Low financial literacy	0.68	
Financial confidence	High financial confidence	0.81	0.0000^{***}
	Low financial confidence	0.77	
Perception of financial knowledge	High perception of financial knowledge	0.016	0.0000^{***}
	Low perception of financial knowledge	0.015	
Digital literacy	High digital literacy	0.02	0.0000^{***}
	Low digital literacy	0.01	
Experience on traditional advisor	With experience on traditional advisor	0.80	0.0000^{***}
	Without experience on traditional advisor	0.56	
Experience on RA	With experience on RA	0.83	0.0000^{***}
	Without experience on RA	0.62	
Numeracy	High numeracy	0.17	0.0000^{***}
	Low numeracy	0.16	

Note: This table presents the mean values and corresponding p-values from a t-test analysis comparing different demographic groups. The mean values represent the average scores or proportions for each category within the specified variables. The p-values indicate the statistical significance of the differences between the groups. In this table, *** p<0.01, ** p<0.05, * p<0.1. A p-value less than 0.1 suggests a statistically significant difference between the groups. For example, a mean of 0.81 for individuals with high financial literacy compared to 0.68 for those with low financial literacy, with a p-value of 0.0000, indicates a significant difference in the measured variable between these two financial literacy groups. Specifically, people who have higher level of financial literacy have higher intention to use RA compared with those who have lower level of financial literacy.

Chapter 5 Influence of sociodemographic factors on intention to use RA

5.1 Introduction to the relationship between sociodemographic factors and intention to use RA

The burgeoning field of fintech, especially the adoption of RAs, is reshaping investment management globally. In China, understanding the sociodemographic predictors that influence intention to use such technologies is crucial when tailoring financial services. In this chapter, I first analyze the relationships between sociodemographic factors and intention to use RA. These sociodemographic factors include age, gender, place of residence (rural or urban), marital status, financial dependent, employment status, monthly income, residential status, and educational background. Research has indicated that older adults are more likely to embrace new technologies, including financial tools, due to their rich investment experience. Gender differences also play a significant role, as men are typically more inclined to use financial technologies than women (Kumar and Rani, 2024). Meanwhile, urban residents are often more exposed to technological innovations than rural residents, impacting their adoption rates (Demirguc-Kunt et al., 2017). Furthermore, marital status and financial dependent can influence financial behaviors and decision-making processes, thus affecting technology uptake (Brown and Graf, 2013). Employment status and monthly income not only define an individual's economic environment but also shape their financial behavior and attitudes toward risks associated with new financial tools (Agnew and Szykman, 2005). Lastly, a higher level of educational attainment has been associated with greater financial and digital literacy, which are critical in understanding and using complex technologies like RAs (Hastings et al., 2013).

For the current research, I first assumed that the older the potential user, the greater their intention to use RA in the future (Shin et al., 2021), and that males would be more willing to use RA than females. Besides, in our research, urban residents were presumed to have a higher intention to use RA compared to those living in rural areas due to the greater number of opportunities for the former to access inclusive financial products. I also examined the relationship between marital status and intention to use RA; I assumed that married people would be more likely to use RA than those who were single, divorced, or living with partners. Moreover, I speculated that potential users with no or fewer financial dependents may have a greater intention to use RAs in the future, possibly due to having more liquidity and less financial stress. Those employed full-time or with higher monthly incomes were expected to demonstrate an increased probability of using RA in the future for similar reasons. In addition, I also hypothesized that people who were homeowners without mortgages would be more willing to use RA in the future. I was also interested in the relationship between educational background and intention to use RA; for the current research, I assumed that a potential user's intention to use RA would increase for those with a higher level of educational attainment.

To collect the data, I used the questions from the first part of the questionnaire to measure the sociodemographic characteristics of the respondents (Appendix 4.2), and the questions from the third part to measure the respondents' intention to use RAs (Appendix 4.5). Then, I conducted multiple analyses using logit regression and OLS. The results confirmed our hypothesis (H2) that males exhibited a higher intention to use RAs than females. Moreover, due to their sharing of the burden of financial stress, married potential users also showed a higher intention to use RAs than those who were single, divorced, or living with partners, which aligns with the fourth hypothesis (H4) of this thesis mentioned in Chapter 3.3. Similarly, the number of financial dependents also had a significant positive impact on the potential users' intention to use RAs, which is consistent with the fifth hypothesis (H5) described in Chapter 3.3. As predicted in H7, potential users with a higher monthly income exhibited a significantly higher intention to use RAs. This might be partly due to the influence of less financial stress, and partly attributable to the group with relatively high monthly incomes is generally considered to have a stronger educational background. This study also found that individuals with a higher level of educational attainment were more likely to use RAs in the future, supporting the related hypothesis (H9) mentioned in Chapter 3.3.

5.2 Regression models analysing the impact of sociodemographic factors on intention to use RA

This thesis first ran the logit regression using the following model based on formula (4.1) in Chapter 4.6:

$$\begin{aligned} intention\_dummy_i &= \beta_0 + \beta_1 Age_i + \beta_2 Female_i + \beta_3 Urban_i + \beta_4 Married_i \\ &+ \beta_5 Financial\_dependence_i + \beta_6 Employed_i \\ &+ \beta_7 Monthly\_income_i + \beta_8 Homeowner\_without\_mortgage_i \\ &+ \beta_9 Educatinoal\_background_i + \varepsilon_i \qquad (5.1) \end{aligned}$$

Where i subscript represents individuals, β is the regression coefficient based on the logit regression, ε_i is the error. In formula (5.1), based on the regression coefficients of the logit regression model, I conducted further AME analysis to reflect the extent to which the intention of respondents to use RA changed when the sociodemographic variable changed by one unit.

Second, this thesis also performed the following OLS regression model based on formula (4.4) in Chapter 4.7:

$$Intention\_continuous_i = \beta_1 Age_i + \beta_2 Female_i + \beta_3 Urban_i + \beta_4 Married_i + \beta_5 Financial\_dependence_i + \beta_6 Employed_i + \beta_7 Monthly\_income_i + \beta_8 Homeowner\_without\_mortgage_i + \beta_9 Educatinoal\_background_i + \varepsilon_i \quad (5.2)$$

In this formula, i subscript represents individuals, β is the coefficients that need to be estimated, indicating how a change in the sociodemographic factors in this group affects respondents' intention to use RA, ε_i is the error term based on this regression.

5.3 Regression results for the effect of sociodemographic variables on intention to use RA

In this section, based on the regression results from the two models of OLS and logit estimations, a further multivariate analysis of the impact of these sociodemographic variables on the intention to use RA is presented.

*** INSERT TABLE 5.1 HERE ***

Table 5.1 shows the average marginal effects after estimating a logit regression for sociodemographic variables on the intention to use RA. This table also contains nine columns (columns 1 to 9) showing the effects of nine sociodemographic variables individually on intention to use RA, and one column (column 10) covering the multivariate analysis including all the sociodemographic variables together.

Based on the univariate analysis results, males had a higher intention to use RA than females (column 2), which is significant only at a 10% level. Respondents living in urban areas (column 3) had a 7% higher intention to use RA than those living in rural areas, which is also significant at a 10% level. Marital status (column 4), financial dependents (column 5), full-time employment (column 6), monthly income (column 7), and educational background (column 9) all had a significant positive effect on intention to use RA at a 1% level.

Column 10 of Table 5.1 shows the multivariate analysis result for the relationship between sociodemographic factors and intention to use RA. It reveals that female gender had a negative relationship with the intention to use RA, significant at only a 10% level, which means that female respondents were 4% less likely to have the intention to use RA in the future compared to the male respondents. This finding is highly consistent with the gender differences in risk-taking theory. According to Croson and Gneezy (2009) and Charness and Gneezy (2012), women generally exhibit a higher tendency toward risk aversion in financial decision-making, especially regarding innovative financial products. Additionally, women's greater concern for privacy and data security may further inhibit their willingness to adopt RA (Garbarino & Slonim, 2009). These findings align with the technology acceptance model, which suggests that perceived risk and trust are key determinants of technology adoption (Davis, 1989). For women, the potential risks of RA may outweigh its benefits, leading to lower adoption rates. In contrast, men typically exhibit higher risk tolerance and are more willing to try new technologies. Research by Powell and Ansic (1997) indicates that men are more inclined to pursue higher returns than asset preservation in financial decision-making. This risk preference makes men more likely to adopt innovative investment tools like RA. Furthermore, men’s greater comfort with technology and lower sensitivity to privacy concerns may also enhance their interest in RA (Venkatesh & Morris, 2000). These gender differences further support our findings that men are more likely than women to incorporate RA into their investment strategies. Hence, this result supports our H2 whereby males have a relatively higher intention to use RA than females.

I also found that the respondents who were married showed a positive relationship with the intention to use RA, which means that the married respondents were 10% more likely to use RA than respondents under other statuses (single, divorced, or living with partner). This result supports H4 of this thesis and is consistent with the research of Hohenberger, Lee, and Coughlin (2019), indicating that married individuals, due to their greater responsibility for family finances, are more inclined to rely on professional tools for asset allocation and risk management. However, Addo and Lichter (2013) point out that although married individuals have a higher demand for RA, their actual usage may be limited by the availability of liquid funds for investment, revealing a potential contradiction between demand and actual behaviour. On the other hand, the lower acceptance of RA among single individuals may be related to their cautious attitude toward emerging technologies. According to the technology acceptance model (Davis, 1989), an individual's acceptance of new technologies is influenced by perceived ease of use and usefulness. Therefore, single individuals may prefer to use their free time to thoroughly understand the functions of RA before deciding whether to adopt it. This finding contrasts with the research of Barber and Odean (2001), who argue that single individuals rely more on their own judgement for investment decisions. Additionally, research by Gerrans et al. (2014) suggests that divorced individuals may adopt a more cautious attitude toward RA due to their higher risk aversion, further highlighting the complexity of the impact of marital status on investment behaviour. Based on the analysis results of this paper, if RA is to develop further in China, focus could be placed on promoting such services to potential users who are married.

The number of financial dependents is also an important factor influencing people's intention to use RA. Our study found that when the number of a respondent's financial dependents increased by one, their probability of using RA in the future rose by 3%. The more financial dependents a respondent had, the higher their intention to use RA in the future. This result contradicts our fifth hypothesis (H5). Individuals with a higher level of financial dependency often face greater financial pressure, making them more focused on cost-effectiveness in their investment decisions. As a low-cost investment tool, RA can help them achieve asset allocation and investment management within a limited budget. This finding aligns with the research of Potrich et al. (2015) and Zagorsky (2005), indicating that individuals with greater financial dependency pay more attention to budget management in their investment decisions. From an economic perspective, this finding reveals the intrinsic link between financial pressure and the choice of investment tools, suggesting that individuals with limited resources are more inclined to choose cost-effective financial instruments, which aligns with rational choice theory. Additionally, behavioral finance theory (Kahneman & Tversky, 1979) posits that individuals with less financial pressure are more willing to embrace new opportunities and take risks. However, our research results show that individuals with higher financial pressure may also choose to use RA due to their sensitivity to costs. This finding provides a new perspective for behavioral finance theory, indicating that financial pressure not only affects individuals' risk preferences but may also drive the demand for low-cost tools. From an economic standpoint, this finding highlights the potential of fintech in meeting the financial needs of different groups, especially in lowering the barriers to financial services and enhancing financial inclusion, where digital financial tools like RA play a significant role. Generally, when promoting RA, it may be prudent to focus on potential users with more financial dependents.

Income was also found to have a significant positive effect (coefficient = 0.02) on intention to use RA. Our research has found that respondents with a higher monthly income were more likely to use RA. Specifically, the higher-income respondents tended to increase their intention to use RA by 3% compared to the lower-income respondents. This result is in line with our hypothesis (H7). According to Baker et al. (2017), RA can be attractive to people with higher incomes; one of the reasons for that is that RA can provide a cost-effective means of investment management. Compared to traditional financial advisors, RA typically reduces labor and operating costs through automated investment management processes, enabling them to provide services at lower rates. Low cost directly affects the rate of return on investment, especially in long-term investments; the difference in cost can lead to a considerable cumulative impact. Therefore, it would be reasonable to believe that people in higher-income groups could become the priority focus when promoting RA products.

Additionally, this result aligns with the "Wealth Effect" theory in financial behavior. According to this theory, individuals' risk tolerance and willingness to invest increase as personal wealth increases (Guiso et al., 2002). High-income individuals typically have more disposable income, making them more willing to try new investment tools and technologies, such as RA. At the same time, high-income individuals are less sensitive to investment costs but still focus on investment efficiency. Therefore, the low-cost and high-transparency features of RA may better meet their needs (D'Acunto et al., 2019). Furthermore, the findings of this study also suggest potential strategies for RA service providers in marketing and product design. For example, for high-income individuals, RA platforms can emphasize their cost-effectiveness and long-term return advantages. For low-income individuals, efforts can be made to lower the initial investment threshold or provide more educational resources to enhance their willingness to use RA (Fisch et al., 2019). Such differentiated strategies not only help expand RA's user base but may also drive innovation and development across the industry.

Finally, our results also support the ninth hypothesis (H9) that level of educational attainment has a positive and significant effect on intention to use RA; that is, as the levels of educational attainment of respondents increased, their intention to use RA also rose significantly. The result here showed that the probability of using RA increased by 10% when the levels of educational attainment increased by one level (for example, from undergraduate to master's degree). This finding aligns with existing literature, indicating that individuals with higher education levels typically possess greater information processing and technological comprehension abilities, making them more inclined to try and use new technologies (Oreopoulos & Salvanes, 2011; Lusardi & Mitchell, 2014). Additionally, according to human capital theory (Becker, 1964), education not only enhances individuals' knowledge and skills but also increases their willingness to acquire new knowledge and use high-tech products. These abilities are particularly important when using fintech tools like RA, as understanding their operational principles is a prerequisite for effective use (Cole et al., 2011). On the other hand, potential investors with lower education levels may face challenges in understanding and using RAs. Although these groups can benefit from RA technology, they may encounter usage barriers due to unfamiliarity with digital platforms (Hilgert et al., 2003). According to the technology acceptance model, lower education levels may reduce perceived usefulness, thereby affecting their initial trust in RAs (Veena

Parboteeah et al., 2014). Therefore, targeted interventions for this group may help improve their acceptance of modern financial services.

In China, the recent popularisation of undergraduate and graduate education (Li et al., 2017) has significantly raised the education level of the younger generation compared to previous generations (Roberts, 2012). This trend may drive the widespread adoption and effective use of fintech tools like RAs across the country. Furthermore, the algorithmic nature of RAs can reduce the subjective biases of human advisors, providing more consistent and objective investment advice. This advantage is particularly notable among highly educated groups (Bhattacharya et al., 2012). Therefore, the increase in education levels not only enhances individuals' willingness to use RAs but may also promote the further development and optimisation of RA technology.

Appendix 5.1 shows the results of the influence of sociodemographic variables on intention to use RA using the OLS model. This table contains nine separate regression results (columns 1 to 9), showing the impact of nine sociodemographic variables individually on intention to use RA, and a multivariate regression including all the sociodemographic variables together (column 10).

The results of the OLS regression presented in Appendix 5.1 indicate that respondents' marital status (column 4), number of financial dependents (column 5), employment status (column 6), monthly income (column 7), and levels of educational attainment (column 9) are positively related to the intention of using RA. These variables were significant at the 1% level, while respondents who were homeowners without mortgages (column 8) were found to have a significant and positive relationship with intention of using RA at only a 10% level. Column 10 in Appendix 5.1 shows the multivariate analysis results involving all of the sociodemographic variables. The results indicate that being female had a significant negative effect on intention to use RA at a 10% level, while being married had a significant positive effect on the intention to use RA at a 10% level. Significant positive relationships were also detected between financial dependents, monthly income, and educational background, and intention to use RA at a 1% level.

5.4 Cross tabular analysis on the relationship between sociodemographic variables and intention to use RA

After conducting the logit regression analysis, this section further explores the influence of sociodemographic factors on the willingness to use RA through cross-tabular analysis. By cross-grouping key variables (age, gender, living in urban or rural areas, marital status, financial dependence, and educational background), this study reveals how sociodemographic factors affect different groups' intentions to use RA, providing more nuanced empirical evidence for the targeted promotion of RA in China.

Before analysing the data, the variables were treated appropriately to ensure they could be used in cross-tabular analysis. 'Age' was divided into two groups (18–37 and 38–60 years) based on respondents' answers; 'gender' was classified as a binary variable; 'living area' was categorised into urban and rural; 'marital status' was consolidated into married and non-married (including single, divorced, and living with a partner); 'financial dependence' was divided into 'with financial dependence' and 'without financial dependence'; and 'educational background' was classified as lower education (high school or below and associate degrees) and higher education (bachelor's, master's, and doctoral degrees or above).

*** INSERT TABLE 5.2 HERE ***

Firstly, Table 5.2 presents the results of our cross-tabular analysis using gender and age. Our findings reveal that while education level has only a marginally significant effect (at the 10% level) on the intention to use RA among men aged 18–37 (Column 1), it exhibits stronger significance (coefficient = 0.1110, significant at the 1% level) for men aged 38–60 (Column 2). This suggests that older men rely more on their educational background when evaluating new technological tools, possibly due to higher demands for technological credibility at their career stage (Goldsmith & Hofacker, 1991). This result supports Becker's (1964) human capital theory regarding the cumulative effect of education on technology adoption, while also revealing the interaction between gender and age in the technology acceptance model (Venkatesh & Morris, 2000).

The results also indicate that for women aged 18–37 (Column 3), marital status and monthly income significantly and positively influence the intention to use RA. This aligns with research suggesting that younger women prioritise stability and income security in financial decision-making (Croson & Gneezy, 2009). A plausible explanation is that younger married women are more inclined to seek automated financial tools to manage the complexities of household finances (Fonseca et al., 2012). However, this demand weakens among middle-aged women (Column 4), possibly reflecting shifting financial priorities over the life cycle (Hira & Loibl, 2005). The influence of monthly income further supports the tendency of younger women to view RA as an income-security tool, consistent with Gerrans et al.'s (2014) findings that female investors place greater emphasis on financial safety.

*** INSERT TABLE 5.3 HERE ***

Table 5.3 presents the results of our cross-tabular analysis examining the influence of respondents' gender and urban or rural residence on the intention to use RA. The results show that among urban male respondents (Column 1), educational background is the only factor significantly impacting RA usage intention. This finding aligns with Lusardi and Mitchell's (2014) findings on the positive correlation between financial literacy and education level. This further validates the central role of education in the adoption of technology-based financial products, as urban males may develop stronger fintech comprehension and risk assessment skills through higher education (Calcagno & Monticone, 2015). In contrast, rural males' (Column 2) residential status shows a significant negative association with the intention to use RA; this finding aligns with Guiso et al.'s (2008) study on the potential for property ownership to limit financial asset liquidity. This suggests that homeowners without mortgages in rural areas may be less inclined to use newer investment instruments due to the asset lock-in effect, which leads to a lower intention to use RA.

Among urban female respondents (Column 3), marital status and monthly income significantly affect RA usage intention at the 1% level. This finding suggests that family responsibilities associated with marriage may lead them to prefer relatively stable automated financial tools like RA (Gerrans et al., 2014). Meanwhile, the positive income effect corroborates Schmidt and Sevak's (2006) empirical conclusion that economic independence significantly enhances women's acceptance of innovative financial products, likely due to increased risk tolerance and financial autonomy associated with higher incomes. Additionally, the strong positive correlation with employment status among rural female respondents (Column 4) aligns with Demirgüç-Kunt et al.'s (2018) evidence that employment promotes financial inclusion globally, suggesting that work experience may serve as an important channel for rural women to access digital financial tools.

*** INSERT TABLE 5.4 HERE ***

Table 5.4 shows the results of our cross-tabulation analysis examining how gender and marital status affect individuals' intention to use RA. The results indicate that for men, educational background significantly influences their intention to use RA (Columns 1 and 2) at the 1% significance level, regardless of marital status. This finding confirms that educational background is a key factor driving men's adoption of financial technology and is consistent with van Rooij et al.'s (2011) finding that financial literacy significantly enhances the use of complex financial instruments. An important observation is that the level of education has a more significant effect on the intention to use RA among unmarried men than among married men. This result supports Cole et al.'s (2014) education substitution effect theory, which states that unmarried men without the risk-sharing benefits of marriage rely more on their education-based technical understanding to evaluate new financial tools. Financial dependence also has a significant impact on unmarried men's (Column 2) intentions to use RA. This means unmarried men with greater financial dependence are more likely to use RA, which aligns with Gathergood and Weber's (2017) finding that financial pressure makes single individuals prefer automated, low-cost financial tools. Importantly, this effect does not appear among married men, supporting Bertocchi et al.'s (2014) financial responsibility hypothesis, which states that unmarried men, lacking a spouse's financial support, feel financial pressure more strongly and are therefore more likely to choose efficient, transparent investment solutions like RA.

For married women (Column 3), financial dependence, monthly income, and educational background significantly influence their intention to use RA. The significant effect of financial dependence aligns with Schmidt and Sevak's (2006) findings, showing that married women with family financial responsibilities tend to adopt automated tools to manage household assets more effectively. The significance of both monthly income and education level on married women's intention to use RA confirms the two-factor model proposed by Fonseca et al. (2012), which suggests that married women require both sufficient financial resources (income effect) and cognitive ability to evaluate and use innovative financial instruments such as RA effectively. For unmarried women (Column 4), only monthly income significantly influences the intention to use RA. This finding indicates that the intention of unmarried women (single, divorced, or living with a partner) to use RA is primarily driven by financial resources, consistent with Huang et al.'s (2020) findings. This supports the application of resource constraint theory in women's fintech adoption, suggesting that unmarried women's financial decisions are more directly affected by personal disposable income without the economic benefits of marriage (Zagorsky, 2005). The lack of significance for education suggests that potential barriers exist to applying financial knowledge; even with financial literacy, limited income may hinder its practical application in technology adoption (Lusardi & Tufano, 2015). This provides new insights into the relationship between socioeconomic status and financial capability.

*** INSERT TABLE 5.5 HERE ***

Table 5.5 presents the results of our cross-tabulation analysis examining how gender and financial dependence affect the intention to use RA. The results show that among men with financial dependence (Column 1), educational background has a significantly positive effect on the intention to use RA. This finding aligns with Brown et al.’s (2016) research indicating that men with family financial responsibilities tend to actively apply the financial knowledge gained through education to optimise household asset management. The pressure of financial dependence may strengthen men’s ‘instrumental learning motivation’, prompting them to practically apply their financial knowledge to tools like RA that improve household asset management efficiency, rather than simply pursuing maximum investment returns. In contrast, for men without financial dependence (Column 2), educational background shows no significant effect on RA usage intention. This may indicate that without financial dependence, men lack sufficient economic incentives to translate financial knowledge into actual investment behaviour (Gathergood, 2012). Furthermore, men without financial dependence living in urban areas (Column 2) show higher intentions to use RA, which can partly reflect the fact that urban environments facilitate fintech exposure through information spillovers (Guiso et al., 2004), validating the role of urban environments as financial information hubs. The increase in financial institutions and digital infrastructure significantly reduces the transaction costs for residents to access innovative financial instruments (Beck et al., 2007), thus increasing the likelihood of knowing about and using RA. Notably, this geographical advantage only appears significant for financially independent men, suggesting that financial pressures may offset the informational benefits of urban environments (Mullainathan & Shafir, 2013).

Additionally, our analysis reveals that for women with financial dependence (Column 3), both employment status and monthly income significantly influence their intention to use RA. This finding supports Bianchi's (2018) dual burden hypothesis, suggesting that working women with financial dependence tend to use automated tools to balance multiple role demands. Notably, the significant effect of monthly income on the intention to use RA among women with financial dependence indicates that economic resources provide the material foundation for using paid fintech services. Meanwhile, the influence of employment status reflects that workplaces may serve as important channels for these women to access digital financial tools, corroborating Goldin's (2014) discussion about workplace learning effects.

*** INSERT TABLE 5.6 HERE ***

Table 5.6 presents the results of the cross-tabulation analysis examining how marital status and financial dependence affect the intention to use RA. The results show that among married respondents with financial dependence, educational background has a significantly positive effect on the intention to use RA. This indicates that married individuals with financial dependence (Column 1) who have a higher level of education demonstrate a greater intention to use RA. This finding aligns with Doepke and Zilibotti's (2014) research on responsibility-driven human capital investment, proposing that married individuals are more likely to apply financial knowledge gained through education to household asset management. Furthermore, this finding can be understood through Becker's (1991) household production function theory, which shows that married individuals tend to transform human capital into practical skills that improve household productivity rather than simply using it to grow income. This explains why the influence of education on RA adoption is particularly prominent among those with family financial responsibilities.

Additionally, the analysis results show that for married individuals without financial dependence (Column 2), living area and residential status significantly influence their intention to use RA. This indicates that married individuals without financial dependence who live in urban areas and face housing pressures also demonstrate a greater intention to use RA. Notably, this effect only appears among married individuals without financial dependence, suggesting a potential interaction between housing debt and marital status in financial decision-making. Specifically, marital status may enhance financial planning awareness (Bucks & Pence, 2008), making this group more inclined to use tools like RA for proactive asset management when facing housing pressures. This finding provides evidence of how marital status moderates the relationship between housing debt and fintech adoption.

Among unmarried individuals with financial dependence (Column 3), women show a significantly lower intention to use RA compared to men. This finding supports Barber and Odean’s (2001) theory on gender differences in risk-taking investments while also demonstrating how financial pressures amplify women’s inherent risk aversion (Croson & Gneezy, 2009). These results reveal an asymmetric impact mechanism of financial responsibility on fintech adoption decisions between genders, providing new evidence of how gender role socialisation shapes financial behaviour (Bertrand, 2011). Furthermore, the findings indicate that the monthly income and educational background of unmarried individuals with financial dependence significantly affect their willingness to use RA, reflecting the dual challenge that this group faces when investing: the need for a stable income as security and the reliance on financial literacy (McLanahan & Percheski, 2008). Under this dual pressure, they may be more inclined to adopt financial instruments such as RA that can provide automated, low-threshold financial management services to increase financial control and ease decision-making burdens, thus enhancing their willingness to use them. In contrast, none of the variables show significant effects for unmarried individuals without financial dependence, suggesting this group may lack either economic motivation or an urgent need to adopt new financial tools (Bertrand et al., 2004). This discovery provides new evidence for understanding the interaction between marital status and financial behaviour.

*** INSERT TABLE 5.7 HERE ***

Table 5.7 presents the results of the cross-tabular analysis examining how marital status and financial dependence affect individuals' intention to use RA. The results show that among males with a lower educational background (Column 1), monthly income has a significantly negative relationship with the intention to use RA. This means higher-income males with lower education levels are less likely to use RA, possibly reflecting their distrust of financial innovation (Lusardi & Mitchell, 2014) or a preference for spending additional income on immediate consumption rather than long-term investment (Dynan et al., 2004). This group, even with higher incomes, lacks the necessary financial literacy, making it difficult for them to understand the value of an innovative tool such as RA in a short time, leading to a lower intention to use RA (Guiso et al., 2008).

For males with a higher level of educational background (Column 2), not only does monthly income have a significantly positive effect on the intention to use RA, but financial dependence also significantly increases the intention to use RA. This result is supported by Becker's (1991) family responsibility hypothesis, which states that highly educated men are more adept at transforming financial pressures into incentives to adopt efficient management tools. When faced with financial dependence pressures, they actively apply their analytically gained skills to evaluate and adopt innovative tools like RA that can improve household financial management efficiency, rather than simply reducing consumption or increasing savings (Cole et al., 2014).

For females with a lower level of education (Column 3), employment status shows a significant effect (at the 10% level) on the intention to use RA. This result suggests that work experience may partially compensate for financial knowledge gaps caused by lower education levels (Heckman, 2006). For females with a higher educational background (Column 4), marital status and monthly income significantly affect the intention to use RA. This supports Schultz’s (2004) concept of compound returns to women's human capital, which posits that marriage and monthly income jointly enhance the financial decision-making capabilities developed through education. Therefore, it is reasonable to assume that for women with low levels of education, the workplace environment may have gradually developed a basic competence in the use of automated financial instruments through daily digital operations (e.g., electronic payroll payments, corporate annuity management) (Carpena et al., 2019). In contrast, for highly educated females, both marital status and income show a significant effect on intentions to use RA, reflecting the economies of scale characterising household financial management. Higher levels of education enable them to more effectively combine the financial consolidation needs that come with marriage (e.g., joint money management, saving for children's education) with the resources provided by income growth, thus making them more active in adopting a comprehensive asset management tool such as RA (Browning & Lusardi, 2016).

5.5 Conclusion on the relationship between sociodemographic variables and intention to use RA

For this empirical analysis chapter, I employed logit regression, OLS and cross tabular analysis to assess the impact of sociodemographic variables on intention to use RAs. The analyzed sociodemographic factors include age, gender, place of residence (rural or urban), marital status, number of financial dependents, employment status, monthly income, residential status, and educational background. According to our findings, male potential users were more likely to use RAs in the future compared to females, with this result being statistically significant at a 10% level. Moreover, marital status was also found to have a significant positive relationship with the intention to use RAs, indicating that married individuals are more likely to use RAs in the future compared to those who are single, divorced, or living with a partner. In addition, an increase in the number of financial dependents significantly enhanced the respondent's intention to use RAs. Finally, both the monthly income and levels of educational attainment of respondents were positively correlated with intention to use RAs, suggesting that potential users with higher incomes or stronger educational backgrounds would be more likely to utilize RAs in the future.

Cross-tabulation analysis results reveal significant differences in the willingness to use RA across sociodemographic factors. Among males, individuals aged 38-60 rely more on educational background when evaluating RA than younger groups, while unmarried males with financial dependence show a greater intention to use RA. For females, younger married females are more likely to adopt RA due to household financial management needs, whereas females aged 38-60 demonstrate weaker demand. Urban-rural differences show that urban males enhance RA acceptance through education, while rural males' willingness is suppressed by housing assets; urban females are driven by marriage and income factors, whereas rural females depend on employment exposure to RA. Marital status and financial dependence show clear interaction effects: married individuals more effectively translate education into RA usage capability, and financially independent married urban residents facing housing pressure show a stronger intention to use RA; unmarried males with financial dependence have a greater intention to use RA, while unmarried females display lower willingness due to risk aversion. Furthermore, highly educated males with financial dependence are more likely to use RA, whereas less educated high-income males show reduced willingness; less educated females compensate for knowledge gaps through employment, while highly educated females combine marriage and income advantages to increase their willingness to use RA.

The empirical results based on logit regression and cross-analysis demonstrate that the willingness to use RA is significantly influenced by sociodemographic factors, providing important implications for market segmentation, product design, and financial inclusion. The logit regression reveals that males, married individuals, high-income groups, and highly educated populations show higher acceptance of RA, offering clear guidance for financial institutions to optimise marketing resource allocation. Cross-analysis further reveals heterogeneity among groups. Highly educated middle-aged males rely more on their educational background when evaluating technological tools, highlighting the cumulative effect of human capital. Married females show a greater inclination to adopt RA due to household financial integration needs, reflecting how family responsibilities moderate technology adoption. Financial pressures, such as financial dependence, prompt single males to opt for low-cost automated tools, demonstrating rational decision-making under budget constraints. Moreover, urban-rural disparity analysis indicates significantly lower adoption rates in rural areas due to limited financial infrastructure and knowledge barriers, calling for policy-level enhancements in digital infrastructure investment and financial education. This study also finds that work experience can partially compensate for knowledge gaps among less educated females. In contrast, highly educated females' RA adoption intention is jointly driven by marriage and income, indicating that technology adoption results from the synergistic effects of multiple factors. These findings provide micro-level evidence for developing differentiated product strategies (such as designing family financial integration features for married couples) and targeted policy interventions (such as financial literacy programmes for rural residents), which can help lower the barriers to fintech services and promote inclusive finance development.

Table for dependent variables, sociodemographic factors and the relationship between the intention to use RA and sociodemographic factors

Table 5.1 The determinants of intention to use RA based on sociodemographic variables using logit analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Age	0.01									0.01
	(0.01)									(0.01)
Female		-0.04*								-0.04*
		(0.02)								(0.02)
Urban			0.07*							0.02
			(0.04)							(0.04)
Married				0.14***						0.10***
				(0.03)						(0.03)
Financial dependent					0.04***					0.03**
					(0.01)					(0.01)
Employed						0.12***				0.02
						(0.03)				(0.03)
Monthly income							0.05***			0.02***
							(0.01)			(0.01)
Homeowner without mortgage								0.04		-0.01
								(0.02)		(0.02)
Educational background									0.13***	0.10***
									(0.02)	(0.02)
N	1250	1250	1250	1250	1250	1250	1250	1250	1250	1250
Prob > chi2	0.33	0.10	0.06	0.00	0.00	0.00	0.00	0.13	0.00	0.00
Pseudo R2	0.00	0.00	0.00	0.02	0.01	0.01	0.02	0.00	0.04	0.07

Table 5.1 shows the univariate average marginal effect result based on logit regression model for the impact of sociodemographic variables on the intention to use RA. The data in brackets in table represents the standard error of each factor in the regression result. Besides, in this table, *** p<0.01, ** p<0.05, * p<0.1.

Table 5.2 Cross tabular results for the impact of sociodemographic factors on intention to use RA by gender and age group

	(1)	(2)	(3)	(4)
	Male		Female	
	Age (18-37)	Age (38-60)	Age (18-37)	Age (38-60)
Rural & Urban	0.0698	0.0346	0.0314	-0.0565
	(0.0757)	(0.0638)	(0.0847)	(0.0747)
Marital status	0.0378	0.0846	0.1738***	0.1319
	(0.0541)	(0.0791)	(0.0516)	(0.0801)
Financial dependence	0.0279	-0.0009	0.0418	0.0305
	(0.0300)	(0.0258)	(0.0260)	(0.0275)
Employed status	0.0127	-0.0011	0.0235	0.0180
	(0.0695)	(0.0620)	(0.0641)	(0.0639)
Monthly income	0.0159	-0.0082	0.0393**	0.0395
	(0.0193)	(0.0180)	(0.0131)	(0.0177)
Residential status	0.0235	-0.0780	0.0092	0.0238
	(0.0541)	(0.0481)	(0.0560)	(0.0494)
Educational background	0.0838*	0.1110***	0.0566	0.1462
	(0.0441)	(0.0316)	(0.0452)	(0.0321)
N	305	337	307	301
Prob > chi2	0.1091	0.0093	0.0000	0.0000
Pseudo R2	0.0381	0.0578	0.0991	0.1309

The table presents cross tabular analysis based on logit regression coefficients with standard errors in parentheses. Statistical significance is indicated by *** $p<0.01$, ** $p<0.05$, and * $p<0.1$. The dependent variable measures the intention to use RA. Columns represent demographic subgroups stratified by gender and age. Pseudo R^2 values reflect each model's explanatory power, while the varying sample sizes (N) across subgroups account for differences in demographic distribution within the dataset.

Table 5.3 Cross tabular results for the impact of sociodemographic factors on intention to use RA by gender and living in urban or rural group

	(1)	(2)	(3)	(4)
	Male		Female	
	Urban	Rural	Urban	Rural
Age	0.0176	0.0432	-0.0146	0.0404
	(0.0176)	(0.0579)	(0.0177)	(0.0547)
Marital status	0.0313	0.2320	0.1515***	0.1267
	(0.0485)	(0.1580)	(0.04964)	(0.1413)
Financial dependence	0.0130	0.0335	0.0372*	0.0291
	(0.0204)	(0.0596)	(0.0195)	(0.0585)
Employed status	0.0128	0.0032	-0.0179	0.2793***
	(0.0486)	(0.1356)	(0.0503)	(0.0952)
Monthly income	-0.0017	0.0652	0.0522***	-0.0432
	(0.0134)	(0.0398)	(0.0128)	(0.0348)
Residential status	0.0017	-0.2453**	0.0225	-0.1283
	(0.0355)	(0.1162)	(0.0376)	(0.1031)
Educational background	0.1061***	0.0653	0.1290***	0.0634
	(0.0282)	(0.0602)	(0.0296)	(0.0481)
N	567	75	531	77
Prob > chi2	0.0000	0.0716	0.0000	0.1711
Pseudo R2	0.0345	0.1358	0.1266	0.1427

The table presents cross tabular analysis based on logit regression coefficients with standard errors in parentheses. Statistical significance is indicated by *** p<0.01, ** p<0.05, and * p<0.1. The dependent variable measures the intention to use RA. Columns represent demographic subgroups stratified by gender and living in urban or rural. Pseudo R^2 values reflect each model's explanatory power, while the varying sample sizes (N) across subgroups account for differences in demographic distribution within the dataset.

Table 5.4 Cross tabular results for the impact of sociodemographic factors on intention to use RA by gender and marital status group

	(1)	(2)	(3)	(4)
	Male		Female	
	Married	Other relationship	Married	Other relationship
Age	0.0147	0.0476	-0.0174	-0.0028
	(0.0191)	(0.0440)	(0.0191)	(0.0396)
Rural & Urban	0.0276	0.1472	-0.0526	0.0855
	(0.0534)	(0.1168)	(0.0615)	(0.1416)
Financial dependence	-0.0034	0.0748*	0.0452**	0.0181
	(0.0220)	(0.0406)	(0.0212)	(0.0404)
Employed status	0.0237	-0.0217	0.0473	-0.0556
	(0.0590)	(0.0800)	(0.0535)	(0.0902)
Monthly income	0.0005	0.0394	0.0331**	0.0598**
	(0.0142)	(0.0320)	(0.0131)	(0.0294)
Residential status	-0.0404	0.0467	0.0110	0.0738
	(0.0375)	(0.0973)	(0.0363)	(0.1205)
Educational background	0.0848***	0.1704***	0.1217***	0.0320
	(0.0287)	(0.0574)	(0.0264)	(0.0668)
N	512	130	476	132
Prob > chi2	0.0434	0.0243	0.0000	0.4715
Pseudo R2	0.0273	0.1143	0.1119	0.0319

The table presents cross tabular analysis based on logit regression coefficients with standard errors in parentheses. Statistical significance is indicated by *** p<0.01, ** p<0.05, and * p<0.1. The dependent variable measures the intention to use RA. Columns represent demographic subgroups stratified by gender and marital status. Pseudo R^2 values reflect each model's explanatory power, while the varying sample sizes (N) across subgroups account for differences in demographic distribution within the dataset.

Table 5.5 Cross tabular results for the impact of sociodemographic factors on intention to use RA by gender and financial dependence group

	(1)	(2)	(3)	(4)
	Male		Female	
	With financial dependence	Without financial dependence	With financial dependence	Without financial dependence
Age	0.0167	0.0616	-0.0167	-0.0218
	(0.0177)	(0.0661)	(0.0181)	(0.0641)
Rural & Urban	0.0354	0.4458**	-0.0512	0.4567
	(0.0493)	(0.2084)	(0.0572)	(0.3103)
Marital status	0.0299	0.1254	0.1716	0.0461
	(0.0510)	(0.1571)	(0.0488)	(0.1761)
Employed status	0.0049	0.1582	0.0165***	-0.0712
	(0.0495)	(0.1169)	(0.0477)	(0.1830)
Monthly income	0.0025	0.0724	0.0416***	0.0770
	(0.0130)	(0.0560)	(0.0122)	(0.0584)
Residential status	-0.0163	-0.0941	0.0108	0.0001
	(0.0355)	(0.1270)	(0.0367)	(0.1810)
Educational background	0.1100***	-0.0046	0.1151***	0.0356
	(0.0258)	(0.0902)	(0.0261)	(0.1053)
N	588	54	562	46
Prob > chi2	0.0009	0.5173	0.0000	0.5510
Pseudo R2	0.0418	0.0984	0.0981	0.0718

The table presents cross tabular analysis based on logit regression coefficients with standard errors in parentheses. Statistical significance is indicated by *** $p<0.01$, ** $p<0.05$, and * $p<0.1$. The dependent variable measures the intention to use RA. Columns represent demographic subgroups stratified by gender and financial dependence. Pseudo R^2 values reflect each model's explanatory power, while the varying sample sizes (N) across subgroups account for differences in demographic distribution within the dataset.

Table 5.6 Cross tabular results for the impact of sociodemographic factors on intention to use RA by marital status and financial dependence group

	(1)	(2)	(3)	(4)
	Married		Other relationship	
	With financial dependence	Without financial dependence	With financial dependence	Without financial dependence
Age	-0.0014	0.0169	0.0142	0.0245
	(0.0139)	(0.0781)	(0.0323)	(0.0550)
Gender	-0.0039	-0.2018	-0.1790***	-0.0465
	(0.0258)	(0.1242)	(0.0634)	(0.1331)
Rural & Urban	-0.0343	0.5687***	0.1172	-0.0514
	(0.0427)	(0.1563)	(0.0940)	(0.2910)
Employed status	0.0317	-0.0414	-0.0501	0.0801
	(0.0416)	(0.1505)	(0.0676)	(0.1476)
Monthly income	0.0186*	0.0219	0.0489**	0.0683
	(0.0097)	(0.0948)	(0.0244)	(0.0478)
Residential status	-0.0114	-0.3620**	0.0210	0.1482
	(0.0263)	(0.1722)	(0.0832)	(0.1617)
Educational background	0.1067***	0.0379	0.1213**	0.0499
	(0.0199)	(0.0783)	(0.0508)	(0.1022)
N	949	39	201	61
Prob > chi2	0.0000	0.0397	0.0206	0.6496
Pseudo R2	0.0500	0.2635	0.0760	0.0591

The table presents cross tabular analysis based on logit regression coefficients with standard errors in parentheses. Statistical significance is indicated by *** p<0.01, ** p<0.05, and * p<0.1. The dependent variable measures the intention to use RA. Columns represent demographic subgroups stratified by marital status and financial dependence. Pseudo R^2 values reflect each model's explanatory power, while the varying sample sizes (N) across subgroups account for differences in demographic distribution within the dataset.

Table 5.7 Cross tabular results for the impact of sociodemographic factors on intention to use RA by gender and educational background group

	(1)	(2)	(3)	(4)
	Male		Female	
	Low education	High education	Low education	High education
Age	-0.0157 (0.0476)	0.0290 (0.0184)	0.0076 (0.0481)	-0.0092 (0.0186)
Rural & Urban	0.0696 (0.1069)	0.0704 (0.0537)	-0.1092 (0.1017)	0.0250 (0.0631)
Marital status	0.1565 (0.1128)	-0.0118 (0.0555)	0.0247 (0.1448)	0.1812*** (0.0446)
Financial dependence	0.0173 (0.1318)	0.1153* (0.0605)	0.0645 (0.1533)	0.0743 (0.09663)
Employed status	0.0480 (0.0967)	-0.0137 (0.0590)	0.1655* (0.0994)	-0.0422 (0.0521)
Monthly income	-0.0744** (0.0358)	0.02874** (0.0132)	0.0228 (0.0326)	0.0481*** (0.0126)
Residential status	0.0311 (0.0949)	-0.0369 (0.0361)	-0.0544 (0.1026)	0.0212 (0.0384)
N	121	521	114	494
Prob > chi2	0.4173	0.0997	0.6826	0.0000
Pseudo R2	0.0439	0.0244	0.0330	0.0891

The table presents cross tabular analysis based on logit regression coefficients with standard errors in parentheses. Statistical significance is indicated by *** p<0.01, ** p<0.05, and * p<0.1. The dependent variable measures the intention to use RA. Columns represent demographic subgroups stratified by gender and educational background. Pseudo R^2 values reflect each model's explanatory power, while the varying sample sizes (N) across subgroups account for differences in demographic distribution within the dataset.

Chapter 6 Influence of behavioural factors on intention to use RA

6.1 Introduction to the relationship between sociodemographic factors and intention to use RA

As financial technologies evolve, RAs have emerged as a prominent innovation in investment management services, offering convenience and cost-effectiveness to attract investors globally. In China, the adoption of automated financial advisors is gaining momentum, yet the widespread acceptance of, and intention to use, such services face significant challenges. Therefore, after analyzing the impact of the sociodemographic variables on intention to use RA, this study now considers how behavioral factors influence respondents' intention to use RA. Behavioral factors in our thesis include risk aversion, risk perception, BTAE, IOC, confidence, and trust. Risk aversion refers to the tendency of individuals to opt for safer options when facing potential losses, and risk perception involves the subjective evaluation of investment risks (Sukamulja, Meilita, and Senoputri, 2019). Meanwhile, confidence affects how individuals assess their financial decision-making capabilities, while BTAE describes the phenomenon where individuals overestimate their abilities compared to others (Moore and Healy, 2008). The IOC alludes to overconfidence in one's ability to control external events, and trust is a core component in the acceptance of fintech, particularly in scenarios involving human-machine financial interactions (Lee and See, 2004).

Following Gerlach and Lutz (2019), I assumed that a higher level of risk aversion would decrease the potential users' intention to use RA, and that a higher level of risk perception would increase potential users' intention to use RA in the future. I also considered the effect of confidence on intention to use RAs. I hypothesized that more confident potential users would be more likely to use RAs in the future. Conversely, I assumed that potential users perceiving themselves as worse than average would be more likely to try RAs compared to those who are better than average. In addition, a higher level of the IOC among potential users was also expected to inversely affect their probability of using RAs. Trust has also emerged as a potentially significant factor influencing the intention to use RAs. Drawing from existing research, I postulated that among potential users in China, those with higher levels of trust would be more likely to use RAs in the future.

This chapter uses logit regression and OLS analysis to validate the hypotheses above. According to the regression results, as hypothesized (H10) in Chapter 3.3, risk aversion was found to have a significant negative impact on the intention to use RAs in the future. Contrary to the eleventh hypothesis (H11), the results for risk perception indicated that potential users' intention to use RAs decreased as their risk perception increased, possibly due to a lack of sufficient trust in RAs, thereby reducing their intention to use them. In addition, the analysis shows that potential users with a higher level of IOC, the more likely they were to try RAs in the future, which contradicts the fourteenth hypothesis (H14) mentioned in Chapter 3.3. As expected (H15), trust exhibited a significant positive effect on the intention to use RAs; potential users with higher levels of trust showed a more positive intention to use RAs in the future.

By examining these behavioral factors, this chapter seeks to reveal how they individually or collectively influence respondents' acceptance and intentions toward RA technology. Understanding these dynamics will not only aid in optimizing RA services to meet the needs of a broader user base, but also provides insights for financial service providers on how to more effectively design and market these services.

This chapter consists of three parts: the regression models are first used to analyze the relationships between the behavioral factors and intention to use RA; preliminary analysis is then conducted on the effect of behavioral factors on intention to use RA;

and multivariate analysis is then carried out on the influence of behavioral factors on intention to use RA.

6.2 Regression models applied to analyse the impact of behavioural factors on intention to use RA

In order to more comprehensively analyze the impact of behavioral factors on the intention to use RA, our regression model includes not only behavioral factors but also the sociodemographic variables examined in Chapter 5. This thesis first ran logit regression using the following model based on formula (4.1) in Chapter 4.6:

$$
\begin{aligned}
Intention\_dummy_i &= \beta_0 + \beta_1 SF_i + \beta_2 Risk\_aversion_i + \beta_3 Risk\_perception_i \\
&+ \beta_4 Better\_than\_average\_effect_i + \beta_5 Illusion\_of\_control_i \\
&+ \beta_6 Confidence_i + \beta_7 Trust_i \\
&+ \varepsilon_i \qquad (6.1)
\end{aligned}
$$

In formula (6.1), i subscript represents individuals, SF_i is the vector for sociodemographic factors such as age, gender, living area (urban or rural), marital status, financial dependents, employment status, monthly income, residential status and educational background as mentioned in equation (5.1). ε_i is the error term based on logit regression. According to the logit regression result, this thesis then conducted further AME analysis to reflect how respondents' intention to use RA changed when the behavioral variable changed by one unit. β is the regression coefficients from the AME analysis result.

This study also performed the following OLS regression model based on formula (4.4) in Chapter 4.7:

$$
\begin{aligned}
&Intention\_continuous_i \\
&\quad = \beta_0 + \beta_1 SF_i + \beta_2 Risk\_aversion_i + \beta_3 Risk\_perception_i \\
&\quad + \beta_4 Better\_than\_average\_effect_i + \beta_5 Illusion\_of\_control_i \\
&\quad + \beta_6 Confidence_i + \beta_7 Trust_i \\
&\quad + \varepsilon_i \qquad\qquad (6.2)
\end{aligned}
$$

In this formula, i subscript represents individuals, SF_i is the vector for sociodemographic variables such as age, gender, living area (urban or rural), marital status, financial dependents, employment status, monthly income, residential status, and educational background, as mentioned in equation (5.1). β is the coefficients that need to be estimated, indicating how a change in the behavioral factors affected respondents' intention to use RA, ε_i is the error term based on this regression.

6.3 Regression results for the effect of behavioural factors on intention to use RA

This section conducts further multivariate analysis of the impact of behavioral factors on intention to use RA using the regression models mentioned in Chapter 6.1.

*** INSERT TABLE 6.1 HERE ***

Table 6.1 presents how the behavioral factors influenced respondents' intention to use RA, using the AME analysis based on the logit regression. This table comprises seven columns including univariate results (columns 1 to 6) and multivariable result (column 7). The results of the univariate analysis indicate that respondents' intention to use RA was significantly and positively impacted by IOC (column 4) and trust (column

6). On the other hand, risk aversion (column 1) and risk perception (column 2) showed significant negative relationships with intention to use RA.

The multivariate result (column 7) shows that respondents were 3% less likely to use RA in the future for every one-point increase in their risk aversion score. This means that as their level of risk aversion decreases, the probability of the respondent intending to use RA would increase. The result for the risk aversion factor supports our tenth hypothesis (H10), which is consistent with the predictions of prospect theory. Kahneman and Tversky (1979) pointed out that individuals tend to exhibit risk aversion when facing potential losses, preferring safer options to avoid losses. Although RAs can help users minimise risks and prevent investment losses through data-driven investment advice (D'Acunto et al., 2019), in China, RA technology is not yet fully mature, and its associated uncertainty may lead highly risk-averse individuals to approach it with caution. . This finding aligns with the research of Grable (2000) and Hallahan et al. (2004), indicating that an individual’s risk attitude significantly influences their investment behaviour, especially when dealing with emerging technologies. Additionally, in our analysis, risk perception was found to significantly impact the intention to use RAs. Specifically, when a respondent’s risk perception level increased by one point, the probability of their intention to use RAs would decrease by about 2%, meaning that their intention to use RAs decreased in line with an increase in their level of risk perception. This result supports our eleventh hypothesis (H11), indicating that individuals with higher risk perception may tend to have less trust in automated systems. A study by Weber et al. (2002) shows that individuals with high risk perceptions are more sensitive to the risks associated with investment behaviours and related new technologies. The complexity and lack of transparency in RA algorithms may exacerbate this perceived risk (Kahneman & Tversky, 1979), thereby reducing the intention of this group to use RAs. This result is consistent with the research of Schooley and Worden (1996), which indicates that individuals with high risk perceptions are more inclined to avoid investment tools with higher uncertainty.

This result suggests that individuals with higher risk perception may trust automated systems less. Additionally, the complexity and opacity of the algorithms used by automated systems may increase the risk perception of some investors (Kahneman & Tversky, 1979), thereby reducing their intention to use such systems. Therefore, it is reasonable to believe that respondents with lower levels of risk aversion or risk perception would have a higher intention to use RAs. Consequently, product providers can attract customers with risk-averse and low-risk perceptions by emphasising RAs' stability and real-time risk management capabilities. For example, research by D'Acunto et al. (2019) shows that transparent risk communication and user education can significantly enhance trust in automated investment tools. Thus, RA platforms should focus on user-friendly interfaces and algorithmic transparency in their design to reduce users' risk perception.

The respondents' IOC significantly and positively impacted upon their intention to use RA. Specifically, the probability of respondents' intention to use RA increased by 1% for every one-point increase in their IOC score. Our result contradicts the fourteenth hypothesis (H14), which states that the stronger an individual's illusion of control, the less likely they are to use RA. A possible explanation is that investors with a higher illusion of control perceive RA as a tool to enhance their sense of control over investment decisions rather than as a means to diminish it. This finding aligns with the research of Barber and Odean (2001), who noted that overconfident investors tend to use tools to increase their sense of control over investment outcomes. Additionally, Skala (2008) categorised the illusion of control as a manifestation of overconfidence, suggesting that this psychological trait may lead individuals to exhibit a stronger desire for control in decision-making processes. Therefore, investors with a higher illusion of control may be more willing to use RA, as they believe it can help them better manage their investment portfolios, thereby satisfying their need for control (Barber & Odean, 2001; Dhar & Zhu, 2006).

The above result diverges from the studies of Langer (1975) and Yarritu et al. (2014), who argued that the illusion of control typically leads individuals to overestimate their influence over outcomes, thereby reducing their reliance on external tools. The findings of this study may reflect a shift in investors' perceptions of RA's functionality: as RA technology advances, investors may be more inclined to view it as a tool to enhance their sense of control rather than as something to rely on entirely for automated decision-making. This phenomenon warrants further research, particularly in the context of different cultural backgrounds and levels of technology acceptance. From a practical perspective, fintech companies can more effectively attract investors with a higher illusion of control by emphasising how RA enhances their sense of control over investment portfolios, thereby expanding RA's market penetration.

Trust was also found to be an important factor influencing respondents' intention to use RA in our thesis. The probability of using RA in the future increased by 3% when the score for trust increased by one point. This result supports the fifteenth hypothesis (H15) of this thesis according to which a higher level of trust would mean a higher intention to use RA for respondents, highlighting the importance of fostering trust in adopting financial technologies. This finding aligns with the definition by Rousseau et al. (1998), which describes trust as a psychological state based on positive expectations of others' intentions or behaviours, a factor particularly crucial in investment decisions.. Furthermore, our results resonate with the research of Gefen et al. (2003), who pointed out that trust plays a central role in the adoption of new technologies, especially when consumers lack direct control over the technology. However, due to recent scandals and regulatory scrutiny leading to erosion of trust, consumers have become more cautious (Arner et al., 2015). Our study further confirms this, indicating that negative experiences or perceptions of fintech platforms significantly reduce the likelihood of adoption, even among individuals who are open to new technologies (Gomber et al., 2018).

Nevertheless, trust remains a critical factor in the adoption of RA. When a trusted source recommends a product or service, its perceived credibility significantly increases, enhancing the likelihood of adoption (Gefen et al., 2003). Therefore, rebuilding trust through transparency, compliance, and ethical practices is essential for the future development of the RA industry. Our study also shows that individuals with a higher tendency to trust the external world may be more willing to try RA, provided that their concerns about reliability and security are adequately addressed (Jøsang, 2007). Additionally, our findings are consistent with the trust model proposed by Mayer et al. (1995), which emphasises that building trust requires demonstrating reliability, security, and investment management capabilities. Therefore, RA service providers need to showcase their reliability and accuracy through transparent communication and timely information disclosure (Lee & Turban, 2001). These measures not only help enhance consumer trust but also lay the foundation for the long-term development of the RA industry.

Besides, Appendix 6.1 presents how the behavioral factors influence respondents' intention to use RA using the OLS model, involving seven columns. Columns 1 to 6 show the impact of the nine behavioral factors individually on intention to use RA involving all sociodemographic variables, while column 7 contains the multivariate regression including all behavioral factors and sociodemographic variables. The results of OLS are consistent with the AME based on logit regression. In the univariate analysis, IOC (column 4) and trust (column 6) had a significant positive impact on intention to use RA. In contrast, respondents' risk aversion (column 1) and risk perception (column 2) showed a significant negative effect on intention to use RA; the multivariate result (column 7) also showed the same trend.

6.4 Cross tabular analysis on the relationship between behavioural variables and intention to use RA

After conducting the logit regression analysis, this section further explores the influence of behavioural factors on the willingness to use RA through cross-tabular analysis, revealing how behavioural and sociodemographic factors affect different groups' intentions to use RA, providing more nuanced empirical evidence for the targeted promotion of RA in China.

Before analysing the data, the variables were treated appropriately to ensure that they could be used in cross-tabular analysis. 'Gender' was classified as a binary variable; 'living area' was categorised into urban and rural; 'educational background' was divided into lower education (high school or below and associate degrees) and higher education (bachelor's, master's, and doctoral degrees or above); and 'risk aversion' was divided into three groups: risk averse, risk neutral, and risk seeker.

*** INSERT TABLE 6.2 HERE ***

The cross-tabular analysis results in Table 6.2 reveal the varying effects of behavioural factors on the intention to use RA across different gender and risk attitude groups. Firstly, for risk-averse males (Column 1), a higher level of risk perception significantly reduces their willingness to use RA. At the same time, within this group (risk-averse males), a higher level of illusion of control is associated with a higher intention to use RA. This finding aligns with Kahneman and Tversky's (1979) prospect theory, which posits that individuals' sensitivity to losses inhibits the adoption of emerging technologies. The positive effect of the illusion of control on this group's intention to use RA also resonates with Barber and Odean's (2001) observation that overconfident investors may perceive RA as a tool to enhance decision-making control rather than a threat. Meanwhile, confidence significantly influences the intention to use RA among risk-neutral males (Column 2), consistent with Grable and Joo's (2004) findings that risk-neutral investment decisions are more susceptible to self-efficacy adjustments. Furthermore, for male risk-seekers (Column 3), a higher level of risk perception significantly reduces their intention to use RA. In contrast, those with higher general trust are more likely to use RA in the future, which aligns with Gefen et al.'s (2003) technology acceptance model.

For female investors, the illusion of control significantly positively influences the intention to use RA across all three risk-preference groups (Columns 4, 5, and 6). This finding aligns with the research of D'Acunto et al. (2019), who noted that when investors perceive algorithmic tools as decision aids, an enhanced sense of control increases their willingness to use RA. Beyond the effect of the illusion of control, trust also significantly affects the intention to use RA among risk-neutral females (Column 5). This result supports Gefen et al.'s (2003) technology acceptance model and suggests that, for female investors with neutral risk attitudes, building trust in RA systems may be a critical factor in overcoming adoption barriers. For female risk-seekers (Column 6), higher levels of risk perception and confidence are associated with a lower intention to use RA in the future. This observation resonates with Langer and Weber's (2005) prospect theory research, which found that highly confident individuals tend to show stronger risk-averse tendencies when faced with algorithmic decision-making – a phenomenon particularly pronounced among female investors.

*** INSERT TABLE 6.3 HERE ***

Furthermore, based on Table 6.2, we conducted further segmentation of the sample[1]. Table 6.3 presents the differential effects of behavioural factors on the intention to use RA across gender and risk-attitude groups living in urban areas. We found that urban residents' intention to use RA shows similar results to those in Table 6.2 across different gender and risk-preference groups. For risk-averse males living in urban areas (Column 1), risk perception has a significantly negative impact on the intention to use RA. Meanwhile, confidence significantly and positively affects the intention to use RA among risk-neutral males living in urban areas (Column 2). For risk-seeking males in urban areas (Column 3), increased levels of risk perception correspond to a decreased intention to use RA, while higher levels of trust indicate a higher intention to use RA among this group. In contrast, for females living in urban areas, regardless of risk attitude (Columns 4, 5, and 6), their intention to use RA is significantly and positively influenced by the illusion of control. For risk-neutral females (Column 5) living in urban areas, risk perception significantly negatively affects their willingness to use RA, while trust significantly and positively influences the intention to use RA in this group. Additionally, risk perception also has a

[1] We also conduct the cross tabular analysis by living in rural, gender and risk aversion. However, no usable results were obtained because this group did not contain enough samples.

significantly negative impact on the intention to use RA among risk-seeking females living in urban areas (Column 6). These similar findings may be related to the specific financial behavioural characteristics formed during China's rapid urbanisation process (Li & Niu, 2024).

*** INSERT TABLE 6.4 HERE ***

Table 6.4 indicates the differential impacts of behavioural factors on the intention to use RA across groups with varying educational backgrounds and risk attitudes through cross-tabular analysis. The results show that for highly educated risk-averse individuals (Column 1), higher risk perception corresponds to a lower intention to use RA. This negative effect of risk perception aligns with Kahneman and Tversky’s (1979) prospect theory, suggesting that even among the highly educated, loss aversion significantly influences investment decisions. Meanwhile, the illusion of control significantly positively affects the intention to use RA, corroborating Barber and Odean’s (2001) findings. This implies that a higher level of education may enhance investors' perceived mastery of technological tools, thereby increasing their willingness to use such tools (e.g., RAs). For risk-neutral individuals who are highly educated (Column 2), a higher level of trust is associated with a higher intention to use RA, which supports Gefen et al.‘s (2003) technology acceptance model. As for risk-seeking individuals with a high level of education (Column 3), higher risk perception reduces their intention to use RA, whereas a greater illusion of control and trust increases the intention to use RA. This suggests that education-enhanced risk awareness may amplify sensitivity to the potential risks of RAs, thereby influencing their intention to use RA (D'Acunto et al., 2019). Furthermore, a higher level of the illusion of control and trust leads these individuals to believe that new financial technologies like RAs can help mitigate potential investment risks (Grable & Lytton, 1999). These findings particularly highlight the moderating role of education in shaping the relationship between risk preferences and technology adoption.

Regardless of risk preference, risk perception shows a significantly negative impact on the intention to use RAs among low-educated individuals (Columns 4, 5, and 6). This finding aligns with Lusardi and Mitchell's (2014) discovery that financial literacy buffers risk sensitivity, suggesting that a lack of education amplifies fear of uncertainty towards new technologies. Furthermore, for risk-averse individuals with lower educational backgrounds (Column 4), higher levels of the illusion of control and trust correspond to a higher intention to use RA. This supports Grinblatt et al.'s (2011) 'compensation mechanism': when financial knowledge is insufficient, individuals rely more on psychological comfort factors (e.g., perceived control) and interpersonal trust to make decisions. For risk-seeking individuals who are low educated (Column 6), a higher illusion of control increases their willingness to use RA, possibly because they misinterpret algorithmic tools as manipulable 'gamified' interfaces (D'Acunto et al., 2019). Conversely, higher confidence significantly reduces this group's intention to use RA. This may stem from cognitively disadvantaged individuals underestimating the value of algorithms due to overconfidence (Dunning et al., 2003), reducing their willingness to use such products.

Tables 6.5 and 6.6 present the differential impacts of behavioural factors on the intention to use RA across groups with different genders, educational backgrounds, and risk attitudes. The results demonstrate similar findings to those in Table 6.3.

*** INSERT TABLE 6.5 HERE ***

First, Table 6.5 shows the effects of behavioural factors on the intention to use RA among male groups with different educational backgrounds and risk attitudes. For risk-averse males who are highly educated (Column 1), loss-averse tendencies (Kahneman & Tversky, 1979) correspond to a lower intention to use RA. The illusion of control shows a significantly positive effect on the intention to use RA, reflecting the well-documented phenomenon of male overconfidence in financial decisions (Barber and Odean, 2001). Confidence levels also significantly and positively affect the intention to use RA among highly educated, risk-neutral males (see Column 2). As for highly educated risk-seeking males (Column 3), higher risk perception reduces the likelihood of using RA, while a higher level of trust indicates a higher intention to adopt RA. In contrast, less-educated male groups across all risk preference categories (Columns 5 and 6) did not exhibit any significant influence from behavioural factors. The lack of significant effects among less-educated males suggests that financial literacy gaps may suppress behavioural biases (Lusardi & Mitchell, 2014). These findings highlight segmented adoption barriers. Educated males respond to perceived control and risk framing, suggesting RAs should tailor messaging to psychological biases. Meanwhile, less-educated males' disengagement implies a need for financial education to bridge adoption gaps (Hastings et al., 2013), as unequal fintech access could exacerbate wealth disparities (Philippon, 2016).

*** INSERT TABLE 6.6 HERE ***

Table 6.6 presents the differential impacts of behavioural factors on the intention to use RA among female groups with different educational backgrounds and risk attitudes. The results show that for highly educated risk-neutral females (Column 2), higher trust corresponds to a higher intention to use RA. For highly educated risk-seeking females (Column 3), in addition to trust, the illusion of control also shows a significantly positive effect on the intention to use RAs. Meanwhile, among less-educated risk-seeking females (Column 6), both risk perception and confidence demonstrate significantly negative effects on RA usage intention. Economically, these patterns indicate that women's adoption hinges on different behavioural levers than men's. Fintech firms should emphasise trust-building and perceived control features when targeting female users, particularly educated segments. The negative effect of risk perception among less-educated risk-seeking females mirrors 'double disadvantage' dynamics – where low financial literacy compounds gender-based risk sensitivity (Lusardi & Mitchell, 2008). This underscores the need for gender-sensitive financial education programmes to prevent further exclusion from digital finance.

6.5 Conclusion on the relationship between behavioural variables and intention to use RA

In summary, this study employed both logit and OLS regression methods to analyze the effects of risk aversion, risk perception, confidence, BTAE, IOC, and trust on intention to use RAs. According to our analysis, risk aversion and risk perception significantly and negatively influenced intention to use RAs. This could be attributed to individuals with these characteristics typically being more cautious and preferring to avoid the potential uncertainties associated with automated financial advice. Furthermore, our analysis confirmed that IOC has a significant positive effect on intention to use RAs, with potential users' intention to employ RAs significantly increasing as their level of

IOC rose. Lastly, potential users' intention to use RAs also significantly increased in line with their degree of trust.

The cross-tabular analysis further enhanced these findings by highlighting how these effects vary across demographic and risk-attitude subgroups. For instance, risk-averse males and highly educated individuals showed heightened sensitivity to risk perception, underscoring the role of education and gender in moderating risk-related biases. Additionally, the positive impact of the illusion of control was consistent across genders but particularly pronounced among female investors, suggesting that marketing strategies emphasising RAs' ability to augment control could effectively target this demographic. The influence of trust was most salient among risk-neutral, highly educated groups, reinforcing the need for transparency and reliability in RA design.

Our findings carry significant economic implications for understanding consumer behaviour in fintech adoption. The negative effects of risk aversion and risk perception suggest that RA providers must mitigate uncertainties through features like real-time risk management, transparent communication, and tailored reassurances to encourage adoption among cautious individuals. Conversely, the positive roles of the illusion of control and trust highlight opportunities to frame RAs as empowering tools that enhance users' sense of control, particularly for women and educated investors, while robust security assurances can further strengthen trust, which is a critical driver of adoption. However, the urban-rural divide and the paradoxical behaviour of rural risk-seekers, who may prefer traditional networks over algorithmic tools, call for localised strategies such as community-based financial education and partnerships with trusted local institutions. By addressing these multidimensional barriers – ranging from psychological biases to infrastructural disparities – policymakers and fintech firms can develop targeted strategies to enhance financial inclusivity and accelerate RA market penetration across diverse consumer segments.

Tables for behavioural variables and relationship between the intention to use RA and behavioural variables

Table 6.1 The determinants of intention to use RA based on behavioural variables using logit analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sociodemographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Risk aversion	0.04^{***}						0.03^{***}
	(0.01)						(0.01)
Risk perception		-0.02^{***}					-0.02^{***}
		(0.00)					(0.00)
Better than average			-0.01				-0.01
			(0.03)				(0.02)
Illusion of control				0.02^{***}			0.01^{***}
				(0.00)			(0.00)
Confidence					-0.01		-0.00
					(0.01)		(0.01)
Trust						0.03^{***}	0.03^{***}
						(0.01)	(0.01)
N	1250	1250	1250	1250	1250	1250	1250
Prob > chi2	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pseudo R2	0.11	0.08	0.07	0.09	0.07	0.08	0.14

Table 6.1 shows the univariate average marginal effect result based on logit regression model for the impact of behavioural variables on the intention to use RA. The regression result in table involves the influence of sociodemographic factors, so table contains "Sociodemographic controls" line. The data in brackets in table represents the standard error of each factor in the regression result. Besides, in this table, *** p<0.01, ** p<0.05, * p<0.1.

Table 6.2 Cross tabular results for the impact of behavioural factors on the intention to use RA by gender and risk attitude

	(1)	(2)		(3)	(4)	
	Male			Female		
	Risk averse	Risk neutral	Risk seeker	Risk averse	Risk neutral	Risk seeker
Sociodemographic factors	Yes	Yes	Yes	Yes	Yes	Yes
Risk perception	-0.0316**	-0.0222	-0.0165***	-0.0268	-0.0122	-0.0120*
	(0.0153)	(0.0174)	(0.0089)	(0.0173)	(0.0118)	(0.0067)
Better than average effect	-0.0805	0.0428	-0.0123	-0.0861	-0.0542	-0.0105
	(0.1450)	(0.0859)	(0.0384)	(0.1290)	(0.0642)	(0.0457)
Illusion of control	0.0413**	0.0112	0.0053	0.0347**	0.0199**	0.0155***
	(0.0169)	(0.0128)	(0.0044)	(0.0169)	(0.0094)	(0.0044)
Confidence	-0.0108	0.0426**	0.0004	0.0281	-0.0235	-0.0200**
	(0.0278)	(0.0188)	(0.0081)	(0.0223)	(0.0158)	(0.0068)
Trust	0.0307	0.0405	0.0214*	0.0318	0.0746***	0.0169
	(0.0352)	(0.0257)	(0.0118)	(0.0467)	(0.0209)	(0.0126)
N	62	131	449	77	206	325
Prob > chi2	0.1422	0.1185	0.0377	0.1417	0.0004	0.0000
Pseudo R2	0.2301	0.1328	0.0537	0.2060	0.1657	0.1829

The table presents cross tabular analysis based on logit regression coefficients with standard errors in parentheses. Statistical significance is indicated by *** p<0.01, ** p<0.05, and * p<0.1. The sociodemographic factor was included in the results of the cross tabular analysis based on the regression analysis. The dependent variable measures the intention to use RA. Columns represent subgroups stratified by gender and risk attitude. Pseudo R^2 values reflect each model's explanatory power, while the varying sample sizes (N) across subgroups account for differences distribution within the dataset.

Table 6.3 Cross tabular results for the impact of behavioural factors on the intention to use RA by living in urban, gender and risk attitude

	(1)		(2)	(3)		(4)
	Male			Female		
	Risk averse	Risk neutral	Risk seeker	Risk averse	Risk neutral	Risk seeker
Sociodemographic factors	Yes	Yes	Yes	Yes	Yes	Yes
Risk perception	-0.0519***	-0.0210	-0.0157**	-0.0252	-0.0208*	-0.0162**
	(0.0177)	(0.0193)	(0.0062)	(0.0210)	(0.0122)	(0.0067)
Better than average effect	0.1194	0.0511	0.0141	0.0602	-0.0360	0.0159
	(0.1667)	(0.0955)	(0.0397)	(0.1277)	(0.0672)	(0.0487)
Illusion of control	0.0073	0.0174	0.0032	0.0257***	0.0196*	0.0162***
	(0.0202)	(0.0138)	(0.0046)	(0.0175)	(0.0101)	(0.0045)
Confidence	-0.0115	0.0354*	0.0037	0.0206	-0.0168	-0.0134
	(0.0291)	(0.0205)	(0.0083)	(0.0247)	(0.0160)	(0.0087)
Trust	0.0266	0.0403	0.0229*	-0.0248	0.0682***	0.0190
	(0.0361)	(0.0279)	(0.0124)	(0.0402)	(0.0215)	(0.0135)
N	52	116	399	60	187	284
Prob > chi2	0.5736	0.3869	0.1235	0.0924	0.0008	0.0000
Pseudo R2	0.2071	0.1101	0.0462	0.2518	0.1754	0.1879

The table presents cross tabular analysis based on logit regression coefficients with standard errors in parentheses. Statistical significance is indicated by *** p<0.01, ** p<0.05, and * p<0.1. The sociodemographic factor was included in the results of the cross tabular analysis based on the regression analysis. The dependent variable measures the intention to use RA. Columns represent subgroups stratified by living in urban, gender and risk attitude. Pseudo R^2 values reflect each model's explanatory power, while the varying sample sizes (N) across subgroups account for differences distribution within the dataset.

Table 6.4 Cross tabular results for the impact of behavioural factors on the intention to use RA by educational background and risk attitude

	(1)	(2)		(3)	(4)	
	High education			Low education		
	Risk averse	Risk neutral	Risk seeker	Risk averse	Risk neutral	Risk seeker
Sociodemographic factors	Yes	Yes	Yes	Yes	Yes	Yes
Risk perception	-0.0344***	-0.0131	-0.0131***	-0.0829***	-0.0618***	-0.0237*
	(0.0130)	(0.0114)	(0.0045)	(0.0270)	(0.0230)	(0.0134)
Better than average effect	-0.0960	-0.0242	-0.0043	0.2631**	0.0765	-0.0442
	(0.1122)	(0.0567)	(0.0289)	(0.1221)	(0.1116)	(0.0863)
Illusion of control	0.0331**	0.0121	0.0077**	0.0684***	0.0161	0.0199*
	(0.0144)	(0.0088)	(0.0031)	(0.0144)	(0.0223)	(0.0108)
Confidence	0.0045	0.0138	-0.0032	-0.0010	0.0055	-0.0352*
	(0.0195)	(0.0138)	(0.0060)	(0.0335)	(0.0245)	(0.0180)
Trust	0.0350	0.0575***	0.0272***	0.1527***	0.0220	-0.0304
	(0.0362)	(0.0185)	(0.0088)	(0.0562)	(0.0472)	(0.0271)
N	101	260	654	38	77	120
Prob > chi2	0.0506	0.0109	0.0002	0.1373	0.4798	0.0492
Pseudo R2	0.1706	0.1033	0.0716	0.4142	0.1250	0.1455

The table presents cross tabular analysis based on logit regression coefficients with standard errors in parentheses. Statistical significance is indicated by *** p<0.01, ** p<0.05, and * p<0.1. The sociodemographic factor was included in the results of the cross tabular analysis based on the regression analysis. The dependent variable measures the intention to use RA. Columns represent subgroups stratified by educational background and risk attitude. Pseudo R^2 values reflect each model's explanatory power, while the varying sample sizes (N) across subgroups account for differences distribution within the dataset.

Table 6.5 Cross tabular results for the impact of behavioural factors on the intention to use RA by male, educational background and risk attitude

	(1)		(2)	(3)		(4)
	High education			Low education		
	Risk averse	Risk neutral	Risk seeker	Risk averse	Risk neutral	Risk seeker
Sociodemographic factors	Yes	Yes	Yes	Yes	Yes	Yes
Risk perception	-0.0373***	-0.0149	-0.0147**		-0.0604	-0.0090
	(0.0125)	(0.0206)	(0.0065)		(0.0443)	(0.0225)
Better than average effect	-0.3051*	0.0192	-0.0217		0.3713	0.0503
	(0.1696)	(0.0920)	(0.0402)		(0.2319)	(0.1120)
Illusion of control	0.0444***	0.0020	0.0019		0.0283	0.0179
	(0.0159)	(0.0146)	(0.0047)		(0.0480)	(0.0137)
Confidence	-0.0285	0.0713***	0.0038		0.0323	-0.0142
	(0.0354)	(0.0226)	(0.0089)		(0.0444)	(0.0223)
Trust	0.0134	0.0408	0.0369***		-0.0550	-0.0602
	(0.0443)	(0.0279)	(0.0127)		(0.0755)	(0.0676)
N	44	99	378	16	32	71
Prob > chi2	0.4332	0.1437	0.1115		0.5475	0.4630
Pseudo R2	0.2699	0.1495	0.0594		0.2771	0.1503

The table presents cross tabular analysis based on logit regression coefficients with standard errors in parentheses. Statistical significance is indicated by *** p<0.01, ** p<0.05, and * p<0.1. The sociodemographic factor was included in the results of the cross tabular analysis based on the regression analysis. The dependent variable measures the intention to use RA. Columns represent subgroups stratified by male, educational background and risk attitude. Pseudo R^2 values reflect each model's explanatory power, while the varying sample sizes (N) across subgroups account for differences distribution within the dataset.

Table 6.6 Cross tabular results for the impact of behavioural factors on the intention to use RA by female, educational background and risk attitude

	(1)	(2)		(3)	(4)	
		High education			Low education	
	Risk averse	Risk neutral	Risk seeker	Risk averse	Risk neutral	Risk seeker
Sociodemographic factors	Yes	Yes	Yes	Yes	Yes	Yes
Risk perception	-0.0215	-0.0093	-0.0089		-0.0319	-0.0397*
	(0.0224)	(0.0126)	(0.0064)		(0.0352)	(0.0219)
Better than average effect	-0.1000	-0.0441	0.0305		-0.0267	-0.1452
	(0.1662)	(0.0698)	(0.0429)		(0.1365)	(0.1204)
Illusion of control	0.0322	0.0149	0.0149***		0.0291	0.0301
	(0.0229)	(0.0106)	(0.0045)		(0.0277)	(0.0183)
Confidence	0.0247	-0.0174	-0.0121		-0.0261	-0.0716**
	(0.0253)	(0.0160)	(0.0081)		(0.0438)	(0.0290)
Trust	-0.0053	0.0812***	0.0210*		0.0732	0.0225
	(0.0542)	(0.0215)	(0.0126)		(0.0671)	(0.0372)
N	57	161	276	20	45	49
Prob > chi2	0.1544	0.0380	0.0011		0.5918	0.0214
Pseudo R2	0.2321	0.1464	0.1476		0.1914	0.4129

The table presents cross tabular analysis based on logit regression coefficients with standard errors in parentheses. Statistical significance is indicated by *** p<0.01, ** p<0.05, and * p<0.1. The sociodemographic factor was included in the results of the cross tabular analysis based on the regression analysis. The dependent variable measures the intention to use RA. Columns represent subgroups stratified by female, educational background and risk attitude. Pseudo R^2 values reflect each model's explanatory power, while the varying sample sizes (N) across subgroups account for differences distribution within the dataset.

Chapter 7 Influence of financial and skilled behavioural factors on intention to use RA

7.1 Introduction to the impact of financial and skilled behavioural factors on intention to use RA

This chapter analyzes the relationships between financial and skilled behavioral factors and intention to use RA. Financial and skilled behavioral factors in our thesis include financial literacy, financial confidence, perception of financial knowledge, digital literacy, experience of using a traditional advisor, experience of using RA, and numeracy. Financial literacy is often considered a cornerstone of effective personal financial management, influencing the adoption of new fintechs (Lusardi & Mitchell, 2014). Financial confidence and the individual's perception of their financial knowledge could significantly impact their willingness to engage with automated financial advisors, shaping their trust and dependence on such technologies (Allgood & Walstad, 2016). Similarly, digital literacy and numeracy skills are pivotal in enabling individuals to effectively interact with digital platforms, with higher proficiency associated with a greater inclination to adopt such technology (van Rooij, Lusardi, & Alessie, 2011). Furthermore, prior experiences with financial advisors, whether traditional or automated, provide practical insights that could influence future adoption decisions (Xu & Zia, 2012).

Based on the existing literature, I first devised various hypotheses regarding the impact of financial behavioral factors on intention to use RAs. I hypothesized that potential users with higher levels of financial literacy would be more likely to use RAs in the future. Similarly, those with a higher level of financial confidence and a greater perception of their own financial knowledge were expected to be more likely to consider using RAs in the future. On the other hand, I also produced hypotheses about the influence of certain skilled behavioral factors on intention to use RAs. After referring to previous research, I assumed that Chinese potential users with higher numerical skills or greater digital literacy would be more likely to use RAs in the future. In addition, potential users who had had prior experience with financial advisors, whether traditional human advisors or RAs, were also expected to be more likely to use RAs in the future.

In order to conduct the analysis, both logit regression and OLS methods were applied to test these hypotheses. The results show that potential users with higher financial literacy had a higher intention to use RAs in the future, which is consistent with the nineteenth hypothesis (H19) mentioned in Chapter 3.3. This is because a higher level of financial literacy typically means an easier understanding of how RAs work, which can foster trust, and may also be due to such respondents also having stronger educational backgrounds, as multiple factors jointly influence intention to use RAs. Moreover, potential users with higher digital literacy also displayed a greater willingness to use RAs in the future, supporting the relevant hypothesis (H17). Higher digital literacy indicates a greater acceptance of new technologies, therefore making such individuals more willing to try them. Lastly, the study also found that past investment experience, whether it be of using traditional investment advisors or RAs, increased the likelihood of potential users using RAs in the future. This may be because past experiences could help potential users to establish basic trust in RAs, thus making them more willing to try RA. This validates the eighth hypothesis (H8) mentioned in Chapter 3.3.

This chapter comprises three parts: regression models are first used to describe how the financial and skilled behavioral factors influence respondents' intention to use RA; preliminary analysis is then conducted on the financial and skilled behavioral factors' effect on the intention to use RA; and multivariate analysis is then carried out on the influence of financial and skilled behavioral factors on intention to use RA.

7.2 Regression models applied to analyse the impact of financial and skilled behavioural factors on intention to use RA

To perform the analysis, this study first performed a logit regression using the following model based on formula (4.1) in Chapter 4.6:

$$\begin{aligned} Intention\_dummy_i &= \beta_0 + \beta_1 SF_i + \beta_2 Financial\_literacy_i \\ &+ \beta_{11} Financial\_confidence_i \\ &+ \beta_{12} Perception\_of\_financial\_knowledge_i + \beta_{13} Numeracy_i \\ &+ \varepsilon_i \qquad (7.1) \end{aligned}$$

In formula (7.1), i subscript represents individuals, SF_i is the vector for sociodemographic factors such as age, gender, living area (urban or rural), marital status, financial dependents, employment status, monthly income, residential status, and educational background, as mentioned in equation (5.1). ε_i is the error term based on logit regression. This study then conducted further AME analysis to reflect the extent to which respondents' intention to use RA changed when the financial and skilled behavioral factors changed by one unit, based on the logit regression results. β is the regression coefficient based on the AME results. To reduce bias in the analysis results, this study also conducted an additional regression analysis of financial and skilled behavioral factors, including sociodemographic and behavioral factors. Based on the model gleaned from formula (7.2), this study performed AME analysis based on the logit regression for the effect of financial and skilled behavioral factors on intention to use RA.

$$\begin{aligned} Intention\_dummy_i &= \beta_0 + \beta_1 SF_i + \beta_2 BF_i + \beta_3 Financial\_literacy_i \\ &+ \beta_4 Financial\_confidence_i \\ &+ \beta_5 Perception\_of\_financial\_knowledge_i + \beta_6 Numeracy_i \\ &+ \varepsilon_i \qquad (7.2) \end{aligned}$$

In formula (7.2), i subscript represents individuals, SF_i is the vector for sociodemographic factors such as age, gender, living area (urban or rural), marital status, financial dependents, employment status, monthly income, residential status, and educational background, as mentioned in equation (5.1). BF_i is the vector for behavioral factors such as risk aversion, risk perception, BTAE, IOC, confidence, and trust, as mentioned in equation (6.1). ε_i is the error term based on logit regression. This study then conducted further AME analysis to gauge the extent to which respondents' intention to use RA changed when the financial and skilled behavioral factors changed by one unit, based on the logit regression result. β is the regression coefficient based on the AME results.

Besides, this study also includes an OLS regression model including both financial and skilled behavioral factors and sociodemographic variables based on formula (4.4) in Chapter 4.7:

$$Intention\_continuous_i = \beta_0 + \beta_1 SF_i + \beta_2 Financial\_literacy_i + \beta_{11} Financial\_confidence_i + \beta_{12} Perception\_of\_financial\_knowledge_i + \beta_{13} Numeracy_i + \varepsilon_i \qquad (7.3)$$

Meanwhile, i subscript represents individuals, SF_i is the vector for sociodemographic factors such as age, gender, living area (urban or rural), marital status, financial dependents, employment status, monthly income, residential status, and educational background, as mentioned in equation (5.1). ε_i is the error term based on OLS regression. This study then conducted further AME analysis to reflect the extent to which respondents' intention to use RA changed when the financial and skilled behavioral factors changed by one unit, based on the OLS regression results. β is the regression coefficient based on the AME results. Moreover, this study used another OLS model shown in formula (7.4) to analyze how financial and skilled behavioral factors influenced individuals' intention to use RA, including the effect of sociodemographic and behavioral factor.

$$Intention\_continuous_i = \beta_0 + \beta_1 SF_i + \beta_2 BF_i + \beta_3 Financial\_literacy_i + \beta_4 Financial\_confidence_i + \beta_5 Perception\_of\_financial\_knowledge_i + \beta_6 Numeracy_i + \varepsilon_i \qquad (7.4)$$

Similar to equation (7.2), i subscript represents individuals, SF_i is the vector for sociodemographic factors such as age, gender, living area (urban or rural), marital status, financial dependents, employment status, monthly income, residential status, and educational background, as mentioned in equation (5.1). BF_i is the vector for behavioral factors such as risk aversion, risk perception, BTAE, IOC, confidence, and trust, as mentioned in equation (6.1). ε_i is the error term based on logit regression. β is the regression coefficient based on the AME results.

7.3 Regression results for the effect of financial and skilled behavioural factors on intention to use RA

In this section, further multivariate analysis of the impact of the financial and skilled behavioral factors on the intention to use RA using the regression models taken from the two models mentioned in Chapter 7.2 is presented.

*** INSERT TABLE 7.1 HERE ***

Table 7.1 presents the AME after estimating the logit regression for the financial and skilled behavioral factors on intention to use RA, including sociodemographic factors. This table displays the univariate results in seven columns (columns 1 to 7), and the multivariate analysis, which includes all of the financial and sociodemographic factors in one column (column 8). Table 7.1 shows the scores for respondents' financial literacy (column 1), financial confidence (column 2), perception of financial knowledge (column 3), digital literacy (column 4), experience of using a traditional advisor (column 5), experience of using RA (column 6), and numeracy (column 7), all of which have a significant and positive relationship with the intention to use RA in the univariate analysis. The multivariate analysis (column 8) indicates that financial literacy, perception of financial knowledge, digital literacy, experience of using a traditional advisor, experience of using RA, and numeracy all had a significant positive effect on intention to use RA when all sociodemographic and financial and skilled behavioral factors were taken into account.

*** INSERT TABLE 7.2 HERE ***

Table 7.2 shows the AME based on the results of the logit regression for the financial and skilled behavioral factors on the intention to use RA, taking into consideration both sociodemographic and behavioral factors. The univariate results (columns 1 to 7) exhibit similar results to the regression with only sociodemographic factors (columns 1 to 7 in Table 7.1), while the multivariate result differs slightly therefrom (column 8 in Table 7.1).

The results in column 8 of Table 7.2 show that financial literacy had a positive and significant relationship with intention to use RA. For every one-unit increase in respondents' financial literacy score, their intention to use RA increased by 5%. This finding supports the relevant hypothesis (H19) that individuals with higher levels of financial literacy would have a higher intention to use RA. The findings align with the research of Niu et al. (2020) and Karakurum-Ozdemir et al. (2018), who found a positive correlation between education level and financial literacy, with individuals possessing higher financial literacy being more inclined to use advanced financial tools. Our findings further extend this perspective, indicating that financial literacy can significantly affect the acceptance of emerging financial technologies, such as RA. Individuals with higher financial literacy can more effectively understand RA's working principles and potential advantages, making them more willing to adopt this product (Lusardi & Mitchell, 2014).

Secondly, the results are consistent with the core idea of financial literacy theory, which posits that investors with higher financial literacy can better understand the investment environment and use rational advice to make more informed investment decisions (Lusardi & Mitchell, 2014). As an algorithm-based and data-driven investment tool, RA can provide personalised investment advice to investors, and individuals with higher financial literacy are more likely to understand and trust such advice, thereby increasing their intention to use RA (Yi et al., 2023). Additionally, individuals with higher financial literacy often possess ‘practical thinking,’ enabling them to apply theoretical knowledge to real-world investment scenarios, further increasing their trust and willingness to use RA (Niu et al., 2020). Although some studies have found that individuals with lower financial literacy may be more inclined to use RA (Seongsu David, 2019), this thesis tends to support the view of Todd and Seay (2020), who argued that RA users are typically individuals with higher levels of financial literacy.

From an economic perspective, this finding emphasises the importance of improving public financial literacy. Financial literacy is not only a key factor in personal financial health but also a significant driver of financial technology innovation and adoption (Yi et al., 2023). By enhancing public financial literacy, the acceptance of emerging financial tools, such as RA, can be increased, thereby improving the efficiency and inclusivity of the financial system. Furthermore, improving financial literacy can help reduce information asymmetry, enabling investors to better utilise the personalised advice provided by RA and optimise their investment decisions (Lusardi & Mitchell, 2014).

As expected, respondents with higher levels of digital literacy recorded a significant increase in their intention to use RA; for each one-point increase in digital literacy, there was a 3% increase in the probability of intending to use RA in the future. This result is in line with the seventeenth hypothesis (H17) of our thesis. At the same time, our results are consistent with the research of van Deursen and van Dijk (2014), which shows that individuals with higher digital literacy are more capable of effectively utilising digital technologies, making them more willing to adopt financial technology tools. Additionally, Hargittai (2002) supports this view, pointing out that digital literacy is a key factor influencing technology acceptance, especially for complex technological tools, such as RA. From the perspective of the technology acceptance model, digital literacy enhances individuals' acceptance intentions by improving their perceived ease of use and perceived usefulness of the technology (Davis, 1989). Individuals with high digital literacy can better understand how RA works and develop trust in its investment advice, making them more willing to use RA when making investment decisions. Our findings further validate the applicability of the technology acceptance model in the fintech sector and provide new empirical support for the model.

On the other hand, individuals with lower digital literacy may feel confused or distrustful of financial technology, which could lead to lower acceptance of RA. According to the diffusion of innovations theory, early adopters are typically individuals with a higher acceptance of new technologies and a willingness to take risks (Rogers, 2003). Therefore, improving the digital literacy of potential users may be a key strategy for expanding the market reach of RA. Research by Gomber et al. (2017) indicates that the rapid development of fintech is transforming the way traditional financial services are delivered, and enhancing digital literacy will help accelerate this transformation process.

From an economic perspective, improving digital literacy can not only promote the adoption of RA but also have a positive impact on the efficiency and fairness of financial markets. Investors with high digital literacy can more effectively use RA to optimise their investment portfolios, thereby improving capital allocation efficiency. Furthermore, as more investors adopt RA services, information asymmetry in financial markets may be reduced, contributing to the overall healthy development of the market.

Next, I analyze how the respondents' investment experiences influenced their intention to use RA in the future. This part was divided into two: experience of using traditional advisors; and experience of using RA. The regression results are consistent with H18, whereby respondents with experience of using traditional advisors were 5% more likely to use RA compared to those who had never used a traditional advisor. In addition, respondents with experience of using RA in the past were 8% more likely to use RA in the future than those who had never used RA.

First, investors who have used traditional investment advisors are more inclined to use RA. This result aligns with the research of Fisch et al. (2019), which indicates that an individual's past investment experience significantly influences their future investment decisions. Experience with traditional investment advisors makes investors more familiar with the basic mechanisms of investment consulting, thereby making it easier for them to understand how RA works (D'Acunto et al., 2019). Additionally, experience with traditional advisors may enhance investors' trust in this kind of service, which can be transferred to RA (Bhattacharya et al., 2012). Our finding also complements the research of Gomber et al. (2018) to some extent, which states that an individual's trust in new technologies directly affects their willingness to adopt them.

Second, investors who have previously used RA are more likely to continue using it in the future. This result is consistent with the extended research on the technology acceptance model by Jung et al. (2018), which suggests that individuals are more inclined to adopt a new technology when they perceive it as enhancing their performance (perceived usefulness) and easy to use. Investors who have used RA before may have already experienced the advantages of RA in improving investment decision efficiency and potential returns, thereby increasing their intention to continue using it (D'Acunto et al., 2019). Furthermore, this result also aligns with the research of Bhattacharya et al. (2012), which indicates that early successful experiences accelerate the adoption of new technologies.

However, this finding also raises some questions worth further exploration. For example, although investors who have used traditional advisors or RA are more inclined to use RA, those with negative investment experiences may adopt a more cautious attitude toward new technologies (Bhattacharya et al., 2012). Future research could further explore how to enhance these investors' trust in RA by improving transparency, demonstrating the reliability of algorithms, and providing customised services (Gomber et al., 2018).

From an economic perspective, our finding identifies an important target group for promoting RA. Investors who have used traditional advisors or RA are not only more likely to continue using RA but may also become active promoters of RA. Therefore, marketing strategies targeting these groups should emphasise the advantages of RA in replicating successful investment experiences, improving decision efficiency, and offering personalised services (D'Acunto et al., 2019).

Finally, our analysis supports the sixteenth hypothesis (H16) that higher numeracy skills would have a significant positive effect on respondents' intention to use RA. In particular, as numeracy increased by one point, the level of intention to use RA increased by 1.30%. The findings of this thesis align with the research of Lusardi & Mitchell (2014), who pointed out that numeracy skills are a crucial component of financial literacy, directly influencing an individual's ability to understand and utilise complex financial tools. Our study further extends this perspective, showing that numeracy skills also significantly increase acceptance and willingness to use RA. Additionally, our results resonate with the findings of Hastings et al. (2013), who emphasised that individuals with stronger numeracy skills can better understand the investment advice provided by RA, as they are able to interpret the mathematical logic behind RA algorithms and effectively analyse the data and statistical information provided by RA. This ability enables them to make more informed investment decisions and increases their willingness to use RAs. Our study further validates this, demonstrating that improved numeracy skills not only enhance individuals' trust in RA technology but also increase their perceived usefulness, a key factor in the technology acceptance model (Davis, 1989).

However, our study also reveals the sceptical attitude of individuals with weaker numeracy skills toward financial technology like RA. This finding is consistent with the research of Cokely et al. (2023), who noted that individuals with weaker numeracy skills may feel uncomfortable with data-driven RA technology, perceiving it as complex and difficult to understand, thereby reducing their perceived ease of use. Furthermore, these individuals may doubt the reliability of the advice provided by RA, further weakening their perceived usefulness. This discomfort with numerical data may lead to lower acceptance of RA technology. Our study highlights the importance of numeracy skills in adopting financial technology. As financial markets become more complex, individuals' ability to understand and apply numerical data will become a key factor in determining the quality of their financial decisions. Our findings suggest that improving individuals' numeracy skills not only helps enhance their trust and willingness to use RA but may also promote the overall efficiency and stability of financial markets. Therefore, educational initiatives aimed at improving financial literacy and numeracy skills could be key to expanding the acceptance and usage of RA services.

As a new financial tool, the process of promoting RA is significantly influenced by the level of financial literacy, perception of financial knowledge, and numeracy skills of potential users. Therefore, it could be initially promoted in areas where the financial industry is relatively developed because individuals' financial ability in these areas may be relatively more robust, and their willingness to use RA may also be higher as a result. Meanwhile, our research also indicates that improving an individual's financial capacity can boost their adoption and usage of emerging fintech. This, in turn, can improve the efficiency of, and participation in, financial markets, further promoting financial inclusion and innovation.

Appendix 7.1 shows the influence of financial and skilled behavioral factors on the intention to use RA using the OLS model, taking into account sociodemographic factors only. The table there contains seven separate regression results (columns 1 to 7), showing how the financial behavioral factors individually impact upon respondents' intention to use RA, and a multivariate regression including all the financial behavioral factors together (column 8). The results in Appendix 7.1 show that respondents' level of financial literacy (column 1), financial confidence (column 2), perception of financial knowledge (column 3), digital literacy (4), experience of using a traditional advisor (5), experience of using RA (6), and numeracy (column 7) all significantly and positively influenced intention to use RA in the univariate analysis. In comparison, in the multivariate analysis (column 8), only financial literacy, digital literacy, experience of using a traditional advisor, experience of using RA, and numeracy showed a significant positive relationship with intention to use RA.

Elsewhere, Appendix 7.2 shows the influence of financial and skilled behavioral factors on intention to use RA using the OLS model, including sociodemographic variables and behavioral factors. This table also contains eight columns, where columns 1 to 7 show the univariate results concerning how the financial and skilled behavioral factors individually impacted upon respondents' intention to use RA, and column 8 presents the multivariate results. Similar to the results shown in Appendix7.1, in Appendix 7.2 the univariate analysis results show a significant positive effect of each financial and skilled behavioral factor on intention to use RA in columns 1 to 7. However, in contrast to the multivariate results in column 8 of Appendix 7.1, only financial literacy, digital literacy, experience of using a traditional advisor, and experience of using RA significantly positively affected intention to use RA when both sociodemographic and behavioral factors were considered. This finding is consistent with the logit regression results recorded in this thesis.

7.4 Cross tabular analysis on the relationship between financial and skilled behavioural variables and intention to use RA

After conducting the logit regression analysis, this section further explores the influence of financial and skilled behavioural factors on the intention to use RA through cross-tabular analysis. It reveals how these factors, alongside sociodemographic variables, affect different groups' intentions to use RA, providing more nuanced empirical evidence for the targeted promotion of RA in China.

Before analysing the data, the variables were treated appropriately to ensure they could be used in cross-tabular analysis. 'Gender' was classified as a binary variable; 'living area' was categorised into urban and rural; 'educational background' was divided into lower education (high school or below and associate degrees) and higher education (bachelor's, master's, and doctoral degrees or above); and 'financial literacy' and 'digital literacy' were each categorised into high and low groups.

*** INSERT TABLE 7.3 HERE ***

Table 7.3 presents the results of the cross-tabular analysis, showing the influence of various financial and skilled behavioural factors on the intention to use RA among males with different educational backgrounds and varying levels of financial literacy. For males with a low level of financial literacy (see Column 1), the perception of financial knowledge, digital literacy, and past experience with traditional advisors significantly and positively impact the intention to use RA. This partially validates the 'cognitive compensation effect' (Hadar et al., 2013), whereby subjective perceptions can compensate for deficiencies in objective ability. In contrast, for males with a high level of financial literacy (see Column 2), only digital literacy and past experience with traditional advisors have a significantly positive influence on their intention to use RA. This result aligns with the 'high-literacy saturation effect' proposed by Fong et al. (2021), suggesting that the marginal utility of financial literacy diminishes beyond a certain threshold. For females with a low level of financial literacy (see Column 3), the perception of financial knowledge has a significantly negative impact on their intention to use RA, while past experience with RA and numeracy skills have significantly positive effects. This may reflect the 'cognitive vigilance' (Bucher-Koenen et al., 2021) specific to females, whereby awareness of their own knowledge gaps leads to stronger risk aversion. Meanwhile, this group's positive response to past experience with RA and numeracy skills supports Lusardi and Mitchell's (2014) argument regarding the critical role of foundational skills. On the other hand, digital literacy has a significantly positive effect on the intention to use RA among females with a high level of financial literacy (see Column 4). This finding aligns with Huang and Kisgen's (2013) conclusion that women's decision-making tends to prioritise practicality, indicating that this group focuses more on the operational usability of tools rather than additional financial service value.

*** INSERT TABLE 7.4 HERE ***

Building upon Table 7.3, we conducted a further subgroup analysis of our study participants[2]. Table 7.4 presents the varying factors influencing RA adoption intentions among urban-dwelling groups differentiated by gender and financial literacy levels. Our findings reveal that for urban males with low financial literacy (column 1), only past experience with traditional advisors significantly affects their intention to use RAs. This result supports the service inertia effect proposed by D'Acunto et al. (2019), indicating that this group perceives RAs as digital extensions of traditional services rather than standalone products. Conversely, among urban males with high financial literacy (column 2), digital literacy significantly positively impacts RA adoption intentions, reaffirming van Deursen and van Dijk's (2014) assertion that technological competence becomes the critical threshold for fintech adoption in high-density digital environments.

Furthermore, financial confidence and past experience with RAs significantly positively influence the intention to use RAs among urban females with low financial literacy (column 3), reflecting the gender-specific 'experience-dependent' decision-

[2] We also conduct the cross tabular analysis by living in rural, gender and financial literacy. However, no usable results were obtained because this group did not contain enough samples.

making pattern (Barber & Odean, 2001), where females tend to rely more on affective rather than cognitive indicators when making financial decisions. Digital literacy shows a significantly positive effect on the intention to use RAs among urban females with high financial literacy (Column 4), aligning with Huang and Kisgen's (2013) findings regarding the 'pragmatic tendency' of high-literacy women, suggesting this group prioritises operational feasibility in technological tools.

*** INSERT TABLE 7.5 HERE ***

Table 7.5 presents the differential factors influencing the intention to use RA across groups with varying education levels and financial literacy. The results show that digital literacy has a significantly positive impact on the intention to use RA among highly educated groups, regardless of their financial literacy level (Columns 1 and 2). This result aligns with van Deursen and van Dijk's (2014) digital divide theory, demonstrating that education indirectly promotes fintech adoption by enhancing technological adaptability.

Beyond digital literacy's influence, for highly educated individuals with low financial literacy (Column 1), past experience with RAs also increases their intention to use RA. This reflects the 'experiential learning effect' (D'Acunto et al., 2019), indicating that this group relies more on direct product experience than on abstract financial knowledge. For highly educated individuals with high financial literacy (Column 2), past experience with traditional advisors positively affects RA adoption intentions, demonstrating a 'professional transfer pattern' (Fong et al., 2021), where they apply traditional financial service cognition to new technology evaluation.

Furthermore, past experience with traditional advisors also shows significantly positive effects on the intention to use RA among low-education, low-financial literacy groups (Column 3). This finding challenges the expectations of conventional financial literacy theory (Lusardi & Mitchell, 2014), potentially stemming from this group's unique 'confidence-competence mismatch' phenomenon (Hadar et al., 2013), where overconfidence actually reduces trust in automated tools. For low-education, high-financial-literacy groups (see Column 4), financial confidence has a negative impact on RA adoption intentions. Excessive financial confidence reduces acceptance of automated advice (Barber and Odean, 2001), suggesting that this group may reject external tools due to an overestimation of their own decision-making ability. Conversely, digital literacy and numeracy skills positively influence their intention to use RA, supporting Lusardi and Mitchell's (2014) multiple capabilities theory, which posits that technical and basic maths skills become crucial for evaluating fintech value without formal education.

Our findings reveal education's moderating mechanism in fintech adoption (Belanche et al., 2019), showing that education not only enhances financial literacy but also increases technological adaptability to some extent. Moreover, we enrich the multi-level model of fintech adoption (Barber & Odean, 2001), emphasising the need to consider interactions between cognitive ability, technical literacy, and emotional factors. Practically, these results suggest that RA providers should adopt differentiated strategies: highlighting technological advancement for highly educated groups, emphasising service continuity for low-education/low-literacy groups, and balancing technology demonstration with risk education for low-education or high-literacy groups (Huang & Kisgen, 2013).

*** INSERT TABLE 7.6 HERE ***

Building upon the findings from Table 7.5, we further segmented the sample. Table 7.6 presents the differential factors influencing the intention to use RA among male groups with varying education levels and financial literacy. The results show that for high-education, low-financial-literacy male groups (see Column 1), both perceptions of financial knowledge and past experience with traditional advisors significantly and positively impact the intention to use RA. This finding validates the 'cognitive compensation mechanism' (Hadar et al., 2013), indicating that this group compensates for objective financial knowledge gaps through subjective knowledge assessment and service experience. For high-education, high-financial-literacy male groups (see Column 2), only past experience with traditional advisors has a significantly positive effect on the intention to use RA, reflecting the 'professional inertia effect' (D'Acunto et al., 2019). This suggests that service continuity becomes the primary consideration once financial literacy reaches a certain threshold. Meanwhile, digital literacy and numeracy skills significantly and positively influence RA adoption intentions among low-education, high-financial-literacy male groups (see Column 4). This finding supports the 'skill substitution hypothesis' proposed by Hastings et al. (2013), demonstrating that concrete technical and mathematical abilities can substitute for systematic financial knowledge as key drivers of fintech adoption in the absence of formal education. Collectively, these findings expand existing fintech adoption theories, highlighting that different demographic groups may follow distinctly different decision-making pathways.

*** INSERT TABLE 7.7 HERE ***

Table 7.7 presents the differential factors influencing RA adoption intentions among female groups with varying education levels and financial literacy. The results first show that for female groups with high education and low financial literacy (Column 1), past experience with RAs has a significantly positive impact on their intention to use RA. This significant positive effect of RA usage experience confirms the 'experiential learning effect' (Gerrans et al., 2014), indicating that this group relies more on direct product experience than on abstract financial knowledge. Furthermore, digital literacy shows a significantly positive effect on the intention to use RA for females with high education and high financial literacy (Column 2). This finding aligns with Belanche et al.'s (2019) research on technology acceptance, reflecting their greater focus on operational feasibility rather than financial service attributes. In contrast, for female groups with low education and low financial literacy (Column 3), past experience with traditional advisors has a significantly positive impact on future RA adoption intentions. This supports Bucher-Koenen et al.'s (2021) service trust transfer hypothesis, demonstrating that among the most financially vulnerable groups, trust from existing service relationships serves as a crucial bridge for adopting new technologies. These findings collectively reveal the unique decision-making patterns exhibited by female investors in fintech adoption processes. Compared to males, they rely more on concrete experiences and existing trust relationships rather than on abstract capability assessments.

In addition to the cross-tabular analysis for groups with varying degrees of financial literacy, we also conducted a cross-tabular analysis for groups with varying degrees of digital literacy in this chapter. Table 7.8 presents the differential factors influencing RA adoption intentions across groups with varying gender and digital literacy levels.

*** INSERT TABLE 7.8 HERE ***

The results show that for males with low digital literacy (Column 1), both financial literacy and past experience with traditional advisors have significantly positive impacts on the intention to use RA. This aligns with Lachance and Tang's (2019) findings that financially inexperienced individuals rely more on traditional financial advice channels when facing new technologies. Additionally, past experience with RAs also shows significantly positive effects on the willingness to use RAs among males with low digital literacy, complementing Belanche et al.'s (2021) findings about the importance of technology usage experience. This suggests that experiences with both traditional and new advisory channels may create cumulative effects that increase the intention to use RAs.

In contrast, for males with high digital literacy (Column 2), financial confidence and perception of financial knowledge significantly positively influence their willingness to use RAs. This supports Gerrans et al.'s (2014) overconfidence effect theory: individuals tend to rely more on autonomous decision-making than on professional advice, thus showing a higher willingness to use RAs than traditional advisors. However, our study limits this phenomenon to specific technologically proficient groups through digital literacy's moderating effect, providing a more nuanced explanatory dimension for behavioural finance research.

For females with low digital literacy (Column 3), financial literacy, past experience with RAs, and numeracy skills all show significantly positive impacts on RA adoption intentions. This indicates that for digitally disadvantaged female groups, traditional financial literacy and quantitative abilities remain crucial factors in overcoming technological barriers, consistent with Lusardi and Mitchell's (2014) findings that women rely more on basic financial knowledge and quantitative skills in financial decision-making. Meanwhile, the significant impact of past RA experience demonstrates that even with limited digital literacy, direct technology exposure can effectively lower usage barriers. This aligns with the 'experience moderation effect' in Venkatesh et al.'s (2003) technology acceptance model, suggesting differentiated adoption pathways for specific user groups.

For females with a high level of digital literacy (Column 4), the intention to use RAs is significantly positively influenced by the level of financial literacy. This aligns with Hung et al.'s (2009) digital literacy enhancement effect hypothesis that technological competence amplifies the role of traditional financial literacy. These findings collectively challenge the universality of traditional gender difference theories in financial decision-making, suggesting that digital literacy may reshape the relationship patterns between gender and fintech adoption, providing new perspectives for financial inclusion research (Demirgüç-Kunt et al., 2020).

*** INSERT TABLE 7.9 HERE ***

Building upon the conclusions from Table 7.8, we conducted further segmentation of our sample[3]. Table 7.9 presents the differential factors influencing the intention to use RA among urban-dwelling groups with varying gender and digital literacy levels. The results show that for urban males with low digital literacy (Column 1), both past experience with traditional advisors and past experience with RAs have significantly

[3] We also conduct the cross tabular analysis by living in rural, gender and digital literacy. However, no usable results were obtained because this group did not contain enough samples.

positive impacts on the intention to use RAs. This aligns with the findings of Bucher-Koenen et al. (2017), who identified an experience transfer effect among traditional financial service users, where experience with traditional financial services influences their acceptance of new financial technologies. For urban males with high digital literacy (column 2), the perception of financial knowledge significantly affects their willingness to use RAs. This result supports the learning leads to overconfidence theory proposed by Gervais and Odean (2001), suggesting that technologically proficient urban males may overestimate their financial knowledge due to digital competence, thus showing a greater inclination toward using automated tools like RAs.

Additionally, financial literacy and past experience with RAs show significantly positive effects on the intention to use RAs among urban females with low digital literacy (Column 3). This result aligns with the findings of Lusardi and Mitchell (2014), but our study further indicates that in urban environments, even with limited digital capability, improved financial literacy can still promote females' acceptance of financial technology innovations. Finally, the intention to use RAs among urban females with high digital literacy (column 4) is significantly positively influenced by their level of financial literacy. This aligns with Atkinson and Messy’s (2012) perspective on the financial literacy multiplier effect, where the role of financial knowledge becomes amplified when supported by technological capability. These results not only refine gender difference theories in fintech adoption but also provide important foundations for formulating differentiated urban financial education policies, particularly highlighting the need for distinct financial empowerment strategies targeting female groups with varying digital literacy levels (Grohmann et al., 2018).

*** INSERT TABLE 7.10 HERE ***

Table 7.10 presents the differential factors influencing the intention to use RAs across groups with varying educational backgrounds and digital literacy levels. The results show that for high education and low digital literacy groups (Column 1), financial literacy, past experience with traditional advisors, and past experience with RAs all significantly and positively impact their RA adoption intentions. This finding aligns with van Rooij et al.'s (2011) research, which found that highly educated but financially inexperienced groups tend to rely on both traditional and new financial service channels simultaneously. For high education and high digital literacy groups (column 2), individuals' intentions to use RAs are significantly positively influenced by financial literacy and perception of financial knowledge, while they are significantly negatively affected by numeracy skills. This result aligns with Jung et al. (2018), which found that investors with strong quantitative analysis capabilities often maintain scepticism towards automated advisory systems, preferring independent analysis over algorithmic recommendations. The result also supports Fisch and Wilkinson-Ryan's (2014) competency paradox theory, which posits that the enhancement of certain professional competencies may reduce reliance on decision-support tools, as highly capable individuals tend to overtrust their judgments while undervaluing automated tools.

Past experience with RAs significantly affects RA adoption intentions among low education and low digital literacy groups (Column 3). This finding indicates that for groups with both low education levels and limited digital literacy, past experience can effectively lower usage barriers, resonating with the core concept in the Technology Acceptance Model (TAM) that 'usage experience reduces perceived obstacles' (Davis, 1989). Particularly noteworthy is how this result supports Gerrans et al.'s (2014) experience substitution effect hypothesis, suggesting that when individuals lack formal education and digital skills, direct product usage experience can compensate for these fundamental deficiencies and become a key driver of fintech adoption. For low education but high digital literacy groups (Column 4), their intentions to use RAs are significantly positively influenced by their level of financial confidence, past experience with traditional advisors, and numeracy skills. This result partially supports Grinblatt et al.'s (2009) bounded rationality compensation mechanism theory, which proposes that individuals with different capabilities employ distinct decision-making heuristics. These findings collectively reveal the complex interplay between educational background and digital literacy, providing a more nuanced explanatory framework for understanding the 'digital divide' phenomenon in fintech adoption.

*** INSERT TABLE 7.11 HERE ***

Building upon the findings from Table 7.10, we further segmented our sample by gender characteristics. Table 7.11 presents the differential factors influencing the intention to use RAs among male groups with varying educational backgrounds and digital literacy levels. The results show that for high-education but low-digital-literacy male groups (Column 1), individuals's intention to use RAs is significantly positively influenced by both financial literacy and past experience with traditional advisors. This aligns with van Rooij et al.'s (2011) finding that when individuals face barriers to new technology adoption, such as RAs, existing financial knowledge and traditional financial service experience play compensatory roles. Notably, this group's reliance on traditional advisory experience may reflect the path dependency effect, where higher education leads to habitual trust in professional advisory channels, which then transfers to new digital advisory services (Jung et al., 2018), providing new perspectives for understanding the interaction between education level and digital literacy. For males with high education and high digital literacy (Column 2), the perception of financial knowledge significantly positively influences their intention to use RAs. This result reflects the self-efficacy enhancement mechanism proposed by Gervais and Odean (2001), where technological competence amplifies the impact of subjective knowledge evaluation on decision-making, thereby affecting attitudes towards fintech products like RAs. These findings provide new evidence for understanding the disconnection between educational attainment and actual capability transformation. Past experience with RAs significantly affects the intention to use RAs among low-education, low-digital-literacy male groups (Column 3). This finding demonstrates that past experience with RAs becomes the key factor in overcoming capability limitations, supporting the experience reduces uncertainty mechanism in Rogers's (2003) Diffusion of Innovations theory, where direct usage experience can compensate for knowledge and skill deficiencies. Particularly noteworthy, this finding supports Lusardi and Mitchell's (2014) research, showing that even without formal education and digital skills, operational experience accumulated through practice can effectively promote fintech adoption among disadvantaged groups.

*** INSERT TABLE 7.12 HERE ***

Furthermore, Table 7.12 presents the differential factors influencing the intention to use RA among female groups with varying educational backgrounds and digital literacy levels. The results show that for high-education but low-digital literacy female groups (Column 1), financial literacy and past experience with RAs significantly influence their willingness to use RAs. This finding aligns with the research of Fonseca et al. (2012), which indicates that highly educated women tend to first utilise their existing financial knowledge to assess the technological value of new financial technologies like RA, while direct usage experience can effectively alleviate usage anxiety caused by insufficient digital skills. Particularly noteworthy, this result reveals a unique capability compensation mechanism among highly educated female groups; that is, when digital literacy is at a low level, the financial literacy cultivated through formal education and practical technology experience can create synergistic effects that jointly promote fintech adoption (Bucher-Koenen et al., 2021). This finding provides new gender-specific evidence for understanding the interaction between educational background and digital capabilities.

In contrast, for females with high education and high digital literacy (Column 2), only financial literacy shows a significantly positive impact on their intention to use RA. This aligns with the capability stacking effect proposed by Atkinson and Messy (2012), where the role of basic financial knowledge becomes more prominent when both education and digital skills reach higher levels. Unlike their male counterparts (Column 2 in Table 7.11), this female group does not demonstrate reliance on subjective financial knowledge evaluation. This gender difference supports Bucher-Koenen et al.'s (2017) finding that highly educated women exhibit more pragmatic traits in financial decision-making, focusing more on actual financial capabilities rather than self-assessments.

7.5 Conclusion on the relationship between financial and skilled behavioural variables and intention to use RA

In summary, through multiple regression analyses, I have obtained strong evidence to suggest that potential users' level of financial literacy has a significant positive impact on their intention to use RAs in the future. In addition, as potential users' digital literacy increases, their probability of using RAs was also found to rise significantly. Finally, I found that previous experience of using a traditional financial advisor and prior use of RAs both significantly enhanced their willingness to use RA in the future.

The cross-tabular results further show that there is a significant difference in the influence of digital literacy by education level. The intention to use RAs among the highly educated group is significantly and positively influenced by digital literacy, regardless of their level of financial literacy. This validates the mechanism of the digital divide theory, which posits that education indirectly promotes the adoption of fintech through the enhancement of technological adaptability. Notably, for the low-education group, past experience with traditional advisors becomes a key factor driving RA adoption, challenging the expectations of traditional financial literacy theory and revealing the existence of the service inertia effect. In contrast, the acceptance of RAs among the urban, highly digitally literate male group was significantly correlated with their subjective financial literacy ratings, exhibiting the behavioural trait of learning leads to overconfidence.

At a practical level, these findings carry important economic implications. The significantly positive influence of financial literacy and digital literacy on RA adoption intention indicates that improving these skills among the public can promote the adoption of automated financial services, enhancing financial inclusion and market efficiency. The group differences revealed by cross-tabulation analysis suggest that policymakers should adopt targeted strategies: emphasising RA's technological advancement for highly educated groups, focusing on service continuity experience for low-education or ow-financial-literacy groups, and balancing technology demonstration with risk education for low-education but high-financial-literacy groups.

The study also finds that prior financial service experience, whether through traditional advisors or RAs themselves, can enhance trust and acceptance of RAs, providing an important reference for financial institutions designing user migration paths. When transitioning traditional users to RAs, education programmes based on existing experiences should be implemented.

These findings collectively form a multi-level understanding framework, confirming the core role of fundamental capability factors while also revealing complex interactive influences between demographic characteristics and behavioural factors. This provides an empirical basis for precise policy implementation in fintech promotion. In future efforts to promote RA adoption, differentiated education and marketing strategies need to be designed according to the capability characteristics and decision-making patterns of different groups to enhance acceptance of this innovative financial tool effectively.

Tables for financial and skilled behavioural variables and relationship between the intention to use RA and behavioural variables

Table 7.1 The determinants of intention to use RA based on financial and skilled behavioural variables with sociodemographic variables using logit analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sociodemographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Financial literacy	0.05^{***} (0.01)							0.04^{***} (0.01)
Financial confidence		0.03^{***} (0.01)						0.01 (0.01)
Perception of financial knowledge			0.07^{***} (0.01)					0.03^{**} (0.01)
Digital literacy				0.05^{***} (0.01)				0.03^{***} (0.01)
Traditional advisor experience					0.15^{***} (0.02)			0.07^{***} (0.03)
RA experience						0.15^{***} (0.02)		0.10^{***} (0.02)
Numeracy							0.05^{***} (0.01)	0.02^{**} (0.01)
N	1250	1250	1250	1250	1250	1250	1250	1250
Prob > chi2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pseudo R2	0.08	0.08	0.10	0.08	0.09	0.10	0.10	0.17

Table 7.1 shows the univariate average marginal effect result based on logit regression model for the impact of financial variables on the intention to use RA. The regression result in table involves the influence of sociodemographic variables only, so table contains "Sociodemographic controls" line. The data in brackets in table represents the standard error of each factor in the regression result. Besides, in this table, *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 7.2 The determinants of intention to use RA based on financial and skilled behavioural variables with sociodemographic variables and behavioural variables using logit analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sociodemographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Behavioural controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Financial literacy	0.06***							0.04***
	(0.01)							(0.01)
Financial confidence		0.02***						0.01
		(0.01)						(0.01)
Perception of financial knowledge			0.04***					0.01
			(0.01)					(0.01)
Digital literacy				0.03***				0.03***
				(0.01)				(0.01)
Traditional advisor experience					0.10***			0.05**
					(0.03)			(0.03)
RA experience						0.11***		0.08***
						(0.02)		(0.02)
Numeracy							0.03***	0.01
							(0.01)	(0.01)
N	1250	1250	1250	1250	1250	1250	1250	1250
Prob > chi2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pseudo R2	0.15	0.15	0.15	0.17	0.15	0.16	0.16	0.20

Table 7.2 shows the univariate average marginal effect result based on logit regression model for the impact of financial behaviour variables on the intention to use RA. The regression result in table involves the influence of sociodemographic variables and behavioural variables, so table contains "Sociodemographic controls" line and “Behavioural controls” line. The data in brackets in table represents the standard error of each factor in the regression result. Besides, in this table, *** p<0.01, ** p<0.05, * p<0.1.

Table 7.3 Cross tabular results for the impact of financial and skilled behavioural factors on the intention to use RA by gender and financial literacy

	Male		Female	
	Low financial literacy	High financial literacy	Low financial literacy	High financial literacy
Sociodemographic factors	Yes	Yes	Yes	Yes
Behavioural factors	Yes	Yes	Yes	Yes
Financial confidence	0.0320	0.0062	0.0219	-0.0203
	(0.0201)	(0.0176)	(0.0191)	(0.0194)
Perception of financial knowledge	0.0460*	0.0063	-0.0410*	0.0010
	(0.0263)	(0.0227)	(0.0245)	(0.0219)
Digital literacy	0.0205*	0.0289***	0.0198	0.0323***
	(0.0120)	(0.0097)	(0.0129)	(0.0104)
Traditional advisor	0.1897***	0.0725*	-0.0108	0.0046
	(0.0585)	(0.0389)	(0.0548)	(0.0584)
RA	0.0732	0.0480	0.1476**	0.0083
	(0.0512)	(0.0373)	(0.0451)	(0.0467)
Numeracy skills	0.0001	0.0147	0.0345*	0.0166
	(0.0191)	(0.0181)	(0.0193)	(0.0180)
N	244	398	310	298
Prob > chi2	0.0002	0.0002	0.0000	0.0000
Pseudo R2	0.2234	0.1858	0.2868	0.2314

The table presents cross tabular analysis based on logit regression coefficients with standard errors in parentheses. Statistical significance is indicated by *** p<0.01, ** p<0.05, and * p<0.1. The sociodemographic factor and behavioural factors were included in the results of the cross tabular analysis based on the regression analysis. The dependent variable measures the intention to use RA. Columns represent subgroups stratified by gender and risk attitude. Pseudo R^2 values reflect each model's explanatory power, while the varying sample sizes (N) across subgroups account for differences distribution within the dataset.

Table 7.4 Cross tabular results for the impact of financial and skilled behavioural factors on the intention to use RA by living in urban gender and financial literacy

	(1)	(2)	(3)	(4)
	Male		Female	
	Low financial literacy	High financial literacy	Low financial literacy	High financial literacy
Sociodemographic factors	Yes	Yes	Yes	Yes
Behavioural factors	Yes	Yes	Yes	Yes
Financial confidence	0.0246	0.0024	0.0391*	-0.0104
	(0.0230)	(0.0175)	(0.0206)	(0.0198)
Perception of financial knowledge	0.0463	-0.0002	-0.0268	0.0108
	(0.0295)	(0.0241)	(0.0238)	(0.0236)
Digital literacy	0.0186	0.0268***	0.0114	0.0332***
	(0.0130)	(0.0101)	(0.0136)	(0.0110)
Traditional advisor	0.2064***	0.0602	-0.0003	0.0377
	(0.0607)	(0.0426)	(0.0594)	(0.0581)
RA	0.0802	0.0483	0.1407***	0.0028
	(0.0538)	(0.0401)	(0.0497)	(0.0504)
Numeracy skills	0.0045	0.0154	0.0263	0.0067
	(0.0506)	(0.0184)	(0.0207)	(0.0190)
N	210	357	263	268
Prob > chi2	0.0011	0.0031	0.0000	0.0001
Pseudo R2	0.2366	0.1576	0.3115	0.2312

The table presents cross tabular analysis based on logit regression coefficients with standard errors in parentheses. Statistical significance is indicated by *** p<0.01, ** p<0.05, and * p<0.1. The sociodemographic factor and behavioural factors were included in the results of the cross tabular analysis based on the regression analysis. The dependent variable measures the intention to use RA. Columns represent subgroups stratified by gender and risk attitude. Pseudo R^2 values reflect each model's explanatory power, while the varying sample sizes (N) across subgroups account for differences distribution within the dataset.

Table 7.5 Cross tabular results for the impact of financial and skilled behavioural factors on the intention to use RA by educational background and financial literacy

	(1)	(2)	(3)	(4)
	High education		Low education	
	Low financial literacy	High financial literacy	Low financial literacy	High financial literacy
Sociodemographic factors	Yes	Yes	Yes	Yes
Behavioural factors	Yes	Yes	Yes	Yes
Financial confidence	0.0092	0.0027	0.0467	-0.0684**
	(0.0160)	(0.0121)	(0.0318)	(0.0336)
Perception of financial knowledge	0.0212	0.0079	-0.0040	-0.0500
	(0.0607)	(0.0163)	(0.0346)	(0.0606)
Digital literacy	0.0209**	0.0189**	0.0206	0.1136***
	(0.0102)	(0.0082)	(0.0188)	(0.0269)
Traditional advisor	0.0545	0.0723**	0.1395*	-0.1700
	(0.0460)	(0.0330)	(0.0813)	(0.1231)
RA	0.1077***	0.0246	0.1231	0.0498
	(0.0395)	(0.0289)	(0.0810)	(0.0758)
Numeracy skills	0.0051	0.0013	0.0464	0.0829**
	(0.0151)	(0.0129)	(0.0328)	(0.0389)
N	421	594	133	102
Prob > chi2	0.0000	0.0000	0.0416	0.0513
Pseudo R2	0.2059	0.1539	0.2749	0.3322

The table presents cross tabular analysis based on logit regression coefficients with standard errors in parentheses. Statistical significance is indicated by *** p<0.01, ** p<0.05, and * p<0.1. The sociodemographic factor and behavioural factors were included in the results of the cross tabular analysis based on the regression analysis. The dependent variable measures the intention to use RA. Columns represent subgroups stratified by gender and risk attitude. Pseudo R^2 values reflect each model's explanatory power, while the varying sample sizes (N) across subgroups account for differences distribution within the dataset.

Table 7.6 Cross tabular results for the impact of financial and skilled behavioural factors on the intention to use RA by male, educational background and financial literacy

	(1)	(2)	(3)	(4)
	High education		Low education	
	Low financial literacy	High financial literacy	Low financial literacy	High financial literacy
Sociodemographic factors	Yes	Yes	Yes	Yes
Behavioural factors	Yes	Yes	Yes	Yes
Financial confidence	0.0268	0.0159		-0.0694
	(0.0214)	(0.0172)		(0.0882)
Perception of financial knowledge	0.0624**	0.0038		-0.0094
	(0.0273)	(0.0242)		(0.0561)
Digital literacy	0.0123	0.0151		0.0802***
	(0.0136)	(0.0117)		(0.0220)
Traditional advisor	0.2010***	0.0904**		-0.0409
	(0.0652)	(0.0385)		(0.0973)
RA	0.0696	0.0188		0.1936
	(0.0564)	(0.0379)		(0.1775)
Numeracy skills	-0.0148	-0.0017		0.1534***
	(0.0201)	(0.0176)		(0.0588)
N	190	331	54	67
Prob > chi2	0.0015	0.0044		0.0103
Pseudo R2	0.2253	0.1534		0.4633

The table presents cross tabular analysis based on logit regression coefficients with standard errors in parentheses. Statistical significance is indicated by *** p<0.01, ** p<0.05, and * p<0.1. The sociodemographic factor and behavioural factors were included in the results of the cross tabular analysis based on the regression analysis. The dependent variable measures the intention to use RA. Columns represent subgroups stratified by gender and risk attitude. Pseudo R^2 values reflect each model's explanatory power, while the varying sample sizes (N) across subgroups account for differences distribution within the dataset.

Note: no usable results were obtained in column 3 because this group did not contain enough samples.

Table 7.7 Cross tabular results for the impact of financial and skilled behavioural factors on the intention to use RA by female, educational background and financial literacy

	(1)	(2)	(3)	(4)
Female	High education		Low education	
	Low financial literacy	High financial literacy	Low financial literacy	High financial literacy
Sociodemographic factors	Yes	Yes	Yes	Yes
Behavioural factors	Yes	Yes	Yes	Yes
Financial confidence	0.0052	-0.0141	0.0243	
	(0.0242)	(0.0178)	(0.0343)	
Perception of financial knowledge	-0.0375	0.0115	-0.0296	
	(0.0258)	(0.0234)	(0.0520)	
Digital literacy	0.0237	0.0256**	-0.0022	
	(0.0148)	(0.0114)	(0.0227)	
Traditional advisor	-0.0725	0.0585	0.2531**	
	(0.0635)	(0.0583)	(0.0990)	
RA	0.1578***	0.0219	0.0522	
	(0.0517)	(0.0469)	(0.1034)	
Numeracy skills	0.0217	0.0097	0.0795	
	(0.0206)	(0.0181)	(0.0448)	
N	231	263	79	35
Prob > chi2	0.0000	0.0062	0.3583	
Pseudo R2	0.3100	0.1993	0.3192	

The table presents cross tabular analysis based on logit regression coefficients with standard errors in parentheses. Statistical significance is indicated by *** p<0.01, ** p<0.05, and * p<0.1. The sociodemographic factor and behavioural factors were included in the results of the cross tabular analysis based on the regression analysis. The dependent variable measures the intention to use RA. Columns represent subgroups stratified by gender and risk attitude. Pseudo R^2 values reflect each model's explanatory power, while the varying sample sizes (N) across subgroups account for differences distribution within the dataset.

Note: no usable results were obtained in column 4 because this group did not contain enough samples.

Table 7.8 Cross tabular results for the impact of financial and skilled behavioural factors on the intention to use RA by gender and digital literacy

	(1)	(2)	(3)	(4)
	Male		Female	
	Low digital literacy	High digital literacy	Low digital literacy	High digital literacy
Sociodemographic factors	Yes	Yes	Yes	Yes
Behavioural factors	Yes	Yes	Yes	Yes
Financial literacy	0.0446*	0.0141	0.0537**	0.0611***
	(0.0239)	(0.0361)	(0.0233)	(0.0229)
Financial confidence	0.0106	0.0271*	-0.0022	0.0135
	(0.0172)	(0.0154)	(0.0168)	(0.0203)
Perception of financial knowledge	0.0267	0.0604**	-0.0019	0.0019
	(0.0219)	(0.0275)	(0.0198)	(0.0284)
Traditional advisor	0.1325***	0.0638	-0.0053	0.0421
	(0.0421)	(0.0571)	(0.0476)	(0.0822)
RA	0.0790**	0.0141	0.1222***	-0.0042
	(0.0387)	(0.0534)	(0.0388)	(0.0592)
Numeracy skills	0.0156	-0.0076	0.0305*	0.0112
	(0.0167)	(0.0188)	(0.0160)	(0.0187)
N	466	176	457	151
Prob > chi2	0.0000	0.0000	0.0000	0.0003
Pseudo R2	0.1476	0.2986	0.2195	0.3945

The table presents cross tabular analysis based on logit regression coefficients with standard errors in parentheses. Statistical significance is indicated by *** p<0.01, ** p<0.05, and * p<0.1. The sociodemographic factor and behavioural factors were included in the results of the cross tabular analysis based on the regression analysis. The dependent variable measures the intention to use RA. Columns represent subgroups stratified by gender and risk attitude. Pseudo R^2 values reflect each model's explanatory power, while the varying sample sizes (N) across subgroups account for differences distribution within the dataset.

Table 7.9 Cross tabular results for the impact of financial and skilled behavioural factors on the intention to use RA by living in urban gender and digital literacy

	(1)	(2)	(3)	(4)
	Male		Female	
	Low digital literacy	High digital literacy	Low digital literacy	High digital literacy
Sociodemographic factors	Yes	Yes	Yes	Yes
Behavioural factors	Yes	Yes	Yes	Yes
Financial literacy	0.0399	0.0258	0.0459*	0.0587**
	(0.0250)	(0.0364)	(0.0254)	(0.0262)
Financial confidence	0.0044	0.0143	0.0145	0.0293
	(0.0182)	(0.0182)	(0.0184)	(0.0187)
Perception of financial knowledge	0.0176	0.0650**	-0.0032	0.0113
	(0.0235)	(0.0298)	(0.0213)	(0.0325)
Traditional advisor	0.1264***	0.0552	0.0265	0.0494
	(0.0438)	(0.0657)	(0.0509)	(0.1076)
RA	0.0826**	0.0411	0.1017**	-0.0347
	(0.0401)	(0.0559)	(0.0434)	(0.0673)
Numeracy skills	0.0220	-0.0093	0.0190	0.0003
	(0.0176)	(0.0238)	(0.0174)	(0.0197)
N	418	149	396	135
Prob > chi2	0.0001	0.0006	0.0000	0.0003
Pseudo R2	0.1363	0.2914	0.2261	0.4076

The table presents cross tabular analysis based on logit regression coefficients with standard errors in parentheses. Statistical significance is indicated by *** p<0.01, ** p<0.05, and * p<0.1. The sociodemographic factor and behavioural factors were included in the results of the cross tabular analysis based on the regression analysis. The dependent variable measures the intention to use RA. Columns represent subgroups stratified by gender and risk attitude. Pseudo R^2 values reflect each model's explanatory power, while the varying sample sizes (N) across subgroups account for differences distribution within the dataset.

Table 7.10 Cross tabular results for the impact of financial and skilled behavioural factors on the intention to use RA by educational background and digital literacy

	(1)	(2)	(3)	(4)
	High education		Low education	
	Low digital literacy	High digital literacy	Low digital literacy	High digital literacy
Sociodemographic factors	Yes	Yes	Yes	Yes
Behavioural factors	Yes	Yes	Yes	Yes
Financial literacy	0.0671***	0.0428*	-0.0049	0.1814
	(0.0177)	(0.0237)	(0.0385)	(0.1300)
Financial confidence	0.0034	0.0139	0.0084	0.0687**
	(0.0127)	(0.0117)	(0.0304)	(0.0344)
Perception of financial knowledge	0.0108	0.0418**	-0.0010	-0.1296
	(0.0152)	(0.0190)	(0.0335)	(0.0899)
Traditional advisor	0.0753**	0.0100	-0.0163	0.5468*
	(0.0342)	(0.0477)	(0.0807)	(0.3145)
RA	0.0822***	0.0441	0.1924***	-0.0413
	(0.0292)	(0.0368)	(0.0732)	(0.1001)
Numeracy skills	0.0160	-0.0215*	0.0487	0.1883*
	(0.0120)	(0.0128)	(0.0314)	(0.1050)
N	742	273	181	54
Prob > chi2	0.0000	0.0006	0.0719	0.0154
Pseudo R2	0.1640	0.2347	0.1369	0.6599

The table presents cross tabular analysis based on logit regression coefficients with standard errors in parentheses. Statistical significance is indicated by *** p<0.01, ** p<0.05, and * p<0.1. The sociodemographic factor and behavioural factors were included in the results of the cross tabular analysis based on the regression analysis. The dependent variable measures the intention to use RA. Columns represent subgroups stratified by gender and risk attitude. Pseudo R^2 values reflect each model's explanatory power, while the varying sample sizes (N) across subgroups account for differences distribution within the dataset.

Table 7.11 Cross tabular results for the impact of financial and skilled behavioural factors on the intention to use RA by male, educational background and digital literacy

	(1)	(2)	(3)	(4)
	High education		Low education	
	Low digital literacy	High digital literacy	Low digital literacy	High digital literacy
Sociodemographic factors	Yes	Yes	Yes	Yes
Behavioural factors	Yes	Yes	Yes	Yes
Financial literacy	0.0659***	0.0282	0.0080	
	(0.0241)	(0.0422)	(0.0503)	
Financial confidence	0.0169	0.0185	0.0368	
	(0.0175)	(0.0154)	(0.0443)	
Perception of financial knowledge	0.0277	0.0739**	0.0179	
	(0.0232)	(0.0329)	(0.0446)	
Traditional advisor	0.1628***	0.0272	-0.0959	
	(0.0424)	(0.0676)	(0.1087)	
RA	0.0361	0.0197	0.2363**	
	(0.0401)	(0.0555)	(0.1102)	
Numeracy skills	0.0024	-0.0264	0.0656	
	(0.0172)	(0.0208)	(0.0443)	
N	376	145	90	31
Prob > chi2	0.0001	0.0005	0.1176	
Pseudo R2	0.1505	0.3212	0.2513	

The table presents cross tabular analysis based on logit regression coefficients with standard errors in parentheses. Statistical significance is indicated by *** p<0.01, ** p<0.05, and * p<0.1. The sociodemographic factor and behavioural factors were included in the results of the cross tabular analysis based on the regression analysis. The dependent variable measures the intention to use RA. Columns represent subgroups stratified by gender and risk attitude. Pseudo R^2 values reflect each model's explanatory power, while the varying sample sizes (N) across subgroups account for differences distribution within the dataset.

Note: no usable results were obtained in column 4 because this group did not contain enough samples.

Table 7.12 Cross tabular results for the impact of financial and skilled behavioural factors on the intention to use RA by female, educational background and digital literacy

	(1)	(2)	(3)	(4)
	High education		Low education	
	Low digital literacy	High digital literacy	Low digital literacy	High digital literacy
Sociodemographic factors	Yes	Yes	Yes	Yes
Behavioural factors	Yes	Yes	Yes	Yes
Financial literacy	0.0648***	0.0392*	0.0472	
	(0.0248)	(0.0228)	(0.0546)	
Financial confidence	-0.0081	0.0115	0.0027	
	(0.0187)	(0.0181)	(0.0319)	
Perception of financial knowledge	-0.0012	0.0216	-0.0123	
	(0.0201)	(0.0243)	(0.0484)	
Traditional advisor	-0.0163	-0.0194	0.1202	
	(0.0547)	(0.1038)	(0.1093)	
RA	0.1173***	0.0415	0.0853	
	(0.0423)	(0.0677)	(0.1019)	
Numeracy skills	0.0208	-0.0072	0.0511	
	(0.0169)	(0.0228)	(0.0445)	
N	366	128	91	23
Prob > chi2	0.0000	0.0002	0.4345	
Pseudo R2	0.2303	0.3245	0.2606	

The table presents cross tabular analysis based on logit regression coefficients with standard errors in parentheses. Statistical significance is indicated by *** p<0.01, ** p<0.05, and * p<0.1. The sociodemographic factor and behavioural factors were included in the results of the cross tabular analysis based on the regression analysis. The dependent variable measures the intention to use RA. Columns represent subgroups stratified by gender and risk attitude. Pseudo R^2 values reflect each model's explanatory power, while the varying sample sizes (N) across subgroups account for differences distribution within the dataset.

Note: no usable results were obtained in column 4 because this group did not contain enough samples.

Chapter 8 Propensity score matching

8.1 Introduction to the robustness analysis using propensity score matching

After analyzing the logit and OLS regression results, this study also used propensity score matching to examine the influence of each variable on intention to use RA and to test the robustness of the main results. This chapter categorizes all independent variables into three groups and employs propensity score matching analysis using two sets of matching covariates. The analysis is conducted using one nearest-neighbor match per observation, three nearest-neighbor matches per observation, and five nearest-neighbor matches per observation. The first group, behavioral factors (Chapter 8.2), includes risk aversion, risk perception, confidence, BTAE, IOC, and trust. The second group, financial behavioral factors (Chapter 8.3), comprises financial literacy, financial confidence, and perception of financial knowledge. The third group, skilled behavioral factors (Chapter 8.4), consists of digital literacy, numeracy skills, past experience of using a traditional advisor, and past experience of using RAs.

In this chapter, I further validate the empirical findings presented in Chapters 6 and 7 through propensity score matching analysis. The latter technique first corroborates the impact of behavioral factors (risk aversion, risk perception, confidence, BTAE, IOC, and trust) on intention to use RAs, as discussed in Chapter 6. The findings indicate that both IOC and trust significantly positively influenced potential users' future intention to use RAs, whereas risk aversion and risk perception exerted significant negative impacts on that intention. In addition, through propensity score matching analysis, I discovered that besides financial literacy, digital literacy, experience of using a traditional advisor, and experience of using RAs contributing positively to the potential users' future intentions to use RAs, financial confidence, perception of financial knowledge, and numeracy skills also significantly positively affected these future intentions. The remainder of this chapter details the methodology underpinning propensity score matching and presents analysis of the matching results.

8.2 Methodology for propensity score matching

Propensity score matching (PSM) is a statistical technique commonly employed in observational studies to estimate the effect of a treatment or intervention by accounting for the covariates that predict receipt of the treatment, and it can also reduce endogeneity problems (Rosenbaum and Rubin, 1983). The first step in PSM is to estimate the propensity scores for each respondent, where the treatment variable is participation in the intervention (here, factors influencing the intention to use RAs). The propensity scores for our analysis are based on both logit models and OLS models. Mathematically, if I denoted the treatment variable as T (where $T = 1$ meaning treatment received and $T = 0$ meaning control group) and the vector of covariates as X, so the propensity score $p(X)$ can be defined as:

$$p(X) = p(T = 1|X) = \frac{1}{1 + \exp\left(-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k)\right)} \tag{8.1}$$

Once the propensity score has been estimated, respondents were matched based on their scores. The purpose of matching is to find individuals with similar propensity scores in the treatment and control groups to form a balanced sample. Our study used nearest-neighbor matching, one of PSM's most widely used methods. Its algorithm pairs each treated unit with one or more control units recording the most similar propensity scores, effectively minimizing the distance between matched pairs. For the analyses in our thesis, I performed one-to-one, one-to-three, and one-to-five matching. The propensity score represents the probability of receiving a treatment assuming a set of observed covariates. The distance is typically measured using the absolute difference in propensity scores between the treated and control units (Stuart, 2010). Matching can be performed using the following formula to calculate the distance:

$$d(i,j) = \left|e(X_i) - e(X_j)\right| \tag{8.2}$$

where i and j represent members of the treatment and control groups, respectively.

In propensity score matching analysis, it is also essential to assess the balance of covariates across treated and control groups after matching to ensure that the matching process has successfully created comparable groups (Austin, 2011). The average treatment effect on the treated (ATT) can also be estimated (Caliendo and Kopeinig, 2008). The ATT represents the average effect of a treatment on those individuals who receive the treatment, as opposed to the entire population or those who do not. It is especially relevant in studies aiming to understand the impact of a specific intervention on an outcome of interest among those who are exposed to the intervention. Mathematically, it can be expressed as:

$$ATT = E[Y_1 - Y_0 | T = 1] \tag{8.3}$$

where Y_1 is the potential outcome if the individual receives the treatment, Y_0 is the potential outcome if the individual does not receive the treatment, and $T = 1$ indicates individuals who are treated. In observational studies, treatment assignment is often non-random, leading to differences between treated and untreated groups. Estimating the

ATT allows for adjustment for these differences, providing a more accurate estimate of the treatment effect for those who have been treated (Dehejia and Wahba, 2002).

8.2.1 Description of matching covariates

In order to carry out the baseline analysis, this thesis first set age, gender, and monthly income as covariates. These are considered the key factors among the sociodemographic factors in our research, as mentioned in Chapter 5, and minimum numbers in the sample box were set for these three factors when the questionnaire was distributed. According to Cheung et al. (2023), covariates can include various aspects of sociodemographic factors, which means, in addition to age, gender, and monthly income, living area (rural or urban), marital status, financial dependents, employment status, residential status, and educational background were also set set as covariates in the process of propensity score matching. By setting more covariates, selection bias can be reduced (Rosenbaum and Rubin, 1983) and the quality of matching can be improved (Dehejia and Wahba, 1999), thus enhancing the accuracy of the results (Ho et al., 2007). Therefore, to increase the robustness and credibility of the results, I set all sociodemographic factors (age, gender, living area (rural or urban), marital status, financial dependents, employment status, monthly income, residential status, and educational background) as covariates in a separate matching analysis.

8.3 Propensity score matching analysis on the effect of behavioural factors on intention to use RA

This section presents the propensity score matching analysis on the effect of behavioral factors on the intention to use RA, which is used to validate the robustness of the results presented earlier in this thesis. This section contains two parts: firstly, a baseline analysis of the effect of behavioral factors on intention to use RA, where covariates include age, gender, and monthly income only; and, secondly, an alternative analysis, where matching covariates included all sociodemographic factors (age, gender, living area (rural or urban), employment status, financial dependents, marital status, monthly income, residential status, and educational background). All the behavioral factors (risk aversion, risk perception, BTAE, IOC, confidence, and trust) are first divided into two levels (high and low) to set the treatment group and control group (Table 8.1).

*** INSERT TABLE 8.1 HERE***

8.3.1 Baseline analysis of the effect of behavioural factors on intention to use RA

I first matched individuals with higher risk aversion, lower risk perception, stronger BTAE, higher IOC, higher confidence, or higher trust with one, three, or five corresponding nearest neighbors from their low-level counterparts (control variables). Table 8.2 presents the ATT for six behavioral factors (risk aversion, risk perception, BTAE, IOC, confidence, and trust) based on the logit regression model, using age, gender, and monthly income as covariates. The result shows that the ATTs for IOC (column 4) and trust (column 6) were positive and statistically significant with regard to intention to use RA, and risk aversion (column 1) and risk perception (column 2) had a significant negative impact on intention to use RA. These results support the accuracy of our findings presented in Table 6.1 and further substantiate that, for Chinese investors, the level of trust in RA products and their perceived risks significantly influence willingness to use RAs in the future. Specifically, according to the baseline results, respondents with a high level of risk aversion (column 1) were about 16% less likely to use RA than those with lower levels of risk aversion. A higher level of risk perception decreased respondents' intention to use RA by around 4% compared with those having a lower level of risk perception. Besides, people with higher levels of IOC had an approximately 12% higher intention to use RA than those with lower levels of IOC. Similarly, a high level of trust increased respondents' intention to use RA by around 10% compared with those holding a low level of trust. In contrast, BTAE (column 3) and confidence (column 5) did not significantly affect intention to use RA, which is in line with the results reported in Table 6.1 in Chapter 6.3.

*** INSERT TABLE 8.2 HERE ***

Besides, Appendix 8.1 shows the ATT for behavioral factors based on the OLS regression model using age, female, and monthly income as covariates. The result in Appendix 8.1 shows the same result as that presented in Table 8.2.

8.3.2 Alternative matching analysis of the effect of behavioural factors on intention to use RA

Table 8.3 shows the ATT for behavioral factors based on the logit regression using all sociodemographic factors as covariates. Compared with the previous matching result, when I considered all sociodemographic factors as covariates, risk aversion (column 1) and risk perception (column 2) showed a significant negative impact on intention to use RA, and the IOC (column 4) was positive and statistically significant with regard to intention to use RA in in all types of matches (one nearest-neighbor match per observation, three nearest-neighbor matches per observation, or five nearest-neighbor matches per observation).

*** INSERT TABLE 8.3 HERE ***

Firstly, the results show that having a lower level of risk aversion (column 1) increased the respondents' intention to use RA by 15% to 17% compared to those who had a higher level of risk aversion, and this result is statistically significant at a 1% level. This result is similar to those of some relevant research (such as Oehler et al. (2021)) and supports our tenth hypothesis (H10). This may be due to a combination of trust issues, concerns about control and security, the need for transparency and personal interaction, and the influence of negative information and social norms. This cautious approach reflects a broader pattern of behavior where safety, familiarity, and personal reassurance are prioritized.

Next, I found that risk perception (column 2) had a negative and weakly significant effect on intention to use RA when the one, three, and five matches per observation were conducted. A higher level of risk perception led to a 4% to 7% lower intention to use RA compared to those with a lower level of risk perception. The result for the risk perception here is the same as the logit regression and OLS regression results, and this finding is contrary to what has been found in other studies (such as Wu and Gao, 2021). According to Venkatesh et al.'s (2003) UTAUT model, expected effectiveness is one of the main factors influencing technology acceptance, and risk perception can be seen as an important component of expected benefits. Therefore, when individuals with high levels of risk perception seek assistance with their investments, although risk assessments can help them to better manage potential risks during the investment process, it is essential that they first acquire sufficient knowledge about RAs and develop adequate trust in these tools. Only with this degree of understanding and trust can the intention to use RAs effectively increase among individuals with higher levels of risk perception.

Regarding the IOC (column 4), our analysis has found that respondents with a higher level of IOC were more likely to use RA by around 10% to 21% compared to those with a lower level of IOC. Even though this result is contrary to our 11th hypothesis, it is still in line with our main results and some of the existing literature (such as Oehler et al. (2021)). Based on our result here, people who have a higher IOC tend to believe that they have some control over the outcome, even when using automated tools such as RA. This kind of illusion may increase their intention to use these technologies because they feel able to control the behavior of the RA and their final investment decision. Therefore, people with a high level of IOC are quite well suited to using RA for their investments.

Furthermore, trust (column 6) had a positive and significant effect on intention to use RA where three matches and five matches per observation were performed. More specifically, having a high level of trust increased respondents' intention to use RA by around 6% to 8% compared to those with a low level of trust. This is in line with previous analyses and is supported by some of the relevant literature (such as Yi et al. (2023)), thereby further supporting the fifteenth hypothesis (H15). Considering trust-related factors across a wider control group provides for a more stable and consistent assessment of impacts, possibly because as the number of matches increases, the analysis can better capture the impact of trust on intention to use RA more comprehensively across different groups of users, thereby reducing the potential for bias. Trust plays a non-negligible role in individuals' decisions to adopt and use new technologies, especially RA, which relies on complex algorithms and data processing. Trust in this regard may be crucial in the rollout and use of RAs as they involve higher levels of automation and intelligent decision-making processes, requiring potential users to trust that the RAs will provide safe and effective investment decisions meeting their expectations.

As for the BTAE factor (column 3), since it was only shown to be weakly significant in the propensity score matching analysis where one match per observation was applied, I concluded that respondents' BTAE had a relatively small effect on intention to use RA. Meanwhile, the confidence factor (column 5) in our study was not significant in all match results in the propensity score matching analysis and could not validate the twelfth hypothesis (H12) in our thesis.

Appendix 8.2 presents the ATTs for behavioral factors based on the OLS regression using all sociodemographic factors as covariates. Similar to the results presented in Table 8.3, the results for risk aversion (column 1), risk perception (column 2), IOC (column 4), and trust (column 6) all had a significant effect on intention to use RA. Besides, when I set one match per observation, confidence (column 5) also showed a positive and statistically significant effect on the intention to use RA. The ATT for BTAE and confidence showed almost no significance in any of the results, which in turn suggests that the effect of intention to use RA is mainly driven by risk aversion, risk perception, IOC, and trust.

8.4 Propensity score matching for the effect of financial behavioural factors on intention to use RA

This section showcases the propensity score matching analysis for the effect of financial behavioral factors on intention to use RA, which validates the robustness of the results presented earlier in this thesis. This section contains two parts: first, a baseline analysis of the effect of behavioral factors on intention to use RA, where covariates include age, gender, and monthly income only; and, second, an alternative analysis, where the matching covariates include all sociodemographic factors (age, gender, living area (rural or urban), employment status, financial dependents, marital status, monthly income, residential status, and educational background). All the financial behavioral factors (financial literacy, financial confidence, and perception of financial knowledge) were first divided into two levels (high and low) to set the treatment group and control group (Table 8.4).

*** INSERT TABLE 8.4 HERE ***

8.4.1 Baseline analysis of the effect of financial behavioural factors on intention to use RA

The study first matched individuals with higher financial literacy, higher financial confidence, or higher perception of financial knowledge with one, three, or five corresponding nearest neighbors from their low-level counterparts (control variables). Table 8.5 presents the ATTs for financial behavioral factors (financial literacy, financial confidence, and perception of financial knowledge) based on the logit regression model, using age, gender, and monthly income as covariates. The results show that ATTs for financial literacy (column 1), financial confidence (column 2), and perception of financial knowledge (column 3) were positive and statistically significant with respect to intention to use RA, while only the effect of financial literacy on intention to use RA was consistent with the results shown in Table7.2. Specifically, according to the baseline results, respondents who had a high level of financial literacy (column 1) were about 11% to 12% more likely to use RA than those with low levels of financial literacy. A high level of financial confidence increased respondents' intention to use RA by around 8% to 9% compared with those having a low level of financial confidence. Besides, people with a higher perception of financial knowledge had an approximately 17% higher intention to use RA than those with a lower perception of financial knowledge. These results imply that potential users' financial level could directly affect their intention to use RAs. The financial level here includes not only financial literacy but also financial confidence and the perception of financial knowledge. If potential users have a higher level of financial literacy but lack sufficient financial confidence or have a low perception of their own financial knowledge, they would be less likely to proactively try to use RAs.

*** INSERT TABLE 8.5 HERE***

Besides, Appendix 8.3 shows the ATTs for behavioral factors based on the OLS regression model using age, gender, and monthly income as covariates. The results in Appendix 8.3 are the same as theresults presented in Table 8.5.

8.4.2 Alternative matching analysis of the effect of financial behavioural factors on intention to use RA

*** INSERT TABLE 8.6 HERE***

Table 8.6 shows the ATTs for financial behavioral factors based on the logit regression using all sociodemographic factors as covariates. The results show a similar trend with the previous matching result, where financial literacy (column 1), financial confidence (column 2), and perception of financial knowledge (column 3) had a significant positive effect on respondents' intention to use RA when all sociodemographic factors were considered as covariates in the three types of matches (one nearest-neighbor match per observation, three nearest-neighbor matches per observation, and five nearest-neighbor matches per observation).

Firstly, our analysis found that respondents' level of financial literacy can positively and significantly affect their intention to use RA; that is, the higher the level of financial literacy, the higher the intention of individuals to use RA in the future. The results also show that people with a high level of financial literacy (column 1) are about 9% to 15% more inclined to use RA compared with those with a low level of financial literacy. This is in line with our main results shown in Table7.2, supporting the 19th hypothesis in this thesis and in line with the study conducted by Hastings et al. (2013). Besides, according to Woodyard and Grable (2018), financially literate investors are frequent users of RAs. In general, a higher level of financial literacy means that individuals are better equipped to understand various financial products and services, including automated investment and asset management services provided by RA, which often provides personalized investment advice based on algorithms and big data analytics, and that individuals with a high level of financial literacy are more capable of understanding and evaluating these data-driven recommendations, and thus trust and rely on such automated services. Therefore, it would be reasonable to assert that people with high levels of financial literacy could be considered preferred users of RA and could be effective catalysts for this technology's promotion.

The results show that financial confidence (column 2) had a significant positive effect on intention to use RA, which reflects a similar pattern to our main results (Table 7.2), even though the latter did not reveal a significant relationship. In the propensity score matching analysis, compared to respondents with low levels of financial confidence, individuals with high levels of financial confidence expressed a greater intention to use RA, ranging from about 6% to 9%. This finding validates the twentieth hypothesis (H20) of this thesis while echoing the study of Lusardi and Mitchell (2014). People with high levels of financial confidence usually have clear goals for their future financial planning, and using RA could help them to achieve these long-term goals, such as retirement planning and asset enhancement. Moreover, individuals with a high level of financial confidence are more likely to learn and adapt to changes in the financial market independently. They may be more willing to use tools such as RA to benefit from, and react quickly to, complex market information. Thus, a higher level of financial confidence can increase individuals' trust in their financial decisions and drive them to explore and adopt modern financial management tools more readily, including RA, meaning that individuals with high levels of financial confidence are more likely to use RA in the future.

In addition, respondents’ perceptions of financial knowledge (column 3) similarly demonstrated a significant positive impact on intention to use RA under the three matching models, further validating the relevant hypothesis (H21). People who have a higher perception of financial knowledge were about 17% to 20% more willing to use RA than those with a lower perception of financial knowledge. Therefore, our research shows that respondents' perceptions of financial knowledge, to some extent, directly influenced their acceptance of, and intention to use, financial services and, by implication, their intention to use RA; our finding coincides with Bandura's (1986) theory of self-efficacy. Meanwhile, Rosen and Sade's (2022) study also found a positive association between financial knowledge and innovative fintech, reflecting that people with relatively high financial literacy are more likely to use RA. Besides, in order to better promote RA, fintech companies may invest more resources in developing and improving algorithms to enhance the quality of services and user experience, promoting technological innovation and service upgrades across the industry. Individuals with higher perceived financial knowledge may better understand and use market information using RA, prompting the capital market to reflect information more efficiently. Meanwhile, as individuals with a high level of financial literacy awareness invest more and more frequently through RA, other individuals may be motivated to improve their financial knowledge, thus forming a positive feedback loop and promoting the popularization of financial literacy.

Appendix 8.4 presents the ATTs for financial behavior factors based on the OLS regression using all sociodemographic factors as covariates. The results presented in Appendix 9.4 are consistent with the results displayed in Table 8.6. Overall, in our study of the effect of financial behavior factors on intention to use RA using propensity score matching, we set up two groups of covariates and performed score matching based on logit regression and OLS regression, respectively. The results show that financial literacy, financial confidence, and perception of financial knowledge significantly and positively affected intention to use RA. Therefore, based on our results, the effect of intention to use RA was mainly driven by financial literacy, financial confidence, and perception of financial knowledge

8.5 Propensity score matching for the effect of skilled behavioural factors on intention to use RA

This section covers the propensity score matching analysis for the effect of skilled behavioral factors on the intention to use RA, which is used to validate the robustness of the previous results of this thesis. This section contains two parts: first, a baseline analysis of the effect of skilled behavioral factors on intention to use RA, where covariates include age, gender, and monthly income only; and, second, an alternative analysis, where matching covariates include all sociodemographic factors (age, gender, living area (rural or urban), employment status, financial dependents, marital status, monthly income, residential status, and educational background). All skilled behavioral factors (experience of using a traditional advisor, experience of using RA, digital literacy, and numeracy skills) were first divided into two different levels to set the treatment group and control group (Table 8.7).

*** INSERT TABLE 8.7 HERE***

8.5.1 Baseline analysis of the effect of skilled behavioural factors on intention to use RA

We first matched respondents with experience of using a traditional advisor and RA, high digital literacy, and high numeracy skills with one, three, or five corresponding nearest neighbors from their low-level counterparts (control variables). Table 8.8 presents the ATTs for skilled behavioral factors (experience of using a traditional advisor, experience of using RA, digital literacy, and numeracy skills) based on the logit regression model, using age, gender, and monthly income as covariates. The results show that ATTs for experience of using a traditional advisor (column 1), experience of using RA (column 2), digital literacy (column 3), and numeracy skills (column 4) were positive and statistically significant in relation to the intention to use RA, which is almost in line with our main results presented in Table 7.2. These findings imply a certain reliability in our main results and also demonstrate that past investment experiences inevitably influence potential users' future intention to use online investment technology such as RAs. In addition, the acceptance of electronic products and numeracy skills were found to be significant factors affecting future willingness to use RAs. Specifically, according to the baseline results, respondents with experience of using a traditional advisor (column 1) were about 18% to 19% more likely to use RA than those without experience of using a traditional advisor. Respondents with experience of using RA (column 2) were about 19% more likely to use RA than those without experience of using RA. A high level of digital literacy was found to increase respondents' intention to use RA by around 14% compared with those having a low level of digital literacy. Besides, respondents with stronger numeracy skills had a 16% higher intention to use RA than those with weaker numeracy skills.

*** INSERT TABLE 8.8 HERE***

Appendix 8.5 shows the ATTs for skilled behavioral factors based on the OLS regression model using age, gender, and monthly income as covariates. The result in Appendix 8.5 reveal a similar result to that presented in Table 8.8.

8.5.2 Alternative matching analysis of the effect of skilled behavioural factors on intention to use RA

*** INSERT TABLE 8.9 HERE ***

Table 8.9 shows the ATTs for skilled behavioral factors based on the logit regression using all sociodemographic factors as covariates. The results show a similar trend with the previous matching analysis, where experience of using traditional advisor (column 1), experience of using RA (column 2), digital literacy (column 3), and numeracy skills (column 4) significantly positively affected respondents' intention to use RA when all sociodemographic factors were considered as covariates in the three types of matches (one nearest-neighbor match per observation, three nearest-neighbor matches per observation, or five nearest-neighbor matches per observation).

I first analyzed the relationship between experience of using a traditional advisor and intention to use RA (column 1). The result shows that respondents with experience of using a traditional advisor were about 18% to 21% more inclined to use RA than those without experience of using a traditional advisor, meaning individuals' past experience of using a traditional advisor can motivate them to use RA in the future. After experiencing the services of a traditional advisor, individuals may be better placed to compare that type of service with different service models (e.g. RA). Such comparison may be based on cost, risk profiling, emotional factors (Bhatia et al., 2021), or other factors. On the other hand, if individuals feel limited or powerless when using a traditional advisor, they may explore RA as a platform to see whether it provides better decision-making tools. RA typically offers broader data analysis and market monitoring (Bhatia et al., 2021), which may be attractive to individuals seeking to make more granular investment decisions.

Next, experience of using RA (column 2) also showed a positive and significant effect on the intention to use RA, as respondents who had experience of using RA were 12% to 14% more inclined to use RA in the future than those without experience of using RA in the past. If an individual's experience of RA has been positive, this usually means they will trust its quality (Dabholkar and Sheng, 2012). Satisfied users are more likely to become loyal customers, continue to use RA, and even recommend it to others. Moreover, in the early stages of RA development, user feedback is invaluable to RA service providers and can be used to improve RA's products and services. If users see that their feedback is taken on board and that product improvements are realized, this will further motivate them to continue using RA and increase their loyalty to the service provider. Continued use and positive experiences can create a positive feedback loop, and as the user base increases, service providers will have more resources to improve and optimize RA to make their services more efficient and user-friendly, thus attracting more users. The significant positive effect of respondents' experience of using RA on their intention to use RA reflects that users, to some extent, transfer and apply their experience to new technologies (Roh et al., 2022), which implies that prior experience of using an advisory service and the trust built therefrom, whether it be a traditional type of service (e.g. traditional advisor) or a technology-driven service (e.g. RA), could contribute to future acceptance of new technologies (e.g. RA). This finding can further support the eighteenth hypothesis (H18).

In addition, respondents' level of digital literacy (column 3) also showed a significant positive impact on intention to use RA, when all three matching models were considered. Respondents with a higher level of digital literacy were around 12% to 13% more inclined to use RA compared with those with a low level of digital literacy. Hargittai and Hsieh's (2011) study pointed out that digital literacy is one of the key factors influencing people's acceptance and use of online technologies, meaning a high level of digital literacy encourages individuals to accept new technologies such as RA more readily and increases their intention to use products like RA. Individuals with a high level of digital literacy may thus seek more efficient and convenient financial services, and the automated investment solutions offered by RA may fit their needs better, as they may be more likely to understand and trust the mechanics of RA, compared to those with a lower level of digital literacy. Meanwhile, Van Alstyne and Parker (2012) pointed out that a high level of digital literacy is a prerequisite for users' effective engagement with these emerging services. High levels of digital literacy are likely to be linked to more comprehensive financial literacy and understanding, making these users more able to understand both the RA product itself and the rationale behind the services provided. Therefore, individuals with a higher level of digital literacy are more likely to let RA make investment decisions on their behalf because they can understand RA more easily, which is also in line with the seventeenth hypothesis (H17). When there are many digitally literate users in society, this provides a positive market environment for fintech companies, prompting them to invest in and develop new technologies that will further promote the development of RA in China. At the same time, to meet the needs of highly digitally literate users, RA service providers may be inspired to develop more customized features and services, thus promoting the development of RA and making it accessible to a broader range of Chinese investors.

Finally, our results also show a significantly positive relationship between respondents' numeracy skills and their intention to use RA. Our analysis has found that intention to use RA was about 12% to 14% higher among respondents with strong numeracy skills than those with relatively weak numeracy skills. In turn, this result supports our main results reported in Table 7.2 and the sixteenth hypothesis (H16). Individuals' numeracy skills are usually associated with higher financial literacy and more effective financial decisions (Lusardi and Mitchell, 2014). This implies that individuals with stronger numeracy skills find it easier to understand the complex financial advice and investment strategies provided by RAs and are thus more likely to adopt such services. These platforms usually provide vast data-based investment analyses and recommendations, and precisely because they can understand these analyses, recommendations, and their potential efficiencies and benefits, individuals with stronger numeracy skills are more likely to be open to such new developments in fintech and be more willing to experiment with and adopt products such as RA. Furthermore, Banks and Oldfield (2007) found that a high level of numeracy skills not only improves individuals' ability to process and understand financial information but also increases their confidence in their financial decision-making abilities. This is because they are better able to assess investment risks and returns. This confidence may drive them to prefer to use RA, which is based on complex algorithms and mathematical models. The specific needs and preferences of the those with strong numeracy skills may lead to the emergence of more segmented products and services in the financial market. In order to satisfy the needs of these users and provide more refined and personalized services, the RA platforms will have to further optimize its algorithms.

Appendix 8.6 presents the ATTs for skilled behavioral factors based on the OLS regression using all sociodemographic factors as covariates. The results presented in Appendix 8.6 are consistent with those shown in Table 8.9. Overall, in our study of the effect of skilled behavioral factors on intention to use RA using propensity score matching, I set up two groups of covariates and performed score matching based on logit regression and OLS regression, respectively. The results show that respondents' experience of using a traditional advisor and RA, digital literacy, and numeracy skills significantly and positively affected intention to use RA. Therefore, based on our results, it would be reasonable to believe that intention to use RA is mainly driven by experience of using a traditional advisor, experience of using RA, digital literacy, and numeracy skills.

8.6 Conclusion on the robustness analysis using propensity score matching

Based on the results of the propensity score matching analysis in this chapter, this study has further reinforced and supplemented the findings gleaned from the earlier logit regression and OLS analyses. The propensity score matching results for the behavioral factors group aligned with the previous analyses, indicating that higher levels of risk aversion or risk perception among potential users were associated with a relatively low likelihood of using RAs. Conversely, a higher level of IOC significantly and positively impacted upon intention to use RAs in the future. In addition, this study found that potential users with higher levels of trust were more likely to adopt RAs. In the financial behavioral factors group, financial literacy demonstrated a significant positive influence on intention to use RAs. Unlike the findings presented in Chapter 8, the propensity score matching analysis revealed that financial confidence and perception of financial knowledge also significantly and positively affected the likelihood of using RAs in the future. Lastly, for the skilled behavioral factors group, prior experience with traditional financial advisors or RAs significantly and positively influenced intention to use RAs. Moreover, respondents with higher levels of digital literacy also showed a greater intention to use RAs, which is consistent with the analysis in Chapter 8. Notably, the propensity score matching analysis revealed that potential users with higher numeracy skills were also significantly more likely to use RAs in the future.

The implications of these findings are significant, suggesting that targeted marketing and product development strategies should focus on addressing the skilled behavioral factors that influence RA adoption. Enhancing financial and digital literacy could promote greater financial inclusion by enabling a broader demographic to utilize such advanced financial tools. Moreover, leveraging users' past experiences with financial advisors and emphasizing the benefits of numeracy skills can further drive the adoption of RAs, ultimately contributing to a more informed and engaged consumer base in the financial market.

Tables for the propensity score matching analysis

Table 8.1 Description of behavioural variables for propensity score matching

Factors	Description	Objective	Mean	Std. dev	Min	Max
Risk aversion	Continuous variable. Answer the question "Are you a person that takes risks with finances?"	1250	6.72	2.18	1	10
1st Risk aversion	Low (8 - 10)	1250	0.41	0.49	0	1
2nd Risk aversion	High (0 - 7)	1250	0.59	0.49	0	1
Risk perception	Continuous variable. Sum of responses in the risk perception questions	1250	12.49	2.93	4	19
1st Risk perception	Low (4 - 13)	1250	0.39	0.49	0	1
2nd Risk perception	High (14 - 20)	1250	0.61	0.49	0	1
Better than average effect	Continuous variable. Sum of responses' self-score minus sum of responses' evaluate for public.	1250	1.27	1.89	-5	8
1st Worse than average	Low (-5 - 1)	1250	0.56	0.50	0	1
2nd Better than average	High (2 - 8)	1250	0.44	0.50	0	1
Illusion of control	Continuous variable. Sum of responses in the illusion of control questions	1250	10.38	3.80	4	19
1st Illusion of control	Low (4 - 10)	1250	0.54	0.50	0	1
2nd Illusion of control	High (11 - 20)	1250	0.47	0.50	0	1
Confidence	Continuous variable. Sum of responses in the confidence questions	1250	10.97	2.19	3	15
1st Confidence	Low (3 - 11)	1250	0.55	0.50	0	1
2nd Confidence	High (12 - 15)	1250	0.46	0.50	0	1
Trust	Continuous variable. Sum of responses in the trust questions	1250	11.37	1.50	5	15
1st Trust	Low (5 - 11)	1250	0.52	0.50	0	1
2nd Trust	High (12 - 15)	1250	0.48	0.50	0	1

This table displays the variable processing conducted on behavioral variables prior to conducting propensity score matching to assess their impact on the intention to use a RA. This study categorized each variable into groups based on their final score ranges, specifically into low level and high level categories.

Table 8.2 Average treatment effect on the treated (ATT) of behavioural variables on intention to use RA using logit regression

	(1) Risk aversion	(2) Risk perception	(3) Better than average effect	(4) Illusion of control	(5) Confidence	(6) Trust
One match per observation n(1)						
ATT	-0.16***	-0.04*	-0.02	0.12***	-0.01	0.09***
	(-6.13)	(-1.52)	(-0.53)	(4.64)	(-0.41)	(3.65)
N	1250	1250	1250	1250	1250	1250
Three matches per observation n(3)						
ATT	-0.16***	-0.04*	-0.01	0.12***	-0.01	0.10***
	(-6.23)	(-1.54)	(-0.36)	(4.50)	(-0.35)	(3.87)
N	1250	1250	1250	1250	1250	1250
Five matches per observation n(5)						
ATT	-0.16***	-0.04**	-0.01	0.12***	-0.01	0.10***
	(-6.24)	(-1.53)	(-0.52)	(4.56)	(-0.41)	(3.66)
N	1250	1250	1250	1250	1250	1250

This table shows the computation of the average treatment effect of the treated (ATET) based on the logit regression. The covariance used in this result include age, female and monthly income. This study match individuals with high level of risk aversion, risk perception, better than average, illusion of control, confidence and trust with one, three, and five corresponding (nearest neighbour) from their low-level counterparts (control group). Robust z-statistics are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

Table 8.3 Average treatment effect on the treated (ATT) of behavioural variables on intention to use RA using logit regression

	(1) Risk aversion	(2) Risk perception	(3) Better than average effect	(4) Illusion of control	(5) Confidence	(6) Trust
One match per observation n(1)						
ATT	-0.16***	-0.04*	-0.05**	0.11***	-0.01	0.03
	(-5.23)	(-1.33)	(-1.68)	(3.40)	(-0.44)	(0.95)
N	1250	1250	1250	1250	1250	1250
Three matches per observation n(3)						
ATT	-0.17***	-0.07**	-0.03	0.21***	-0.03	0.06**
	(-6.11)	(-2.28)	(-0.91)	(3.67)	(-1.05)	(2.07)
N	1250	1250	1250	1250	1250	1250
Five matches per observation n(5)						
ATT	-0.15***	-0.06**	-0.02	0.10***	-0.02	0.08***
	(-5.65)	(-2.31)	(-0.74)	(3.76)	(-0.84)	(2.77)
N	1250	1250	1250	1250	1250	1250

This table shows the computation of the average treatment effect of the treated (ATET) based on the logit regression. The covariance used in this result include all sociodemographic variables. This study match individuals with high level of risk aversion, risk perception, better than average, illusion of control, confidence and trust with one, three, and five corresponding (nearest neighbour) from their low-level counterparts (control group). Robust z-statistics are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

Table 8.4 Description of financial behavioural variables for propensity score matching

Factors	Description	Objective	Mean	Std. dev	Min	Max
Financial literacy	Continuous variables. Sum of the score in three financial literacy questions.	1250	2.36	0.83	0	3
1st Financial literacy	Low (0 - 2)	1250	0.44	0.50	0	1
2nd Financial literacy	High (3)	1250	0.56	0.50	0	1
Financial confidence	Continuous variables. Answer the question “How confident do you feel managing your money?”	1250	8.04	1.49	1	10
1st Financial confidence	Low (1 - 8)	1250	0.58	0.49	0	1
2nd Financial confidence	High (9 - 10)	1250	0.42	0.49	0	1
Perception of financial knowledge	Continuous variables. Answer the question “How would you assess your overall financial knowledge?”	1250	4.84	1.15	1	7
1st Perception of financial knowledge	Low (1 - 5)	1250	0.71	0.45	0	1
2nd Perception of financial knowledge	High (6 - 10)	1250	0.29	0.45	0	1

This table displays the variable processing conducted on financial behavioural variables prior to conducting propensity score matching to assess their impact on the intention to use a RA. This study categorized each variable into groups based on their final score ranges, specifically into low level and high level categories.

Table 8.5 Average treatment effect on the treated (ATT) of financial behavioural variables on intention to use RA using logit regression

	(1) Financial literacy	(2) Financial confidence	(3) Perception of financial knowledge
One match per observation n(1)			
ATT	0.12***	0.08***	0.17***
	(4.44)	(3.18)	(6.52)
N	1250	1250	1250
Three matches per observation n(3)			
ATT	0.12***	0.08***	0.17***
	(4.32)	(3.21)	(6.24)
N	1250	1250	1250
Five matches per observation n(5)			
ATT	0.11***	0.09***	0.17***
	(4.07)	(3.28)	(6.43)
N	1250	1250	1250

This table shows the computation of the average treatment effect of the treated (ATET) based on the logit regression. The covariance used in this result include age, female and monthly income. This study match individuals with high level of financial literacy, financial confidence and perception of financial knowledge with one, three, and five corresponding (nearest neighbour) from their low-level counterparts (control group). Robust z-statistics are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

Table 8.6 Average treatment effect on the treated (ATT) of financial behavioural variables on intention to use RA using logit regression

	(1) Financial literacy	(2) Financial confidence	(3) Perception of financial knowledge
One match per observation n(1)			
ATT	0.15***	0.09***	0.20***
	(4.30)	(2.65)	(5.48)
N	1250	1250	1250
Three matches per observation n(3)			
ATT	0.09***	0.06**	0.20***
	(2.99)	(2.14)	(6.56)
N	1250	1250	1250
Five matches per observation n(5)			
ATT	0.11***	0.07***	0.17***
	(3.56)	(2.59)	(6.33)
N	1250	1250	1250

This table shows the computation of the average treatment effect of the treated (ATET) based on the logit regression. The covariance used in this result include all sociodemographic variables. This study match individuals with high level of financial literacy, financial confidence and perception of financial knowledge with one, three, and five corresponding (nearest neighbour) from their low-level counterparts (control group). Robust z-statistics are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

Table 8.7 Description of skilled behavioural variables for propensity score matching

Factors	Description	Objective	Mean	Std. dev	Min	Max
Experience on traditional advisor	Binary dummy: 0 for No, 1 for Yes	1250	0.76	0.43	0	1
Having experience on traditional advisor	Yes (1)	1250	0.76	0.43	0	1
Do not have experience on traditional advisor	No (0)	1250	0.76	0.43	0	1
Experience on RA	Binary dummy: 0 for No, 1 for Yes	1250	0.62	0.49	0	1
Having experience on RA	Yes (1)	1250	0.629	0.49	0	1
Do not have experience on RA	No (0)	1250	0.629	0.49	0	1
Digital literacy	Continuous variable. Sum of responses in the digital literacy questions	1250	12.10	2.00	4	15
1st digital literacy	Low (1 - 13)	1250	0.74	0.44	0	1
2nd digital literacy	High (14 - 15)	1250	0.26	0.44	0	1
Numeracy	Continuous variables. Answer the question "How confidence do you feel working with numbers when you need to in everyday life?"	1250	7.72	1.51	1	10
1st digital literacy	Low (1 - 9)	1250	0.68	0.47	0	1
2nd digital literacy	High (10)	1250	0.32	0.47	0	1

This table displays the variable processing conducted on skilled behavioural variables prior to conducting propensity score matching to assess their impact on the intention to use a RA. This study categorized each variable into groups based on their final score ranges, specifically into low level and high level categories.

Table 8.8 Average treatment effect on the treated (ATT) of skill behavioural variables on intention to use RA using logit regression

	(1) Experience on traditional advisor	(2) Experience on RA	(3) Digital literacy	(4) Numeracy
One match per observation n(1)				
ATT	0.18^{***}	0.19^{***}	0.14^{***}	0.16^{***}
	(4.87)	(6.48)	(5.47)	(6.34)
N	1250	1250	1250	1250
Three matches per observation n(3)				
ATT	0.19^{***}	0.19^{***}	0.14^{***}	0.16^{***}
	(4.81)	(6.09)	(5.28)	(6.25)
N	1250	1250	1250	1250
Five matches per observation n(5)				
ATT	0.189^{***}	0.19^{***}	0.14^{***}	0.16^{***}
	(4.81)	(6.13)	(5.37)	(6.07)
N	1250	1250	1250	1250

This table shows the computation of the average treatment effect of the treated (ATET) based on the logit regression. The covariance used in this result include age, female and monthly income. This study match individuals with have experience on traditional advisor, experience on RA, high level of digital literacy and numeracy with one, three, and five corresponding (nearest neighbour) from their low-level counterparts (control group). Robust z-statistics are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

Table 8.9 Average treatment effect on the treated (ATT) of skill behavioural variables on intention to use RA using logit regression

	(1) Experience on traditional advisor	(2) Experience on RA	(3) Digital literacy	(4) Numeracy
One match per observation n(1)				
ATT	0.21***	0.12***	0.13***	0.12***
	(4.38)	(3.21)	(3.87)	(3.60)
N	1250	1250	1250	1250
Three matches per observation n(3)				
ATT	0.18***	0.13***	0.12***	0.14***
	(4.57)	(3.79)	(4.17)	(4.65)
N	1250	1250	1250	1250
Five matches per observation n(5)				
ATT	0.20***	0.14***	0.13***	0.13***
	(5.11)	(4.38)	(4.68)	(4.80)
N	1250	1250	1250	1250

This table shows the computation of the average treatment effect of the treated (ATET) based on the logit regression. The covariance used in this result include all sociodemographic variables. This study match individuals with have experience on traditional advisor, experience on RA, high level of digital literacy and numeracy with one, three, and five corresponding (nearest neighbour) from their low-level counterparts (control group). Robust z-statistics are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

Chapter 9 Conclusion

9.1 Outline

This thesis has provided an extensive analysis of the factors that motivate investors to try RA in China's rapidly growing financial market. Through a detailed investigation of how a series of factors influence respondents' intentions to use RA in the future, this research offers insights to inform the promotional strategies regarding RA in China. Given the involvement of multiple independent variables in this study, a grouped analysis of these variables was conducted, using sociodemographic factors (Chapter 5), behavioral factors (Chapter 6), and financial and skilled behavioral factors (Chapter 7). Following an online survey of 1,277 Chinese respondents, the data were curated and filtered, retaining 1,250 usable responses for subsequent analytical examination. These data underwent validity and correlation analyses, demonstrating high reliability. Subsequent logit regression analysis revealed significant influences for some factors including gender, marital status, financial dependents, monthly income, educational background, risk aversion, risk perception, IOC, trust, financial literacy, digital literacy, experience of using a traditional advisor, and experience of using RA. In addition, after addressing potential endogeneity issues in the survey data through propensity score matching, this study found that financial confidence, perception of financial knowledge, and numeracy skills also significantly impacted upon future RA usage.

9.2 Detailed summary of empirical findings

The first empirical chapter of this thesis (Chapter 5) analyzed the relationships between sociodemographic factors and respondents’ intention to use RA. I first found that males displayed a higher intention to use RA in the future than females, and that those who were married showed a greater intention to use RA in their future investments compared to those unmarried. Respondents with more financial dependents also demonstrated a higher intention to use RA. Moreover, compared to those with lower monthly incomes, individuals with higher incomes were more inclined to use RA, a trend typically influenced positively by level of educational attainment. Our findings suggest that having a stronger educational background makes an individual more likely to use RAs in the future. This trend clearly gives RA providers market positioning opportunities and ideas for strategies in marketing and product development.

We also explored the effects of socio-demographic factors on Chinese residents' intention to use RAs through cross tabular analyses. We found that there were significant differences in the decision-making mechanisms of different groups. For males, educational background was a key factor influencing willingness to use RA, especially older males aged 38-60 and married males with financial dependence showed a stronger educational effect, while males without financial dependence were more positively influenced by urban living environment. In the female group, RA intentions of young women (18-37 years) and married women are more significantly driven by marital status and monthly income, while rural women are more dependent on the increased financial inclusion that comes with employment status. Unmarried men's decisions are influenced by both education and financial dependence, while unmarried women are dominated by only a single factor of monthly income. Notably, low-education males instead reject RA the higher their income is, while highly educated males are able to transform financial pressure into a motivation to adopt RA; low-education females compensate for knowledge deficits through employment, while highly educated females are able to combine marital and income strengths to utilize the RA tool more efficiently. In addition, the interaction between marital status and financial dependence is significant, with married non-financially dependent individuals being more affected by housing stress and unmarried financially dependent individuals facing decision-making asymmetries due to gender differences. These findings reveal complex group heterogeneity between socio-demographic characteristics and fintech adoption behavior.

From a behavioral factors perspective (Chapter 6), individuals with a lower level of risk aversion were more likely to use RA in the future, possibly due to their current ‘wait-and-see’ attitude towards the development of RAs in China. By integrating adaptive risk assessment tools and personalized investment strategies, RA providers could attract a broader range of investment styles and preferences, thereby enhancing user satisfaction and adoption rates, and even securing customers with higher levels of risk aversion. A higher level of IOC, typically associated with overconfidence, showed a correlation with a higher intention to use RA compared to individuals with lower levels of IOC. Similarly, groups with higher levels of trust also showed a higher intention to use RA.

We also revealed the differential influence of behavioral factors on the willingness to use RAs in different groups through cross tabular analyses. Risk averse males' perception of risk significantly reduced their willingness to use RA, but the illusion of control (i.e., overestimation of one's control over decision making) boosted their propensity to use it; their confidence level more influenced males who are risk neutral, whereas risk-seeking men's decision making was driven by both risk perception (negatively) and trustworthiness (positively). In the female group, the level of the illusion of control significantly enhanced their RA use propensity regardless of risk preference, with risk-neutral females also positively influenced by trust level, while risk-seeking females reduced their use propensity due to both high level of risk perception and confidence. The moderating effect of educational background is significant: among the highly educated, risk perception generally inhibits RA use, but the illusion of control and trust can effectively offset this negative effect; the low-education group relies more on psychological comfort factors (e.g., control illusion) and interpersonal trust for decision-making due to insufficient financial literacy, but overconfidence reduces their willingness to use instead. The analysis of urban-rural differences shows that urban residents' behavioural patterns are consistent with the overall sample. In contrast, the cross tabular analysis between education and gender further indicates that the decision-making of highly educated men is influenced by risk framing and psychological bias. At the same time, highly educated women rely more on trust and control. Low-educated women show stronger exclusionary tendencies due to the "double disadvantage" of low financial literacy overlaid with gender risk sensitivity. These findings reveal complex group heterogeneity in the relationship between behavioral factors and RA adoption decisions, with significant divergences, particularly in the interaction of risk preference, gender, and educational background.

Lastly, from the perspective of financial and skilled behavioral factors (Chapter 7), our analysis has underscored that financial literacy significantly influences individuals' decisions to try to use RA. Our analysis indicates that individuals with a clear understanding of financial products and greater financial confidence in managing their financial affairs were significantly more willing to choose RA in the future, highlighting the need for educational initiatives to enhance the national financial literacy rate, potentially increasing the market penetration of RA services. In addition, higher levels of digital literacy and numeracy skills positively influenced potential users' future intention to use RA. Our study also provided evidence that past experiences with traditional advisors or RA prompted investors to use RAs in the future.

We also reveal the differential impact of financial literacy and digital literacy on the intention to use RA through cross-tabulation analysis. We found that the male group with low financial literacy relies more on the subjective perception of financial knowledge, digital literacy, and experience with traditional advisors to make decisions, whereas the high financial literacy men are driven only by digital literacy and experience with traditional advisors. In the female group, low financial literacy reduces the willingness to use RA if they have a high perception of their own knowledge, but practical experience and numeracy significantly increase their propensity to adopt it, while high financial literacy women are more concerned with the operational utility of digital literacy. Rural-urban differences show that urban low-financial literacy males are only influenced by traditional advisor experience, while high-financial literacy urban males rely more on digital literacy; urban females show an “experience-dependent” decision-making pattern, with low-financial literacy being positively influenced by financial confidence and experience in RA use, while high-financial literacy is completely dominated by digital literacy. The moderating effect of educational background is significant: the highly educated group is generally positively influenced by digital literacy, with the low financial literate also relying on RA experience, while the high financial literate migrate traditional advisor perceptions to the new technology assessment; in the low-education group, the traditional advisor experience positively affects the low-literate, while the high-literate inhibit RA use due to overconfidence, but digital literacy and numeracy effectively compensate for educational deficits. Segmentation analysis of digital literacy further suggests that low-digital literate men rely on financial literacy and traditional experience, while women need to overlay computational ability; high digital literate males are prone to overestimation of knowledge due to technological proficiency, while women maintain a pragmatic approach focusing only on actual financial competence. These findings reveal a complex substitution and complementary relationship between the competency elements (financial literacy, digital literacy, education level) and the experience elements (traditional/RA usage experience) in financial decision-making, with significantly differentiated decision-making paths, especially in the gender dimension.

9.3 Limitations and implications

This study contributes empirical evidence to the development of RAs in China by revealing how behavioural, sociodemographic, financial, and skill literacy factors shape users' intentions to adopt such technologies. The findings carry significant policy implications for investment advisory firms, regulatory bodies, and the broader fintech sector.

From a practical standpoint, investment advisory firms can use these findings to optimise user onboarding processes and tailor financial education according to user segmentation. For instance, firms may integrate basic financial literacy modules into RA platforms or adopt interactive, visual-based interfaces to lower cognitive entry barriers, especially for users with low financial literacy or educational attainment. Furthermore, our findings highlight the importance of trust and digital literacy, implying that RA platforms should improve algorithmic transparency, clearly communicate risk management protocols, and explicitly explain how user data are collected and used to build user confidence.

On the regulatory side, the government should adopt differentiated financial inclusion policies based on the demographic disparities revealed in our study. For example, digital finance awareness campaigns could be launched in rural areas via village information kiosks or WeChat mini-programmes. For low-education or elderly users, simplified RA interfaces and voice-guided systems could be promoted to enhance accessibility and usability. We also recommend continued policy support to standardise

RA operations and enhance regulatory oversight, ensuring the RA industry develops within a safe and transparent framework.

Despite covering a comprehensive range of variables and generating valuable findings, several methodological limitations should be acknowledged. First, data were collected during the late stages of the COVID-19 pandemic, when societal conditions had not yet normalised. This likely led to more conservative investment behaviours, potentially underestimating RA acceptance under typical market conditions. Second, while the sample size (1,250 respondents) is reasonably robust, the use of online surveys may have skewed responses toward digitally literate populations, possibly inflating the effect of digital literacy on RA intention.

Additionally, the study did not control for certain confounding factors, such as regional economic development levels or prior usage of financial products, which could bias the model estimates. Given the cross-sectional nature of the data, our findings are limited to correlation rather than causality. Moreover, self-reported data may suffer from social desirability bias, with some respondents likely over- or underestimating their actual willingness or financial capabilities.

Future studies could address these issues by employing longitudinal panel data to track changes in the intention to use RA over time. Incorporating qualitative interviews would also help explore the psychological and cognitive barriers experienced by specific groups (e.g., elderly females or rural youth). Finally, cross-country comparative studies could enrich the theoretical and practical understanding of RA adoption across different cultural and institutional environment.

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Appendix

Appendix 4 Questionnaire

Appendix 4.1 Consent form

Title of the Project: Intentions to adopt Robo investment advisors

Please initial box

1. I understand that my participation is voluntary and that I am free to withdraw from the project at any time without giving any reason and without penalty. I understand that any data collected up to the point of my withdrawal will be destroyed and cannot be withdrawn because it cannot be identified.
2. I understand that the available data provided will be securely stored and accessible only to the members of the research team directly involved in the project, and that confidentiality will be maintained.
3. I understand that the data from my anonymously answered questionnaire will be used in the study "Intentions to adopt Robo investment advisors"
4. I understand that the data collected about me will be used to support other research in the future and may be shared anonymously with other researchers.
5. I agree to take part in the above study.

The consent form was placed before the questionnaire to ensure that respondents answered the questionnaire voluntarily and that they understood that the data would be stored securely and that no personal information would be disclosed. It was also ensured that the respondent understood the purpose of the study and reconfirmed their consent to participate in the questionnaire.

Appendix 4.2 Questionnaire – Part 1 sociodemographic factors

Section 1: About you:

1. Please tell us your age ________

2. What is your gender?
   ☐1 Male
   ☐2 Female

3. Where are you living?
   ☐1 North Region (Beijing City, Tianjin City, Hebei Province, Shanxi Province)
   ☐2 Northeast Region (Heilongjiang Province, Jilin Province, Liaoning Province, Inner Mongolia Autonomous Region)
   ☐3 East Region (Shanghai City, Jiangsu Province, Zhejiang Province, Anhui Province, Fujian Province, Jiangxi Province, Shandong Province)
   ☐4 South Central Region (Henan Province, Hubei Province, Hunan Province, Guangdong Province, Guangxi Zhuang Autonomous Region, Hainan Province)
   ☐5 Southwest region (Chongqing City, Sichuan Province, Guizhou Province, Yunnan Province, Tibet Autonomous Region)
   ☐6 Northwest region (Shaanxi Province, Gansu Province, Qinghai Province, Ningxia Hui Autonomous Region, Xinjiang Uygur Autonomous Region)

4. Would you say you live in a rural or an urban area?
   ☐1 Rural
   ☐2 Urban

5. What is your marital status?
   ☐1 Single
   ☐2 Married
   ☐3 Divorce
   ☐4 Living with partner

6. How many financial dependents in your home (such as: children, friends, spouses, parents)
   ☐1 0
   ☐2 1
   ☐3 2
   ☐4 3 or more
   ☐5 Prefer not to say

7. What is your employment status?
   ☐1 Employed (full time)

☐2 Employed (part time)
☐3 Self employed
☐4 Unemployed
☐5 Student
☐6 Homemaker
☐7 Retired

8. What is your monthly income?
☐1 Below ¥5,000
☐2 ¥5,001 –¥10,000
☐3 ¥10,001 - ¥15,000
☐4 ¥15,001 – ¥20,000
☐5 Above ¥20,001
☐6 Prefer not to say

9. What is your residential status?
☐1 Homeowner without mortgage
☐2 Homeowner with mortgage
☐3 Private renting
☐4 Social renting
☐5 Living with parents/ friends/ relatives (no rent to pay)
☐6 Living with others and need to pay the rent together
☐7 Prefer not to say

10. What is your educational background?
☐1 High school or below
☐2 College (associate's degree; vocational or trade school after high school)
☐3 Undergraduate
☐4 Postgraduate
☐5 PhD or above

This section is the first part of the questionnaire for this study, the sociodemographic questions, and contains a total of 10 questions.

Appendix 4.3 Questionnaire – Part 2 behavioural factors, financial and skilled behaviour factor

Section 2: Insight questions

In this section we are interested in learning more about you generally, in particular about your choice or preference behaviours and about financial matters.

For the two questions (Question 11 and 13) in the table below, choose any one from 1 to 10.
→ **1 is very unwilling or very unconfident, 10 is very willing or very confident**.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
11. Are you a person that takes risks with finances?	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8	☐9	☐10
12. How confidence do you feel working with numbers when you need to in everyday life?	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8	☐9	☐10
13. How confident do you feel managing your money?	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8	☐9	☐10
13-1. How confident do you think the public is in being able to manage their money?	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8	☐9	☐10

14. Suppose you have ¥100 in a saving account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?
    - ☐1 More than ¥102
    - ☐2 Exactly ¥102
    - ☐3 Less than ¥102
    - ☐4 Do not know
    - ☐5 Refuse to answer

15. Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?
    - ☐1 More than today
    - ☐2 Exactly the same
    - ☐3 Less than today
    - ☐4 Do not know
    - ☐5 Refuse to answer

16. Please tell me whether this statement is true or false. 'Buying a single company's stock usually provides a safer return than a stock mutual fund'
    - ☐1 True
    - ☐2 False
    - ☐3 Do not know
    - ☐4 Refuse to answer

Please answer the following two questions in relation to how you think you answered the three questions (14 to 16) above.

17. How many points do you think you scored in the previous four questions (Question 14 to 16)? (1 mark for a correct answer to questions 14 to 16)
    _______(0 to 3)

18. How many marks do you think other people could have gained for their answers to the previous three questions (Question 14 to 16)? (1 mark for a correct answer to questions 14 to 16, please write what you think is the average score for the general public)
    ________(0 to 3)

For the question (Question 19) in the table below, choose any one from 1 to 7.
→ **From 1 to 7 means you are becoming more confident in your financial knowledge**

	1	2	3	4	5	6	7
19. How would you assess your overall financial knowledge?	☐1	☐2	☐3	☐4	☐5	☐6	☐7

For the questions (Question 20 to 36) in the table below, choose any one from strongly disagree to strongly agree.

	Strongly disagree	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
20. Prayer helps me win when have to play gambling games	☐1	☐2	☐3	☐4	☐5
21. When having to play gambling games, specific numbers and colours can help increase my chances of winning	☐1	☐2	☐3	☐4	☐5
22. When have to play a gambling game, I collect specific items that help increase my chances of winning before start	☐1	☐2	☐3	☐4	☐5
23. When having to play gambling games, I have specific rituals and behaviours to	☐1	☐2	☐3	☐4	☐5

increase my chances of winning					
24. There will be more accidents and catastrophes in the future than we had in the past	☐1	☐2	☐3	☐4	☐5
25. Nowadays, things seem to be getting more and more out of control.	☐1	☐2	☐3	☐4	☐5
26. A person can never have too much insurance to protect against the inevitable disasters in life.	☐1	☐2	☐3	☐4	☐5
27. In general, one can trust people	☐1	☐2	☐3	☐4	☐5
28. These days you cannot rely anybody else	☐1	☐2	☐3	☐4	☐5
29. When dealing with strangers, it is better to be careful before you trust them.	☐1	☐2	☐3	☐4	☐5
30. I do not trust that my credit card number will be secure	☐1	☐2	☐3	☐4	☐5
31. It is difficult for me to judge quality of a product/service	☐1	☐2	☐3	☐4	☐5
32. I do not trust that my personal information will be kept private	☐1	☐2	☐3	☐4	☐5
33. It is faster/ easier to purchase locally	☐1	☐2	☐3	☐4	☐5
34. I am curious about new things	☐1	☐2	☐3	☐4	☐5
35. I usually take the lead in trying new technologies compare to people around me	☐1	☐2	☐3	☐4	☐5
36. I think it is very interesting to try out the new technology	☐1	☐2	☐3	☐4	☐5

37. Have you consulted a personal financial advisor (including via phone or internet) at a bank or saving bank or a financial advisor on fee basis during the last two years?
    ☐1 Yes
    ☐2 No

38. Have you used a RA during the last two years?
    ☐1 Yes
    ☐2 No

This section is the second part of the questionnaire for this thesis, including the questions related the behavioural factors and financial factors, and contains a total of 10 questions.

Appendix 4.4 Introduction to RA in questionnaire

We are interested in the intention to adopt RA investment services. RAs are algorithm-driven digital platforms that provide investment management services with no human intervention. RA clients are assessed for their finances, investment goals and their willingness to take risks and the RA then selects from a choice of tailored investment portfolios based on the client's financial profile. RAs can be thought of as automated portfolio managers.

The description in Appendix I is used in front of the Intention question in the questionnaire. As the respondents may not have heard or known about RA, asking the Intention question would cause unnecessary confusion to the respondents and could lead to errors in the analysis of the experiment. Therefore, I have designed this short description to be of a moderate length that will not cause the reader to lose patience. In order to make it more accessible, I have avoided proper nouns as much as possible and have introduced the basic concepts and working principles of RA in a more accessible way.

Appendix 4.5 Questionnaire – Part 3 Dependent variables

For the questions (Question 39 to 42) in the table below, choose any one from strongly disagree to strongly agree.

	Strongly disagree	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
39. I intend to use RA in the future.	☐1	☐2	☐3	☐4	☐5
40. I predict I would use the RA in the future.	☐1	☐2	☐3	☐4	☐5
41. I will use RA in the future.	☐1	☐2	☐3	☐4	☐5
42. I prefer to use the investment method I am familiar with rather than RA	☐1	☐2	☐3	☐4	☐5

Thank you for completing this questionnaire in full.
Thank you for your support and cooperation!

This is the final part of the questionnaire for this study. Once respondents had read the introduction to RA in the previous section, the likelihood that respondents might use RA in the future was measured by asking four questions related to their intention to use it in the future.

Appendix 4.6 Pilot feedback questions 1

1. Do you find this survey to be engaging?
2. How long did it take you to complete this questionnaire?
3. Do you think that the questions in the questionnaire are logical?
4. Are there any parts of the questionnaire that make it difficult for you to understand the meaning of the question in any way?
5. Are there any parts of the questionnaire that make it difficult for you to remember the questions in any way?
6. Are there any parts of the questionnaire that make it difficult for you to understand the meaning of particular words or concepts in the question?
7. Do you have any further comments or questions about this questionnaire?

The questions in this section were used to gather some feedback on content, description and logic, as well as approximate elapsed time. I used it for the first pilot of the questionnaire and translated them for the third pilot.

Appendix 4.7 Pilot feedback questions 2

1.	Are there any descriptions in the questionnaire that are unclear?
2.	Are there any descriptions in the questionnaire that are confusing?
3.	Are there any parts of the questionnaire that do not correspond to everyday usage?
4.	Were there any problems with wording found in the answers?
5.	Were there any spelling errors found in the responses?

The questions in Appendix III were used in the second pilot, and its Chinese translation was used in the fourth pilot.

Appendix 5 Sociodemographic factors

Appendix 5.1 The determinations of RA's usage intention based on sociodemographic variables using ordinary least squares

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Age	0.00 (0.06)									-0.04 (0.06)
Female		-0.21 (0.13)								-0.21* (0.13)
Urban			0.18 (0.20)							-0.04 (0.20)
Married				0.61*** (0.16)						0.35* (0.19)
Financial dependent					0.25*** (0.07)					0.19*** (0.07)
Employed						0.73*** (0.18)				0.30 (0.18)
Monthly income							0.28*** (0.05)			0.17*** (0.05)
Homeowner without mortgage								0.24* (0.13)		0.09 (0.14)
Educational background									0.58*** 0.09	0.41*** (0.10)
N	1250	1250	1250	1250	1250	1250	1250	1250	1250	1250
Prob > F	0.97	0.10	0.37	0.00	0.00	0.00	0.00	0.06	0.00	0.00
R-squared	0.00	0.00	0.00	0.01	0.01	0.01	0.03	0.00	0.03	0.06

Appendix 5.1 shows the univariate analysis results of this thesis using ordinary least squares to study the influence of sociodemographic variables on the intention to use RA. The data in brackets in table represents the standard error of each factor in the regression result.
Besides, in this table, *** p<0.01, ** p<0.05, * p<0.1.

Appendix 6 Behavioural factors

Appendix 6.1 The determinations of RA's usage intention based on behavioural variables using ordinary least squares

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sociodemographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Risk aversion	0.25^{***} (0.03)						0.23^{***} (0.03)
Risk perception		-0.12^{***} (0.02)					-0.14^{***} (0.02)
Better than average			-0.01 (0.147)				-0.01 (0.13)
Illusion of control				0.07^{***} (0.02)			0.06^{***} (0.012)
Confidence					0.02 (0.02)		0.04 (0.03)
Trust						0.15^{***} (0.04)	0.19^{***} (0.04)
N	1250	1250	1250	1250	1250	1250	1250
Prob > F	0.00	0.00	0.00	0.00	0.00	0.00	0.00
R-squared	0.12	0.08	0.06	0.08	0.06	0.07	0.16

Appendix 6.1 shows the univariate analysis results of this thesis using ordinary least squares to study the influence of behavioural variables on the intention to use RA. The regression result in table involves the influence of sociodemographic variables, so table contains "Sociodemographic controls" line. The data in brackets in table represents the standard error of each factor in the regression result.

Besides, in this table, *** p<0.01, ** p<0.05, * p<0.1.

Appendix 7 Financial and skilled behaviour factors

Appendix 7.1 The determinants of intention to use RA based on financial and skilled behaviour variables with sociodemographic variables using ordinary least squares (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sociodemographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Financial literacy	0.35***							0.26***
	(0.08)							(0.07)
Financial confidence		0.22***						0.04
		(0.04)						(0.05)
Perception of financial knowledge			0.39***					0.07
			(0.06)					(0.06)
Digital literacy				0.37***				0.27***
				(0.03)				(0.03)
Traditional advisor experience					1.19***			0.66***
					(0.15)			(0.15)
RA experience						0.91***		0.50***
						(0.13)		(0.13)
Numeracy							0.33***	0.12**
							(0.04)	(0.05)
N	1250	1250	1250	1250	1250	1250	1250	1250
Prob > F	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
R-squared	0.08	0.08	0.10	0.16	0.11	0.10	0.11	0.21

Appendix 7.1 shows the univariate analysis results of this thesis using ordinary least squares to study the influence of financial and skilled behaviour variables on the intention of using RA. The regression result in table involves the influence of sociodemographic variables only, so table contains "Sociodemographic controls" line. The data in brackets in table represents the standard error of each factor in the regression result.
Besides, in this table, *** p<0.01, ** p<0.05, * p<0.1.

Appendix 7.2 The determinants of intention to use RA based on financial and skilled behaviour variables with sociodemographic variables and behavioural variables using ordinary least squares (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sociodemographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Behavioural controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Financial literacy	0.33^{***}							0.27^{***}
	(0.08)							(0.07)
Financial confidence		0.14^{***}						0.07
		(0.05)						(0.05)
Perception of financial knowledge			0.17^{***}					-0.01
			(0.06)					(0.06)
Digital literacy				0.28^{***}				0.24^{***}
				(0.03)				(0.03)
Traditional advisor experience					0.86^{***}			0.58^{***}
					(0.15)			(0.15)
RA experience						0.65^{***}		0.42^{***}
						(0.13)		(0.13)
Numeracy							0.18^{***}	0.06
							(0.05)	(0.05)
N	1250	1250	1250	1250	1250	1250	1250	1250
Prob > F	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
R-squared	0.17	0.17	0.16	0.21	0.18	0.18	0.17	0.24

Appendix 7.2 shows the univariate analysis results of this thesis using ordinary least squares to study the influence of financial variables on the intention to use RA. The regression result in table involves the influence of sociodemographic variables and behaviour variables, so table contains "Sociodemographic controls" line and “behavioural” control” line. The data in brackets in table represents the standard error of each factor in the regression result. Besides, in this table, *** p<0.01, ** p<0.05, * p<0.1.

Appendix 8 Average treatment effect on the treated using ordinary least squares

Appendix 8.1 Average treatment effect on the treated (ATT) of behavioural variables on intention to use RA using ordinary least squares (OLS)

	(1) Risk aversion	(2) Risk perception	(3) Better than average effect	(4) Illusion of control	(5) Confidence	(6) Trust
One match per observation n(1)						
ATT	-0.76***	-0.37***	-0.02	0.44***	0.10	0.58***
	(-5.45)	(-2.64)	(-0.12)	(3.30)	(0.69)	(4.34)
N	1250	1250	1250	1250	1250	1250
Three matches per observation n(3)						
ATT	-0.15***	-0.35**	0.02	0.43***	0.10	0.62***
	(-5.20)	(-2.43)	(0.15)	(3.12)	(0.69)	(4.47)
N	1250	1250	1250	1250	1250	1250
Five matches per observation n(5)						
ATT	-0.73***	-0.35***	0.04	0.47***	0.11	0.62***
	(-5.10)	(-2.47)	(0.30)	(3.36)	(0.77)	(4.45)
N	1250	1250	1250	1250	1250	1250

This table shows the computation of the average treatment effect of the treated (ATET) based on the ordinary least squares regression. The covariance used in this result include age, female and monthly income. I match individuals with high level of risk aversion, risk perception, better than average, illusion of control, confidence and trust with one, three, and five corresponding (nearest neighbour) from their low-level counterparts (control group). Robust z-statistics are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

Appendix 8.2 Average treatment effect on the treated (ATT) of behavioural variables on intention to use RA using ordinary least squares (OLS)

	(1) Risk aversion	(2) Risk perception	(3) Better than average effect	(4) Illusion of control	(5) Confidence	(6) Trust
One match per observation n(1)						
ATT	-0.89***	-0.50***	-0.10	0.34**	0.23*	0.31**
	(-5.32)	(-2.83)	(-0.54)	(1.94)	(1.31)	(1.80)
N	1250	1250	1250	1250	1250	1250
Three matches per observation n(3)						
ATT	-0.93***	-0.47**	-0.01	0.40***	0.09	0.44***
	(-6.23)	(-2.99)	(-0.08)	(2.61)	(0.57)	(2.91)
N	1250	1250	1250	1250	1250	1250
Five matches per observation n(5)						
ATT	-0.82***	-0.44**	-0.00	0.36***	0.13	0.47***
	(-5.63)	(-2.97)	(-0.01)	(2.46)	(0.88)	(3.24)
N	1250	1250	1250	1250	1250	1250

This table shows the computation of the average treatment effect of the treated (ATET) based on the ordinary least squares regression. The covariance used in this result include all sociodemographic variables. I match individuals with high level of risk aversion, risk perception, better than average, illusion of control, confidence and trust with one, three, and five corresponding (nearest neighbour) from their low-level counterparts (control group). Robust z-statistics are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

Appendix 8.3 Average treatment effect on the treated (ATT) of financial behaviour variables on intention to use RA using ordinary least squares (OLS)

	(1) Financial literacy	(2) Financial confidence	(3) Perception of financial knowledge
One match per observation n(1)			
ATT	0.77***	0.51***	0.95***
	(5.45)	(3.74)	(6.41)
N	1250	1250	1250
Three matches per observation n(3)			
ATT	0.79***	0.49***	0.95***
	(5.42)	(3.49)	(6.29)
N	1250	1250	1250
Five matches per observation n(5)			
ATT	0.76***	0.64***	1.01***
	(5.16)	(3.82)	(6.60)
N	1250	1250	1250

This table shows the computation of the average treatment effect of the treated (ATET) based on the ordinary least squares regression. The covariance used in this result include age, female and monthly income. I match individuals with high level of financial literacy, financial confidence and perception of financial knowledge with one, three, and five corresponding (nearest neighbour) from their low-level counterparts (control group). Robust z-statistics are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

Appendix 8.4 Average treatment effect on the treated (ATT) of financial behaviour variables on intention to use RA using ordinary least squares (OLS)

	(1) Financial literacy	(2) Financial confidence	(3) Perception of financial knowledge
One match per observation n(1)			
ATT	0.93^{***}	0.52^{***}	0.89^{***}
	(4.96)	(2.89)	(4.58)
N	1250	1250	1250
Three matches per observation n(3)			
ATT	0.70^{***}	0.46^{***}	0.94^{***}
	(4.32)	(2.96)	(5.68)
N	1250	1250	1250
Five matches per observation n(5)			
ATT	0.78^{***}	0.43^{***}	0.93^{***}
	(5.06)	(2.94)	(5.98)
N	1250	1250	1250

This table shows the computation of the average treatment effect of the treated (ATET) based on the ordinary least squares regression. The covariance used in this result include all sociodemographic variables. I match individuals with high level of financial literacy, financial confidence and perception of financial knowledge with one, three, and five corresponding (nearest neighbour) from their low-level counterparts (control group). Robust z-statistics are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

Appendix 8.5 Average treatment effect on the treated (ATT) of skill behaviour variables on intention to use RA using ordinary least squares (OLS)

	(1) Experience on traditional advisor	(2) Experience on RA	(3) Digital literacy	(4) Numeracy
One match per observation n(1)				
ATT	1.24***	1.04***	1.04***	0.94***
	(6.26)	(6.82)	(7.38)	(6.54)
N	1250	1250	1250	1250
Three matches per observation n(3)				
ATT	1.31***	1.07***	1.01***	0.94***
	(6.33)	(6.71)	(7.09)	(6.43)
N	1250	1250	1250	1250
Five matches per observation n(5)				
ATT	1.28***	1.02***	1.01***	0.93***
	(6.39)	(6.47)	(7.05)	(6.30)
N	1250	1250	1250	1250

This table shows the computation of the average treatment effect of the treated (ATET) based on the ordinary least squares regression. The covariance used in this result include age, female and monthly income. I match individuals with have experience on traditional advisor, experience on RA, high level of digital literacy and numeracy with one, three, and five corresponding (nearest neighbour) from their low-level counterparts (control group). Robust z-statistics are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

Appendix 8.6 Average treatment effect on the treated (ATT) of skill behaviour variables on intention to use RA using ordinary least squares (OLS)

	(1) Experience on traditional advisor	(2) Experience on RA	(3) Digital literacy	(4) Numeracy
One match per observation n(1)				
ATT	1.09***	0.81***	0.97***	0.79***
	(4.39)	(4.07)	(5.36)	(4.37)
N	1250	1250	1250	1250
Three matches per observation n(3)				
ATT	1.07***	0.81***	1.07***	0.79***
	(5.16)	(4.71)	(6.59)	(4.83)
N	1250	1250	1250	1250
Five matches per observation n(5)				
ATT	1.16***	0.79***	1.09***	0.79***
	(5.78)	(4.93)	(7.11)	(5.07)
N	1250	1250	1250	1250

This table shows the computation of the average treatment effect of the treated (ATET) based on the ordinary least squares regression. The covariance used in this result include all sociodemographic variables. I match individuals with have experience on traditional advisor, experience on RA, high level of digital literacy and numeracy with one, three, and five corresponding (nearest neighbour) from their low-level counterparts (control group). Robust z-statistics are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.