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The roles of financial capability and social influence in the uptake of robo-advisors: A latent profile approach

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ABSTRACT

Many individuals perceive investing as complex, but cannot access personalized investment advice. Robo-advisors offer cost-effective, automated financial advice with the potential to democratize investing for particularly underserved groups. However, global adoption remains low, hindered by barriers related to financial literacy, trust, and technology acceptance. This study investigates whether robo-advice serves as a substitute for financial capability, a multidimensional construct encompassing knowledge, behavior, and self-efficacy, thereby broadening access to investing. Using a nationally representative survey of 983 New Zealanders aged 18–83, we employ latent profile analysis to identify six distinct segments of robo-advisor adoption mindsets based on openness to new technology, financial capability, and financial product experience. Our findings suggest that greater financial capability supports the adoption of robo-advice, rather than robo-advice serving as a substitute for low financial capability. However, social influence, especially from traditional media, reviews, and social media, is significantly associated with psychological comfort and with greater consideration of robo-advice, especially among financially vulnerable groups. These insights highlight actionable opportunities for financial institutions to expand adoption and ultimately foster financial inclusion by leveraging social media influence.

1. Introduction

The rapid expansion of financial technology has transformed how individuals access, evaluate, and engage with financial services. Among these innovations, robo-advice has emerged as a prominent application of artificial intelligence in personal finance, offering automated, low-cost, high-quality, individualized investment advice (Sironi, 2016; Baker and Dellaert, 2017). These tools are widely promoted as a means of expanding access to financial advice by reducing cost, complexity, and reliance on human intermediaries. Empirical research indicates that robo-advisors can enhance portfolio diversification, mitigate behavioral biases, and improve investment outcomes (Bianchi and Briere, 2020; D'Acunto et al., 2019). Despite these potential benefits, real-world uptake of robo-advisors remains limited. Even in highly developed financial markets, adoption rates lag behind expectations: As of 2022, robo-advisors manage less than 2.5% of U.S. retail funds under management (Morningstar, 2023). This raises important questions about how consumers evaluate and engage with automated financial advice.

Existing research has identified numerous factors associated with robo-advisor adoption, including trust, technological readiness, financial knowledge, and demographic characteristics (Phoon and Koh, 2017; Belanche et al., 2019; Bhatia et al., 2020; Brenner and Meyll, 2020; Figà-Talamanca et al., 2022). However, this literature has produced mixed and sometimes contradictory findings, particularly regarding the role of financial knowledge and experience. Some studies find that lower financial literacy increases adoption, suggesting robo-advisors act as a substitute for expertise (Brenner and Meyll, 2020), while others show that higher financial literacy is associated with greater interest in robo-advisors and higher propensity to follow robo-advice (Alemanni et al., 2020; Caratelli et al., 2019). This inconsistency highlights an important empirical puzzle. More broadly, much of the existing work implicitly assumes that consumer investors respond to robo-advisors in relatively uniform ways, estimating average effects across heterogeneous populations. As a result, it remains unclear whether robo-advisors primarily appeal to financially capable and confident individuals, or whether they function as compensatory tools for those who lack

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financial capability but seek accessible guidance.

A related limitation of the literature is the treatment of adoption as an individual and largely asocial decision. While robo-advisors are designed to operate autonomously, investor engagement with new financial technologies often occurs in socially embedded contexts (Belanche et al., 2019). Within this process, an individual's familiarity with the robo-advisors and their technology readiness can amplify the impact of information from mass media, peers, and opinion leaders. Credible endorsements from trusted sources appear to strengthen adoption intentions, whereas security concerns can suppress them (Belanche et al., 2019). Yet the relative influence of these social channels, and whether their effects differ across consumer types, remains underexplored.

This study addresses these gaps by employing a person-centered approach on robo-advisor adoption. Rather than focusing on isolated predictors, we argue that adopting decisions reflect coherent configurations of financial capability, psychological orientations, technology readiness, and openness to social influence. To capture this heterogeneity, we employ Latent Profile Analysis (LPA) to identify distinct consumer-investor adoption mindsets (Spurk et al., 2020). This approach represents a core contribution to the robo-advisor literature, which has relied almost exclusively on variable-centered methods (see meta-analysis from de Oliveira Santini et al., 2026) that can obscure meaningful differences in how consumer investors evaluate automated financial advice.

Using a nationally representative survey of New Zealand adults aged 18–83, we identify six distinct consumer profiles characterized by shared patterns of financial capability, trust in financial institutions, and social influence. These segments include *Sceptics, Financially Vulnerable, Capable Traditionalists, Financially Engaged, Traditionalists, and Financially Confident*. We then estimate separate regressions to examine how intention to adopt robo-advisors varies across these segment profiles. By focusing on adoption intention, we capture consumers' evaluative and psychological readiness to engage with robo-advisory services, independent of immediate access, investment needs, or platform constraints.

Our findings demonstrate that robo-advisor adoption and its associated psychological behaviors are highly contingent on profile membership, providing a clear resolution to the puzzle surrounding the role of financial capability. Higher financial capability supports adoption intention across profiles. Lower-capability groups may rely more heavily on external social influence cues when forming adoption intentions, while higher-capability groups show greater association with perceived benefits and autonomy in adoption intention. For instance, while *Sceptics* perceive limited usefulness in robo-advisors despite moderate financial capability, the *Capable Traditionalists* and *Financially Confident* profiles, high financial capability profiles, report the strongest adoption intention and see the greatest benefits. Yet *Financially Engaged* respondents show greater adoption willingness when influenced by both personal networks and social media, while *Financially Vulnerable* respondents, those with the lowest capability scores, are strongly influenced by social factors. Importantly, social influence exerts a positive relationship with adoption intention across all profiles, highlighting its independent role in shaping comfort with automated advice. Together, these results clarify longstanding ambiguities in the literature and show that understanding robo-advisor adoption requires moving beyond average effects toward a segmentation-based perspective.

The remainder of this paper proceeds as follows. Section 2 reviews the literature on robo-advisor adoption, financial capability, and social influence, and develops conceptual framework guiding the analyses. Section 3 outlines the methodology and data. Section 4 presented the results, and Section 5 discussed implications for theory, practice and policy.

2. Literature review

2.1. Robo-advisor adoption and financial capability

Robo-advisors represent a prominent application of artificial intelligence in financial services, offering algorithmically generated investment advice that is standardized, scalable, and comparatively low-cost (Sironi, 2016; Baker and Dellaert, 2017). Prior research on robo-advisor adoption has primarily focused on individual-level characteristics such as financial literacy, demographic traits, trust, and technology readiness (Belanche et al., 2019; Brenner and Meyll, 2020; de Oliveira Santini et al., 2026; Figà-Talamanca et al., 2022). Oehler et al. (2022) show that less risk-averse retail investors are more likely to use robo-advisors, and personal characteristics such as locus of control and financial knowledge influence investment decisions. While financial literacy has received particular attention, empirical findings remain inconsistent. Some studies suggest that lower levels of financial knowledge increase the likelihood of adopting robo-advisors, consistent with a substitution logic in which automated advice compensates for limited expertise (Brenner and Meyll, 2020). Aristei, Gallo (2026) more recently reveal that financial literacy lowers uptake of robo-advisors, showing a clearer relationship between the role of literacy and robo-advisor use that replaces and substitutes human advisors. In contrast, other work finds that financially knowledgeable individuals are more willing to engage with robo-advisors and more likely to follow algorithmic recommendations (Alemanni et al., 2020; Caratelli et al., 2019). Experimental evidence further suggests that financially knowledgeable investors are better able to interpret and act on robo-advice, particularly in complex or volatile market conditions (D'Acunto et al., 2019). To further complicate such findings, a recent meta-analysis of 41 robo-advisor studies (de Oliveira Santini et al., 2026) shows no significant differences in adoption based on financial literacy.

This inconsistency suggests that financial knowledge alone may be insufficient to explain engagement with AI-based financial advice. Drawing on broader work in consumer finance, financial capability has been conceptualized as a multidimensional construct encompassing not only knowledge, but also confidence, self-efficacy, and perceived control over financial decisions (Sherraden, 2010; Xiao and O'Neill, 2016). Financial capability is most commonly defined as the ability to effectively manage financial resources, encompassing not only financial knowledge but also behaviors and the capacity to apply that knowledge in practice (e.g., Xiao, 2014; Sherraden, 2010). Empirical evidence indicates that these broader dimensions are more strongly associated with financial behavior, resilience, and engagement than objective literacy measures alone (Shanmuganathan, 2020). A financial capability approach therefore assesses whether a person has not only the knowledge (objective literacy), but also the behaviors and capacity (self--assessment of ability) to enact financial decisions. A growing body of literature has shown that self-assessment of knowledge and ability are a critical component in the willingness to enact knowledge (Allgood and Walstad, 2016; Xiao et al., 2014).

In the context of robo-advisors, studies indicate that subjective perceptions of competence and comfort with automation play a decisive role in shaping adoption intentions (Belanche et al., 2019). Evidence suggests that perceived financial competence and trust in automated systems often outweigh objective measures of knowledge when individuals evaluate robo-advisory services. These findings align with a financial capability perspective, in which confidence and self-efficacy shape willingness to delegate financial decision-making to algorithmic systems. Nevertheless, financial capability remains under-theorized and under-examined in empirical studies of robo-advisor adoption, leaving unresolved the question of whether these tools primarily attract financially confident users or serve as compensatory technologies for those with lower capability.

In addition to financial capability, we include financial product experience as an indicator of individuals' familiarity with financial markets. Prior research suggests that financial experience shapes individuals' willingness to adopt robo-advisory services, as more experienced investors tend to exhibit greater openness to technology-enabled investment tools (Hohenberger et al., 2019). Including financial experience therefore allows the latent profiles to capture differences in both financial knowledge and real-world engagement with financial products. However, in addition to user traits, product features and the external environment interact to yield trust and adoption of these tools. Even humanoid robot features affect trust and loyalty for adoption of robo advice (Chen et al., 2025). We explore a key feature to build trust in the next section.

2.2. Social influence and adoption of AI-enhanced financial tools

In addition to individual financial characteristics, robo-advisor adoption is increasingly understood as a socially embedded process. Drawing on technology acceptance and social influence theories, prior studies suggest that individuals rely on social cues to evaluate the legitimacy, trustworthiness, and safety of novel financial technologies (Belanche et al., 2019). Recommendations from peers, family members, and trusted opinion leaders can reduce uncertainty and increase psychological comfort, especially in contexts where technologies involve automated decision-making and users might anticipate a loss of control over financial decisions.

Empirical evidence from the robo-advisor literature supports the relevance of social influence but also highlights heterogeneity in effects. In qualitative work, social influence is a key factor shaping trust in robo advisors (Cao et al., 2026). Social influence emerges as an important antecedent driving positive attitudes to robo-advisor adoption intentions in China (Roh et al., 2023). Belanche et al. (2019) demonstrate that information from mass media and interpersonal networks amplifies perceived usefulness and trust in robo-advisors, while security and privacy concerns attenuate these relationships. Importantly, these social influence cues appear to be particularly salient for individuals with limited prior experience or confidence in financial decision-making, suggesting that social influence may operate as a compensatory mechanism under conditions of uncertainty. This contrasts with evidence from more traditional financial contexts, where higher-SES individuals embedded in information-rich social networks often exhibit superior financial decision-making and reduced reliance on other external cues (Mugerman et al., 2014).

At the same time, the literature provides mixed and sometimes contradictory findings regarding the role of social influence across different investor segments, raising questions about the generalizability of these effects to robo-advisory services. While social networks can generate cumulative financial advantages in conventional investment settings (Mugerman et al., 2014), it remains unclear whether these same dynamics translate to the adoption of emerging digital tools that fundamentally alter the advice relationship. Evidence from AI-enabled consumer technologies more broadly suggests that normative pressure and observational learning play a critical role during early stages of adoption, particularly when users lack direct experience with the technology (Venkatesh et al., 2003; Belanche et al., 2019). Participants who already have strong trust relationships with friends told Cao et al. (2026) that their trust of friends effectively extended to trust in recommendations for robo-advisors. These insights underscore the need to explicitly test social influence within robo-advisor contexts rather than assuming its effects mirror those observed in traditional finance.

Since recent robo-advisor research highlights that adoption patterns can vary systematically across demographic profiles (Brenner and Meyll, 2020), social influence is also unlikely to exert uniform effects across consumers. This heterogeneity reinforces the value of a latent profile analysis (LPA) approach, which allows for the identification of distinct consumer segments for whom social influence may differentially shape adoption intentions.

In this way, social influence warrants explicit testing in robo-advisor contexts, where uncertainty, automation, and perceived loss of control may heighten reliance on social cues. Examining social influence through an LPA framework likewise enables a more nuanced understanding of how different consumer profiles, beyond individual financial characteristics alone, vary in their responsiveness to social signals when forming adoption intentions.

2.3. Adoption Intention

A recurring methodological challenge in the study of robo-advisor uptake concerns the distinction between intention to adopt and observed adoption behavior. While actual adoption provides an objective outcome, it is often constrained by institutional and structural factors, including product availability, minimum investment thresholds, regulatory settings, and the timing of salient investment decisions. As a result, observed adoption may underestimate underlying consumer willingness to engage with robo-advisory services.

Consistent with established technology adoption frameworks, intention to adopt is widely used as a theoretically meaningful antecedent to behavior, particularly for emerging technologies with low market penetration (Venkatesh et al., 2003). In the robo-advisor context, prior studies demonstrate that adoption intention captures consumers' evaluative judgements, trust, and psychological readiness to engage with automated financial advice, even when immediate adoption is not feasible (Belanche et al., 2019; Bhatia et al., 2020). Experimental and survey-based evidence further suggests that intention measures are strongly associated with subsequent use when opportunities arise (Alemanni et al., 2020).

Focusing on intention is therefore particularly appropriate for examining the psychological, financial, and social mechanisms underlying robo-advisor adoption. This approach allows researchers to isolate behavioral associations without conflating them with access constraints or lifecycle effects, and is especially relevant in national survey data where respondents may not yet face an immediate investment decision.

2.4. Summary

Taken together, the existing literature suggests that robo-advisor adoption is shaped by a complex interaction of financial capability, psychological comfort with automation, and social influence. However, most prior studies employ variable-centered approaches that assume homogeneous effects across consumers. This limits understanding of how different configurations of financial confidence, experience, and susceptibility to social cues jointly shape adoption decisions.

Addressing this gap, the present study adopts a person-centered approach to identify distinct consumer profiles characterized by shared patterns of financial capability, trust, experience, and social influence. By examining how these segments differ in their intention to adopt robo-advisory services, this study offers a more nuanced account of the behavioral mechanisms underlying engagement with AI-enabled financial technologies.

3. Design and methodology

3.1. Survey design and measures

To investigate the role of financial capability and social influence in the adoption of robo-advisory services, we conducted a structured online survey of New Zealand adults. To ensure a consistent understanding of what robo-advice is, especially given its low profile in New Zealand, participants first viewed a short, 35 s introductory video outlining the concept, function, and benefits of robo-advisors created by the researchers for this study (see Appendix A for full text of the video). The survey then measured the respondents' financial capability, along with social factors such as family, friends, or social media endorsements, which influence trust and behavioral intention to adopt these platforms.

To measure financial capability, we drew on Xiao et al. (2014), who constructed a measure of financial capability based on four components: objective financial literacy based on 13 questions (Gignac and Ooi, 2022, find that short literacy quizzes typically lack internal validity), subjective financial literacy, financial behaviors, and perceived financial capability. Consistent with Xiao et al. (2014) each component score was scaled to a maximum score of 5 and then the component scores were summed giving a financial capability score out of a maximum 20.

To identify other factors that may influence the decision to adopt robo-advice, we drew on the Technology Acceptance Model (Davis, 1989) and the Personal Financial Management System. Specifically, drawing on the technology acceptance model, we included pre-validated questions regarding respondents' perceptions of the perceived usefulness, and ease of use (Patterson et al., 1996; Venkatesh et al., 2012; Venkatesh et al., 2003; Davis, 1989), and trust in the technology of robo-advice platforms (Van der Cruijsen et al., 2023). We also asked about respondents' personal innovativeness using the Technology Readiness Index (Parasuraman and Colby, 2015), and based on the personal financial management system, we asked respondents about their trust in financial institutions, social influence, motivation, and opportunities to invest (Lučić et al., 2020). Additionally, we asked respondents about their current investment situation and their experience with basic (transaction accounts, savings accounts, KiwiSaver,[4] and term deposit/certificate of deposit) and advanced financial investments (stocks, bonds, cryptocurrencies, peer-to-peer lending, crowdfunding, exchange traded funds or mutual funds). Respondents were asked to rate their frequency of use of each product which was then averaged over the products to create the basic and advanced financial experience scales. We also collected demographic information, including age, gender, education, employment, and household income (reported annually in New Zealand dollars). Finally, we asked questions about intention to use a robo-advisor; full details on the questions asked, scoring, and the source of the questions are presented in Appendix B's Table A1.

The survey was administered via Qualtrics and distributed by Cint, an independent panel provider, using age- and ethnicity-based quotas to ensure representativeness of the New Zealand adult population. A total of 1557 participants accessed the survey, and 1029 completed it. After data cleaning and the removal of cases with missing values, a final sample of 983 valid responses was retained for analysis.

Table 1 presents the sample characteristics, organized into two panels. Panel A summarizes the demographic profile of respondents, including gender, age, ethnicity, education, marital status, dependency status, employment status, and income levels. The final sample was predominantly female (64%) with respondents aged from 18 to 83 years ($M = 39.7$, $SD = 14.3$). In terms of education, 43% of participants held a bachelor's degree or higher. Employment was high, with 75% of respondents reporting current employment. Reported incomes were evenly distributed, with the largest group (30%) falling into the lower-middle income band.

Panel B outlines key aspects of respondents' investment and financial profiles. Percentages are based on valid responses for each item and may not total 100% due to rounding or multiple selections where applicable. Just over 60% of our sample currently invest, including in retirement savings scheme KiwiSaver, with half of those respondents self-managing their investments. Additionally, 47 respondents identified as using robo-advice for their investments. Of the nearly 40% who didn't identify as investing, nearly 1 in 3 felt they didn't have enough money to invest. However, sizeable percentages of respondents indicated that a lack of knowledge, concerns about poor decisions, and a lack of time all prevented them from investing. Interestingly, these three concerns are all factors that would be resolved through robo-advice. Around 9% indicated they didn't trust either online or financial advice in general. In general, respondents' financial behaviors were positive, with nearly all respondents saving for retirement, and between 66% and 80% avoiding overdrafts, spending within their budget, and saving for a rainy day.

Table 1
Sample Characteristics: Demographic, Investment, and Financial Profiles.

Variable	#	%
Panel A: Demographic Profile		
Gender		
Female	628	63.89
Male	348	35.4
Gender Diverse	7	0.71
Age		
18–29	249	25.33
30–39	309	31.43
40–49	182	18.51
50–59	169	17.19
60 +	74	7.53
Education		
Didn't finish High School	103	10.48
High School	438	44.56
Bachelor's degree or higher	427	43.44
Prefer not to say	15	1.53
Dependent Children		
Has Dependent Children	472	48.02
No Children/ No Dependent Children	496	50.46
Prefer not to say	15	1.53
Employment		
Employed	738	75.08
Unemployed	114	11.6
Not in Labour Force	119	12.11
Prefer not to say	12	1.22
Income		
< 25,000	91	9.26
25,000–50,000	158	16.07
50–000–100,000	369	37.54
100,000 +	365	37.13
Panel B: Investment and Financial Profile		
Investment Status		
Invest Currently	592	60.22
Not Invest	391	39.78
Investment Management (if currently investing)		
Manage investments by myself	495	50.36
Use a financial advisor to manage investments	154	15.67
Use robo-advice to manage investments	47	4.78
Investment Barriers (If not investing)		
Not enough money to invest	309	31.43
Worried about making poor investment decisions	167	16.99
No one taught me how to invest	159	16.17
Don't have time	108	10.99
Financial advisor costs a lot	48	4.88
Anxious about using online financial advice	46	4.68
Not sure I trust investment advice	43	4.37

This table reports the distribution of respondents across key demographic (Panel A) and investment/financial profile variables (Panel B). Percentages are based on valid responses for each item and may not sum to 100% due to rounding or because some items allowed multiple responses.

To address the reliability and distributional properties of the key psychometric and financial constructs, Table 2 reports the number of items, means, standard deviations, and Cronbach's alpha coefficients for each scale used in the survey. Most constructs demonstrated acceptable to excellent reliability, with Cronbach's alpha values ranging from 0.70 (Financial Capability) to 0.96 (Intent to Use). Two single-item measures, Perceived Ease of Use and Trust in Financial Institutions, are excluded from alpha calculations.

To reduce the likelihood of common method bias arising from the use of a single self-reported survey, we adopted survey design remedies. Specifically, we ensured anonymous participation, we employed validated scales, and separated constructs into separate survey sections. We also statistically tested for a common method bias using Harman's single-factor test, where we conducted principal component analysis of the study's constructs. The first component accounted for 46.1% of the total variance, below the commonly accepted threshold of 50%,

[4] KiwiSaver is New Zealand's government-supported defined-contribution retirement savings scheme (similar to a 401(k) or superannuation).

Table 2
Descriptive Statistics and Reliability of Construct Scores.

Construct	Items	Mean	SD	Cronbach's alpha
Intent to Use	2	3.519	1.776	0.96
Perceived Ease of Use*	1	4.937	1.454	
Perceived Usefulness	2	4.713	1.409	0.87
Psychological comfort	4	4.557	1.405	0.95
Social Influence	2	4.236	1.675	0.84
Trust in Financial Institutions*	1	4.287	1.552	
Technological Readiness	6	4.348	0.920	0.61
Personal Innovativeness	4	4.217	1.244	0.76
Financial Capability	4	12.28	1.288	0.70
Financial Experience Basic	4	5.400	1.166	0.87
Financial Experience Advanced	6	2.368	1.582	0.86

This table reports the descriptive statistics (mean and standard deviation) and internal consistency (Cronbach's α) of multi-item constructs based on 7-point Likert scales. Definitions and measurement details for all constructs are presented in Table A1. *Cronbach's alpha is not applicable for single-item constructs.

suggesting that common method variance is unlikely to substantially bias our findings. Additionally, variance inflation factors range from 1.95 to 2.99, below recommended thresholds, again indicating that multicollinearity and common methods are unlikely to materially affect the results.

3.2. Analytical strategy

To explore underlying heterogeneity in respondents' psychological and financial predispositions toward robo-advice adoption, we employ Latent Profile Analysis (LPA), a model-based clustering technique that identifies subpopulations (latent classes) within the data based on shared patterns in continuous variables (Spurk et al., 2020). This approach is particularly valuable when theoretically grounded variables are expected to segment individuals into psychologically distinct groups (Woo et al., 2018) that may respond differently to financial technology. This method has proven effective in revealing how the psychological drivers of financial behavior, such as savings, differ across distinct consumer segments (Gerhard et al., 2018).

In this context, the variables used to form latent profiles were selected for their conceptual relevance to technology-based financial decision making. We include financial capability and financial experience indicators to reflect individuals' sophistication and confidence in managing financial matters, which prior literature suggests are critical in shaping receptivity to new financial products. We also include trust in financial institutions, which captures general institutional confidence, while technological readiness and innovativeness are theorized to reflect openness to automated and digital financial tools. By clustering individuals across these six indicators, we aim to uncover distinct psychological 'adoption mindsets' that influence receptivity to robo-advice.

LPA models were estimated using Mplus with standardized inputs. Latent Profile Analysis (LPA) was conducted using Mplus to identify latent subgroups based on the six observed variables. Models with increasing numbers of profiles (we tested models ranging between 2 profiles and 7 profiles) were estimated using maximum likelihood estimation based on a Gaussian mixture model,

$$P(y_i) = \sum_{k=1}^{6} \pi_k N(y_i|\mu_k, \Sigma_k)$$

where $\pi_k$is the probability of membership in class k, μ_k is a vector of indicator means for class k, and $\Sigma_k$is the covariance matrix. Consistent with standard LPA specifications, indicator means were allowed to vary across profiles while within-profile covariances were fixed to zero. Model selection was guided by information criteria (AIC, BIC, adjusted BIC), entropy, and likelihood ratio tests (LMR-LRT and BLRT), together with profile interpretability. Latent Profile Analysis models with two to seven profiles were estimated. Model selection was based on information criteria (AIC, BIC, and adjusted BIC), entropy, and likelihood ratio tests (LMR-LRT and BLRT). Information criteria decreased as additional profiles were added, which is typical in mixture modelling. The six-profile solution was selected as the optimal model. While the seven-profile model produced slightly lower information criteria, the Lo–Mendell–Rubin test comparing the six- and seven-profile models was not statistically significant, indicating that the additional profile did not significantly improve model fit. Entropy was also lower for the seven-profile solution dropped below 0.8, the typical threshold above which there is strong class separation and model fit (Weller et al., 2020). Taken together, these results supported the six-profile model as providing the best balance between statistical fit and parsimony.

4. Results

4.1. Identification and description of latent profiles

A series of latent profile models was estimated, and the six-profile solution was retained as optimal based on statistical fit and theoretical interpretability (as detailed in Section 2.2). Table 3 provides a conceptual summary and the assigned label for each profile. The corresponding mean scores for the six indicator variables: financial capability, trust in financial institutions, technological readiness, personal innovativeness, and experience with basic and advanced financial products are reported in Table 4, which also details the proportion of the sample assigned to each class. Additionally, we also include the tests used to determine the appropriate number of profiles. These latent profiles provide the foundation for examining differences in behavioral intention and adoption patterns across consumer segments.

Fig. 1 provides a visual comparison of the six latent profiles based on their mean scores for the indicator variables (reported in Table 4). The distinct patterns, particularly the pronounced contrasts in financial capability, personal innovativeness, and advanced financial product experience, clearly support the interpretation and labelling of the segments. In describing the profiles, "high", "moderate", and "low" refer to

Table 3
Latent Profile Descriptions Based on LPA Results.

Class ID	Profile Label	Profile Description
Class 1	Sceptics	Moderate scores on financial capability, low trust in financial institutions and technological readiness, lowest innovativeness, with moderate experience of basic or advanced financial products.
Class 2	Financially Vulnerable	low trust in financial institutions and technological readiness, lowest innovativeness, lowest capability, and least experience with basic or advanced financial products.
Class 3	Capable Traditionalists	Higher financial capability, trust, innovativeness, and experience with basic financial products, but relatively lower experience with more advanced financial products
Class 4	Financially Engaged	Balanced profile with average capability, trust, and innovativeness, moderate experience with basic financial products, but second second-highest engagement experience with more advanced products
Class 5	Traditionalists	Balanced profile with average capability, trust, and innovativeness, moderate experience with basic financial products, but very low experience with more advanced products
Class 6	Financially Confident	Higher financial capability, trust, innovativeness, and experience with basic and advanced financial products

This table provides brief descriptions of the six profiles identified using latent class analysis based on respondents' financial capability, trust in financial institutions, technological readiness, personal innovativeness, and experience with basic and advanced financial products.

Table 4
Respondent Profile Attributes.

Panel A: Profile Selection Scores

Profiles	LogLK	AIC	BIC	Entropy	LMRT	BLRT
2	−10371.8	20781.6	20874.5	0.673	825.4***	843.4***
3	−10162.9	20377.7	20504.6	0.772	409.4***	417.9***
4	−10056.7	20179.4	20340.8	0.796	207.9	212.3***
5	−9952.3	19984.7	20180.3	0.835	204.5**	208.72***
6	−9852.7	19799.4	20029.3	0.827	195.2**	199.3***
7	−9803.5	19714.9	19979.1	0.784	96.4	98.4

Panel B: Respondent Profile Attributes

	Class 1 Sceptics	Class 2 Financially Vulnerable	Class 3 Capable Traditionalists	Class 4 Financial Engaged	Class 5 Traditionalists	Class 6 Financially Confident
% of Sample	7.30%	13.90%	14.10%	9.20%	47.40%	8.00%
Financial Capability	11.98	7.78	15.11	12.53	12.35	14.81
Trust in Financial Institutions	3.14	2.98	5.05	4.45	4.29	6.16
Technological Readiness	2.63	3.78	5.30	4.12	4.43	5.17
Innovativeness	2.06	3.54	5.43	4.23	4.16	5.66
Basic Financial Experience	5.52	3.92	6.03	5.13	5.53	6.34
Advanced Financial Experience	1.48	1.32	2.76	4.50	1.63	6.03

Panel A reports the values for the various tests used to determine the appropriate number of profiles. Panel B reports the mean scores for the indicators used to identify the latent profiles, including financial capability, trust in financial institutions, technological readiness, personal innovativeness, and experience with basic and advanced financial products. Definitions and measurement details for all constructs are presented in Table A1. The "% of Sample" column denotes the percentage of respondents assigned to each profile.

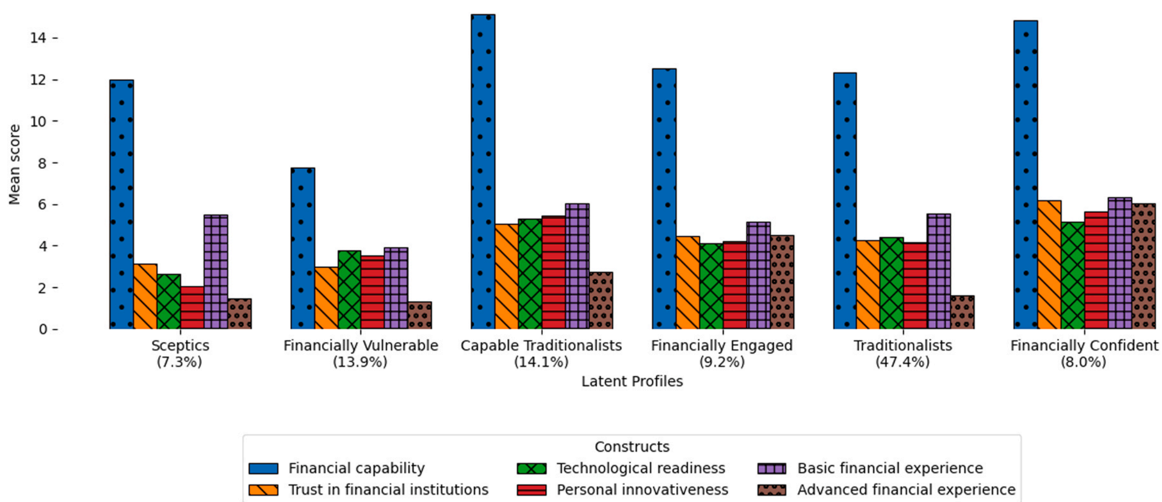

Fig. 1. Mean Scores of Indicators Across Latent Profiles.
This figure is based on the profile mean values reported in Table 4. It displays the mean scores for the variables used to identify the latent profiles: financial capability, trust in financial institutions, technological readiness, personal innovativeness, and experience with basic and advanced financial products. Definitions and measurement details for all constructs are presented in Table A1. The percentage shown for each profile reflects the proportion of respondents assigned to that class.

values relative to the sample mean across indicators. Moderate scores indicate values close to the overall sample average, whereas high and low scores indicate values meaningfully above or below the sample mean respectively.

The profiles are interpreted and labelled as follows:

The first profile, Sceptics (7.3%), is characterized by moderate financial capability, but is defined by its very low trust in financial institutions and technological readiness. This group also reports the lowest levels of personal innovativeness, suggesting a general reluctance toward new, technology-driven financial solutions. Their financial experience is moderate with basic products but limited with advanced ones.

In contrast, the *Financially Vulnerable* (13.9%) share the Sceptics' low trust, technological readiness, and innovativeness, but are distinguished by having the lowest levels of financial capability (7.78 out of 20) and the least experience with both basic and advanced financial products. This profile likely represents individuals who are disengaged or feel excluded from the traditional financial system.

The third profile, *Capable Traditionalists* (14.1%), represents the most financially capable respondents. They exhibit higher trust in financial institutions, stronger technological readiness, and high innovativeness. Despite their high capability and comfort with technology, their financial experience is concentrated in basic financial products, while their experience with advanced financial products remains only modestly above average. This appears to indicate a potential preference for traditional, lower-risk instruments over complex or novel investments.

Conversely, the *Financially Engaged* (9.2%) are marked by the second-highest level of advanced financial product experience. They maintain moderate levels of financial capability, trust, and innovativeness, positioning them as active and self-directed investors who are neither the most nor least optimistic about institutions or technology.

The *Traditionalists* (47.4%), the largest segment of the sample, represent the average consumer. They demonstrate moderate financial capability, trust, and innovativeness, with reasonable experience in basic products but minimal familiarity with advanced products such as stocks, bonds, and exchange-traded funds. This group likely represents the mainstream consumer who follows conventional financial paths without strong inclinations toward either innovation or scepticism.

Finally, the *Financially Confident* (8.0%) profile emerges as a well-rounded and receptive one. They are characterized by high financial capability, trust, technological readiness, and personal innovativeness, accompanied by strong experience with both basic and advanced financial products. While the *Capable Traditionalists* exhibit the highest financial capability score, the *Financially Confident* profile is distinguished by its consistently high scores across trust, technological readiness, innovativeness, and advanced financial product experience, making this group the most broadly receptive to robo-advisor adoption.

4.2. Validation and characterization of the profiles

Following the identification of the six latent profiles, Table 5 summarizes the demographic characteristics, including gender, age, education, employment, and income, for each profile. The demographic patterns offer an important point of comparison, indicating the extent to which the profiles reflect meaningful differences in respondent characteristics beyond the variables used to identify them.

The *Sceptics* and the *Financially Vulnerable* are predominantly composed of older women (50 + and 40 +, respectively) with lower educational attainment (high school or below) and lower annual incomes (typically under NZD $50,000). These demographics suggest that their financial skepticism and vulnerability are intertwined with life stage and socioeconomic position.

The *Traditionalists*, the largest profile, are typically women aged 50–59 with a high school education and a middle-income (NZD $75,000–100,000). This group represents the demographic "centre" of the sample.

In contrast, the profiles most open to innovation are demographically distinct. The *Financially Engaged* are notably younger (under 39), more likely to be men, university-educated, and have no dependents, despite currently earning lower incomes (NZD $25,000–50,000). The *Capable Traditionalists* and the *Financially Confident* are both predominantly male, university-educated, and high-earners (NZD $100,000 +). They are distinguished primarily by age: the *Capable Traditionalists* are split between the youngest (18−29) and oldest (60 +) cohorts, while the *Financially Confident* are squarely in their prime earning years (30−39).

In summary, the profiles show clear demographic patterns. These range from older women with lower incomes and education, who tend to be disengaged or sceptical, to younger, highly educated, and affluent men, who are more financially confident and engaged. These logical patterns confirm that the profiles represent distinct, real-world segments, thereby strengthening their value in understanding and targeting different types of consumers.

4.3. Profile Perceptions, Behaviors, and Adoption Intention

Table 6, Panel A, presents the average scores for respondents' perceptions of robo-advice. A clear pattern emerges across the profiles. The *Sceptics* and the *Financially Vulnerable* hold the most negative views, reporting the lowest levels of perceived benefit, comfort, and susceptibility to social influence regarding robo-advisors.

Positive perceptions rise with financial capability and experience with advanced financial products. The *Traditionalists* and *Financially Engaged* groups, who have similar, moderate capability scores, also share similar, neutral-to-moderate perceptions of robo-advice. The most positive views are held by the *Capable Traditionalists* and, most notably, the *Financially Confident,* who see the greatest potential and benefits in using robo-advisors. The latter group's strong openness to advanced financial products is likely a key association for their markedly positive perceptions.

This pattern is mirrored in the intention to use robo-advice measured on a 1–7 Likert scale (1 = Strongly Disagree, 7 = Strongly Agree). On average, the sample is neutral (3.52 out of 7). However, intention ranges from strong disagreement among the *Sceptics* (1.88) and *Financially Vulnerable* (2.76) to moderate agreement among the *Capable Traditionalists* (4.47) and strong agreement from the *Financially Confident* (6.00). The *Financially Engaged* group shows that even with moderate capability, high advanced experience can lead to above-average intention (3.98).

Table 6-Panel B provides insights into the investment behaviors of each profile. Current investing behaviors (excluding retirement saving scheme KiwiSaver) vary significantly across the profiles. Fewer than half of the *Financially Vulnerable* (24%) and *Sceptics* (43%) are currently investing. The two profiles with the most advanced financial experience, the *Financially Engaged* and *Financially Confident,* have the highest investment rates, both over 90%.

Among those who invest, self-management is common (around 82%)

Table 5
Demographic Characteristics of Latent Profiles.

Demographic category	Overall (%)	Class 1 Sceptics	Class 2 Vulnerable	Class 3 Capable Traditionalists	Class 4 Financially Engaged	Class 5 Traditionalists	Class 6 Confident
		7.30%	13.90%	14.10%	9.20%	47.40%	8.00%
Men	35.70%	5.20%	9.80%	17.80%	10.30%	41.70%	15.20%
Women	64.30%	8.60%	16.40%	12.10%	8.10%	50.60%	4.10%
18–29	25.30%	3.60%	12.90%	16.10%	12.90%	47.40%	7.20%
30–39	31.40%	3.90%	13.60%	14.20%	13.30%	40.80%	14.20%
40–49	18.50%	7.10%	15.90%	10.40%	6.60%	51.10%	8.80%
50–59	17.20%	15.30%	13%	12.40%	2.40%	56.20%	0.60%
60 +	7.60%	16.20%	16.20%	20.30%	1.30%	45.90%	0%
Prefer not to say	1.63%	20.0%	33.33%	0	13.33%	33.33%	0%
Didn't Finish High School	10.47%	11.65%	36.89%	7.77%	1.94%	40.78%	0.97%
High School	44.51%	9.13%	17.12%	12.10%	7.53%	52.74%	1.37%
Bachelor's degree or higher	43.39%	3.98%	4.45%	18.27%	12.41%	44.03%	16.86%
Employed	76.00%	7.50%	8.50%	16.00%	11.40%	46.20%	10.40%
Unemployed	11.70%	10.50%	32.50%	7.90%	1.80%	46.50%	0.90%
Not in the workforce	12.30%	3.40%	26.10%	10.10%	3.40%	56.30%	0.80%
No Children/ No dependents	50.50%	9.70%	14.30%	15.10%	7.10%	51.20%	2.60%
No Dependent Children	48%	4.90%	12.70%	13.10%	11.20%	44.10%	14.00%
< 25,000	9.30%	11%	27.50%	8.80%	2.20%	50.50%	0%
$25000-$49,999	16.10%	9.50%	27.20%	4.40%	17.10%	39.20%	2.50%
$50,000-$99,999	37.50%	5.70%	12.20%	13.30%	9.20%	51.80%	7.90%
$$99,999 +	37.10%	7.10%	6.60%	20.50%	7.40%	45.80%	12.60%

This table reports the percentage of respondents in each demographic category across the six latent profiles. The “Overall (%)” column shows the full-sample distribution, while the subsequent columns present the proportion of each demographic group found within each latent profile. Percentages may not sum to 100% because some respondents selected “Prefer not to say” or due to rounding

Table 6
Robo-advice Perceptions and Investing Characteristics of Latent Profiles.

		Class 1	Class 2	Class 3	Class 4	Class 5	Class 6
		Sceptics	Financially Vulnerable	Capable Traditionalists	Financially Engaged	Traditionalists	Financially Confident
Panel A: Robo-advice perception variables.							
Ease of Use	4.94	3.53	4.05	5.83	4.89	4.90	6.43
Usefulness	4.91	3.53	4.39	5.62	4.73	4.83	6.49
Technological Readiness	4.82	3.97	4.24	5.29	4.57	4.84	5.87
Psychological Comfort	4.56	2.90	3.96	5.45	4.54	4.42	6.38
Social Influence	4.24	2.73	3.46	5.01	4.27	4.12	6.26
Intention to Use	3.52	1.88	2.76	4.47	3.98	3.2	6
Panel B: Investing Characteristics of Latent Profiles							
Currently Invest - Yes	60.2%	43.1%	24.1%	87.8%	91.1%	53.2%	96.2%
Currently Invest - No	39.8%	57%	75.9%	12.2%	8.9%	46.8%	3.8%
Invest - Self Managed	83.6%	83.9%	72.7%	82.8%	86.6%	83.9%	85.5%
Invest - Advisor	26%	16.1%	18.1%	23.0%	32.9%	16.9%	60.5%
Invest – Robo-Advisor	7.9%	3.2%	9.0%	1.6%	3.7%	1.2%	46.1%
Invest - Lack Time	11.0%	9.7%	19%	3.6%	3.3%	14.4%	0%
Invest - Cost	4.9%	12.5%	10.2%	2.1%	3.3%	3.6%	2.5%
Invest - Money	31.4%	45.8%	62.0%	9.4%	5.6%	36.9%	1.3%
Invest - Knowledge	16.2%	22.2%	34.3%	6.5%	4.4%	17.6%	1.3%
Invest - Worry	17.0%	27.8%	23.4%	6.5%	2.2%	22.1%	1.3%
Invest - Trust	4.4%	8.3%	8.%	0.0%	1.1%	5.2%	1.3%
Invest - Online	4.7%	11.1%	7.3%	0.7%	2.2%	5.2%	1.3%

Note: Panel A reports the mean scores for the factors associated with respondents' perceptions of robo-advice and their intention to adopt it. Definitions and measurement details for these variables are presented in Table A1. Panel B shows the distribution of responses to investment-related questions, expressed as the percentage of respondents selecting each option within each latent profile.

across all groups except for the *Financially Vulnerable* (72%). The use of traditional financial advisors is highest among the *Financially Engaged* and *Financially Confident* groups, with over 60% of the latter using an advisor. Current use of robo-advisors is low overall (7.9% of investors), but nearly half of the *Financially Confident* respondents report using one, aligning with their positive perceptions and advanced experience.

For non-investors, the primary barrier to investing is a lack of money. This reason is most prevalent among the *Sceptics* and the *Financially Vulnerable* groups. The second and third most common barriers are a lack of investment knowledge and a worry about making poor investment decisions. These are notable, as they are precisely the concerns that robo-advice is designed to mitigate. Among the minority of non-investors within the *Financially Engaged* profile, concerns about cost and a lack of time were more prominent than worry about poor decisions. For the few non-investing *Capable Traditionalists*, the cost of investing was the most frequently cited barrier.

Overall, these findings support the hypothesis that intention to adopt robo-advice is shaped by financial capability. However, rather than substituting for financial capability, greater capability appears to be an important variable for individuals to feel sufficiently confident to engage with robo-advice. In addition, the findings show that trust in financial institutions and prior experience with more complex financial products further strengthen the intention to adopt robo-advice.

4.4. Relationship to adoption intention within profiles

To understand whether adoption intention differs across the six latent profiles, we estimate a separate linear regression with robust standard errors for each latent profile in which we regress 'Intention to Use' on the four perception variables that include 'Ease of Use', 'Perceived Usefulness', 'Psychological Comfort', and 'Social Influence'. The results are presented in Table 7.

A central finding is that psychological comfort, measured by feelings of security and confidence after viewing the introductory video, is a significant positive influence across all profiles. Its influence is strongest for those with limited advanced financial experience. For the *Financially Vulnerable, Traditionalists,* and *Capable Traditionalists,* a one-point increase in psychological comfort is associated with an increase in adoption intention of approximately 0.50–0.60 points. The effect, while still significant, is smaller for the other profiles (0.30–0.40), with the *Sceptics* and *Financially Engaged* showing the weakest response. This indicates that building user comfort is a critical lever for adoption, especially among less experienced investors.

Social influence, the impact of friends, family, and media, also exerts

Table 7
Latent Profile Regressions on Intention to Adopt Robo-advice.

	Sceptics	Financially Vulnerable	Capable Traditionalists	Financial Engaged	Traditionalists	Financially Confident
Constant	−0.096	−0.432	−1.400***	−0.417	−0.859***	−1.449
	(0.330)	(0.352)	(0.522)	(0.434)	(0.241)	(0.925)
Ease of Use	0.206	−0.047	0.037	−0.008	−0.018	0.041
	(0.124)	(0.077)	(0.097)	(0.104)	(0.049)	(0.149)
Usefulness	−0.195	−0.124	0.069	0.129	0.106*	0.303*
	(0.144)	(0.106)	(0.101)	(0.088)	(0.064)	(0.159)
Psychological comfort	0.301*	0.543***	0.599***	0.301**	0.502***	0.396**
	(0.163)	(0.116)	(0.130)	(0.117)	(0.067)	(0.175)
Social Influence	0.391***	0.513***	0.400***	0.576***	0.345***	0.429***
	(0.0949)	(0.0783)	(0.0770)	(0.0846)	(0.0418)	(0.142)
Observations	72	137	139	90	466	79
R-squared	0.509	0.484	0.590	0.644	0.491	0.514

Note: This table reports linear regression coefficients estimating the association between respondents' intention to adopt robo-advice and key perception factors: ease of use, usefulness, psychological comfort, and social influence, within each latent profile. Definitions and measurement details for all variables are presented in Table A1. Robust standard errors are shown in parentheses. ***, **, * denotes significant at 1%, 5% and 10% levels, respectively.

a strong effect. This relationship is most powerful for the *Financially Engaged* (a 0.58-point increase per unit) and the *Financially Vulnerable* (0.51-point increase per unit). All other profiles also show positive and significant coefficients, ranging from 0.35 to 0.43.

The impact of other variables is more limited and profile-specific. The adoption intention of the *Sceptics*, *Financially Vulnerable*, *Capable Traditionalists,* and *Financially Engaged* respondents is not significantly affected by the other perception variables. Perceived usefulness has a positive impact only for the *Financially Confident* and *Traditionalist respondents,* while ease of use was not statistically significant for any profile.

As a final step in our analysis, we examine which social influence channels most effectively drive intention to adopt robo-advice. Social influence may operate through interpersonal sources, such as friends and family, who are known to shape financial decision-making (Schotter, 2003), or through broader media-based sources, including social media, online reviews, and financial news. To distinguish the influence of these channels, we re-estimate our regression models using the two components of social influence separately, rather than the composite social influence score used in Table 7.

The complete results are presented in Table 8, and Fig. 2 provides a visual summary of the relative magnitude of these coefficients across the six latent profiles. Despite prior evidence suggesting that friends and family have the strongest influence on financial decision-making (Schotter, 2003; Brown et al., 2008), our findings reveal a crucial nuance that was masked by the composite score. While both channels generally exert a positive influence, their relative impact varies substantially across profiles. Social media and reviews emerge as the more universally powerful associations, showing statistical significance across all six profiles. As shown in Fig. 2, the coefficients for social media/news/reviews are consistently larger than those for friends and family, with the contrast being especially pronounced for the Traditionalists and Financially Confident profiles. In most cases, media-based influence also shows stronger statistical significance, except for the *Financially Engaged* profile, where friends and family and media-based influence are significant at the 1% level. The influence of friends and family is insignificant for *Financially Confident* respondents. This suggests that our most financially experienced respondents may view themselves as better informed than their social networks and therefore rely more heavily on impersonal, information-rich channels when evaluating digital advisory tools.

Similarly, among the *Sceptics*, *Financially Vulnerable*, and *Traditionalist profiles*, media-based influence has the largest and most significant effect than friends and family, indicating that even for respondents with lower financial capability or lower technological readiness, curated online content remains a more effective prompt than interpersonal advice. Although *Sceptics* exhibit the weakest overall responsiveness to social influence, the relative strength of media-based effects persists.

Overall, these findings underscore the importance of both financial capability and social influence in shaping adoption behavior. A foundational element is the enhancement of consumer financial capability and familiarity with more advanced financial products, which appears essential for increasing the willingness to engage with robo-advice. At the same time, strategies that enhance psychological comfort and leverage effective social influence channels, particularly social media, news, and influencer marketing, have the potential to substantially increase the adoption intention across diverse consumer segments. Importantly, this pattern remains consistent across varying levels of financial capability, highlighting a clear opportunity for financial platforms and policymakers to employ social channels to raise awareness, trust, and expand robo-advice uptake, especially among groups that have historically been underserved.

5. Discussion

We contribute to the literature on the adoption of artificial intelligence tools in financial decision-making by employing Latent Profile Analysis (LPA) to identify distinct consumer-investor adoption mindsets. Our study examines a broad range of New Zealand consumers as target groups for robo-advisor use and identifies six distinct latent profiles that reflects clear segments. These consumer segments reveal that robo-advisor adopting decisions reflect coherent configurations of financial capability, psychological orientations, technology readiness, and openness to social influence. Across these profiles, we find that overall, the intention to adopt a robo-advisor is driven most clearly by financial capability and trust and is significantly affected by experience with more complex financial products. Notably, however, our results show that even respondents who are least inclined to invest and display the lowest levels of financial capability exhibit a greater willingness to consider robo-advice when social influence is taken into account, whether through family and friends, online reviews, social media, or news sources. This pattern is striking, suggesting that social influence can meaningfully shift adoption intentions, even among those who appear least likely to engage with digital financial advice.

Consumer investors often describe robo-advisor platforms as both empowering and limited in their ability to enhance financial capability (Caratelli et al., 2019). Robo-advisors come at a lower cost than traditional investment advice, with lower minimum investment requirements, and offer greater accessibility and ease of use to retail and consumer investors. They can automate portfolio management and

Table 8
Latent Profile Regressions on Intention to Adopt Robo-advice with Separate Influence Channels.

	Sceptics	Financially Vulnerable	Capable Traditionalists	Financial Engaged	Traditionalists	Financially Confident
Constant	−0.0817	−0.489	−1.378***	−0.399	−0.788***	−1.459
	(0.334)	(0.356)	(0.524)	(0.437)	(0.242)	(0.900)
Ease of Use	0.204	−0.0367	0.0388	−0.00896	−0.0177	0.121
	(0.124)	(0.0777)	(0.0968)	(0.105)	(0.0492)	(0.149)
Usefulness	−0.198	−0.102	0.0653	0.126	0.121*	0.328**
	(0.145)	(0.108)	(0.101)	(0.0886)	(0.0639)	(0.155)
Psychological Comfort	0.306*	0.533***	0.599***	0.295**	0.483***	0.354**
	(0.164)	(0.116)	(0.130)	(0.118)	(0.0675)	(0.171)
Friends and Family	0.165*	0.192**	0.154*	0.243***	0.0790*	0.028
	(0.0894)	(0.0763)	(0.0788)	(0.0816)	(0.0446)	(0.108)
Media	0.230**	0.321***	0.248***	0.343***	0.262***	0.339***
	(0.0981)	(0.0760)	(0.0806)	(0.0953)	(0.0431)	(0.088)
Observations	72	137	139	90	466	79
R-squared	0.511	0.488	0.592	0.646	0.497	0.514

This table reports linear regression coefficients that estimate the association between respondents' intention to adopt robo-advice and key perception factors, including ease of use, usefulness, psychological comfort, and separate social influence channels (Friends and Family; Media), within each latent profile. Definitions and measurement details for all variables are presented in Table A1. Robust standard errors are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

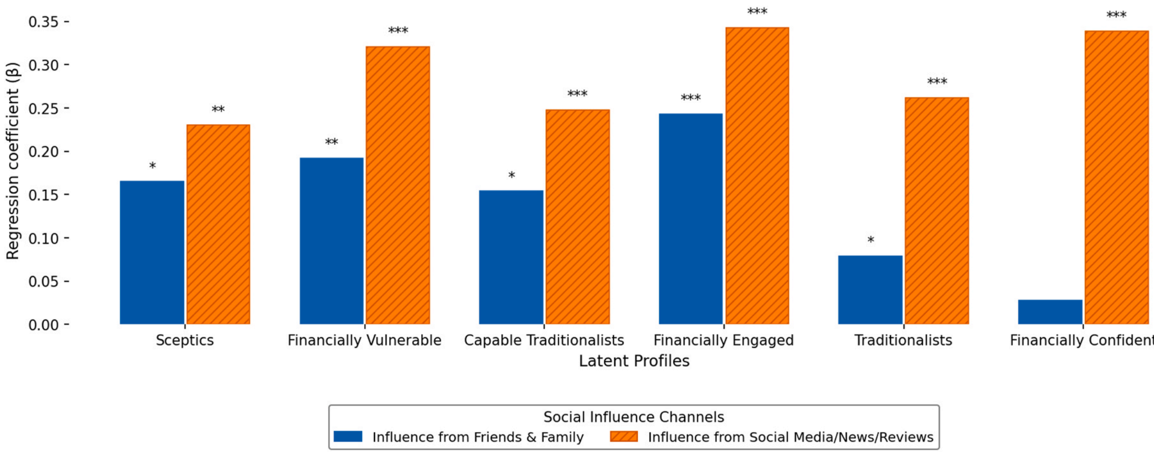

Fig. 2. Differential Effects of Social Influence Channels on Intention to Adopt Robo-advice Across Latent Profiles.
This figure displays the linear regression coefficients for the two social influence channels, influence from friends and family, and influence from social media, online reviews, and news sources, estimated separately for each latent profile. The coefficients represent the marginal effects of each influence channel on respondents' intention to adopt robo-advice. Significance levels correspond to the estimates reported in Table 8 (**$p < 0.01$, *$p < 0.05$, $p < 0.10$). Definitions and measurement details for all variables are provided in Table A1.

incorporate behavioral nudging and goal tracking, all while providing greater transparency and control in asset allocation and fee structures through algorithm-driven investment choices. Robo-advisors, in short, are an affordable, convenient, and effective entry point into the world of investing and wealth management, especially for underserved markets. Our findings highlight that financial capability (Sherraden, 2010; Xiao and O'Neill, 2016), rather than financial knowledge (Oehler et al., 2022), has a strong association with consumers' perceived benefits and willingness to use robo-advice. At the same time, this study also reveals how social influence, whether from family and friends or from social media and online information sources, is positively related to the adoption of robo-advisors for financial decision-making for segments with the lowest financial capability.

Surveys report that users experience increased financial satisfaction, a sense of empowerment, and convenience through lower fees and accessible digital services (Bai, 2024). In contrast, qualitative studies reveal concerns over insufficient transparency, inept risk profiling, and a lack of emotional nuance in algorithmic advice (Caratelli et al., 2019). Yet robo-advising tools increase portfolio diversification and decrease volatility for less diversified investors, while having minimal impact on well-diversified investors. They also reduce behavioral biases, such as the disposition effect and trend chasing, for all investors (D'Acunto et al., 2019). Several investigations note that robo-advisors are viewed as supplementary to human advisors, with a preference for hybrid models in managing complex or educational needs. Less risk-averse retail investors are more drawn to use robo-advisors, while financial knowledge also influences such investment decisions (Oehler et al., 2022). These findings point to important implications for researchers and providers seeking to tailor robo-advisory services to more risk-averse individuals. We extend this line of inquiry, and our results demonstrate that social influence is another arena that can encourage consumer adoption and better investment decisions.

6. Limitations and future research directions

This study is subject to several limitations that suggest productive directions for future research. First, the analysis focuses on intention to adopt robo-advisory services rather than observed adoption behavior. While intention is a well-established and theoretically meaningful precursor to behavior in technology adoption research, particularly for emerging technologies with limited market penetration, it does not capture downstream constraints such as access, timing of investment decisions, or platform-specific barriers. Future research could address this limitation through longitudinal designs or the use of behavioral data to examine how adoption intentions translate into actual usage and sustained engagement with robo-advisory platforms. Second, the study relies on cross-sectional survey data, which limits causal inference regarding the relationships among financial capability, social influence, and adoption intention. Experimental or panel-based studies could more directly assess causal mechanisms and track how changes in financial capability or exposure to social cues shape adoption trajectories over time. We also apply single-item measures of nonfocal variables that warrant future testing in another setting to generalize results.

A further limitation concerns the context-specific nature of the sample, which is drawn from a national population in New Zealand. Institutional settings, regulatory frameworks, and cultural norms surrounding financial advice and trust in automation vary internationally, which may affect the generalizability of the identified consumer profiles. Comparative cross-national studies would help establish the robustness of these findings across different financial systems. We also found lower reliability for the full Technology Readiness scale (Parasuraman and Colby, 2015), indicating that the U.S.-based scale may not extend to consistent and reliable use in the New Zealand setting. This indicates future psychometric testing and revision of this valuable scale with non-U.S. samples may help increase reliability.

While the study distinguishes between multiple sources of social influence, the measures capture perceived influence rather than underlying social network structures, limiting insight into the mechanisms through which social cues operate. Future research could incorporate social network data or experimental manipulations of endorsements and peer behavior to disentangle these effects. Finally, although the latent profile analysis offers a nuanced, person-centered perspective on adoption mindsets, the resulting profiles are necessarily contingent on model specification and variable selection. Replication across samples and alternative segmentation approaches would further validate and extend the 6 robo-advisor adoption mindsets identified in this study.

7. Implications

Our findings may have compelling implications for researchers and practitioners. In our study, novice investors (including both financially capable and financially vulnerable respondents) appeared to demonstrate greater willingness to engage with robo-advisors when they reported higher levels of social influence scores. Although it can be challenging for institutions and platforms to foster greater trust among family and friends, they can more directly harness social media and digital communication channels to support the wider adoption of robo-advisors. This is important, as the greater use of these individualized investment tools has clear implications for financial inclusion, trust, and the democratization of investment services. Social media testimonials, credible success stories, and endorsements from reputable institutions and influencers may help normalize digital investment behavior, positioning robo-advisors as mainstream, legitimate, and trustworthy. Such strategies can play a key role in breaking down stigma and fear and reducing the psychological barriers observed in our study and highlighted more broadly in literature.

Targeted financial education and literacy campaigns delivered through platforms such as TikTok, Instagram, and YouTube can also provide institutions with opportunities to share educational content on investment basics, risks, and how robo-advisors work. Similar to how the 35 s introductory video in our study showed the basic use of robo-advisors to the respondents (Appendix A), social media channels can help lower the threshold for entry and potentially build financial capability through the use of engaging, digestible content. Such content on social media can help ensure a broader reach across demographics that target younger investors and those who, as in our New Zealand study, might be bilingual or rely on more interdependent or family-based values for decision-making.

The most salient implication for scholars and practitioners is the potential of social media platforms to enhance trust and transparency through interactive communication. The real-time features of social media, such as questions and answers, reviews, feedback, and community discussions, provide a strong foundation for building legitimacy around digital financial tools. Institutions that adopt a clear social media strategy can leverage influencers and peer networks to strengthen the credibility of robo-advice through targeted influencer marketing. In the New Zealand context, in particular, collaborations with Māori and Pacific influencers, as well as trusted financial expert voices, can position robo-advisors as tools that support not only the individual financial development but also broader community wellbeing. The key strategic considerations for institutions, therefore, include cultural responsiveness and a commitment to digital equity in their content marketing strategies to foster wider adoption of robo-advisors.

Declarations

- This research was funded by a university internal grant.
- All research was conducted in full compliance with university ethics processes and approvals. All participants involved gave informed consent by completing the survey.
- All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

CRediT authorship contribution statement

Sara Ali: Writing – review & editing, Visualization, Software, Resources, Investigation, Formal analysis, Data curation. **Aaron Gilbert:** Writing – original draft, Validation, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Sommer Kapitan:** Writing – review & editing, Validation, Methodology, Investigation, Data curation.

Declaration of Competing Interest

All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

Appendix A. Robo-advisor information video

Full text of video (35 s): "Want to invest but don't know how to start? Try a robo-advisor. Robo-advisors are digital tools that will give you investment advice and help you trade based on your needs and circumstances. They are easy to set up, can be monitored online or via an app, and best of all, are cheaper than human advisors. You can also start investing with less money. Robo-advisors are a great alternative to a human financial advisor. Try robo-advisor for a friendly and affordable way to start investing and watch your financial future grow."

Appendix B. - Table A1

Overview and Description of Variables Used in the Analysis

Scale	Questions	Source (adapted from)	Scoring
Intention to Use	I intend to use robo-advisors in the next 3 months I plan to use robo-advisors in the next 3 months.	Venkatesh et al., (2012)	7-point scale (SD – SA) - averaged
Ease of Use	I would find a robo-advisor easy to use	Venkatesh et al., (2003)	7-point scale (SD – SA) - averaged
Perceived Usefulness	Using a robo-advisor would improve my investment portfolio. Using a robo-advisor would make me more comfortable making investment decisions.	Davis, (1989)	7-point scale (SD – SA) - averaged
Psychological Comfort	After watching the introductory video and thinking about robo-advisor, I feel Comfortable. After watching the introductory video and thinking about robo-advisor, I feel Secure. After watching the introductory video and thinking about robo-advisor, I feel Calm. After watching the introductory video and thinking about robo-advisor, I feel Confident.	Spake et al., (2003)	7-point scale (SD – SA) - averaged
Social Influence	If I saw family or friends using a robo-advisor, it would make me more likely to adopt a robo-advisor. If social media, news or reviews suggested using robo-advisor to manage my investments, I would be more likely to adopt a robo-advisor.	Venkatesh et al., (2003)	7-point scale (SD – SA) - averaged
Technological Readiness	Technology gives people more control over their daily lives. Products and services that use the newest technologies are more convenient to use. I keep up with the latest technological developments in my areas of interest. I can usually figure out new high-tech products and services without help from others. Technology improves the quality of relationships by reducing personal interaction. Technology improves the quality of relationships by making personal interaction easier	Parasuraman and Colby, (2015)	7-point scale (SD – SA) - averaged
Trust in Financial Institutions	How much trust do you have in financial institutions?	Van der Cruijsen et al., (2023)	7-point scale (SD – SA)
Personal Innovativeness	If I heard about a new technology, I would look for ways to experiment with it. Among my peers, I am usually the first to try out new information technologies. In general, I am hesitant to try out new information technologies. I like to experiment with new information technologies.	Yi et al., (2006)	7-point scale (SD – SA) - averaged
Financial Capability	Sum of the standardized scores (0−5) of four components: Objective Financial Literacy, Subjective Financial Literacy, Financial Behavior, Perceived Financial Capability	Xiao and O'Neill, (2016)	0–20
Objective Financial Literacy	13 question financial literacy test with some adaption to match local terminology	Van Rooij et al., (2011)	Sum of the number of correct answers Standardized to 0–5
Subjective Financial Literacy	How would you assess your overall financial knowledge?	Xiao et al., (2014)	7-point scale –standardized to 0–5.
Financial Behavior	Have you set aside emergency savings or rainy-day funds? Have you ever tried to figure out how much you need to save for retirement? Do you save or invest for the future? Have you ever contributed to a KiwiSaver plan? I do not spend more than I earn. I avoid overdrawing from my bank's transaction account.	Xiao et al., (2014)	Sum of the number of behaviors respondents answered yes to Standardized to 0–5
Perceived Financial Capability	Overall, thinking of your assets, debts, and savings, how satisfied are you with your current personal financial condition? I am good at dealing with day-to-day financial matters, such as bank accounts, credit and debit cards, and tracking expenses.	Xiao et al., (2014)	7-point scale – averaged and standardized to 0–5.
Basic Financial Products Experience	What types of financial products have you used: Bank transaction account Bank savings account Term deposits KiwiSaver		7-point scale (Never used to always use) - averaged
Advanced Financial Products Experience	What types of financial products have you used: Stocks Bonds Crypto currency Peer-to-peer lending Crowdfunding Managed Fund/ETF		7-point scale (Never used to always use) - averaged
Demographics	Respondent's self-identified gender Respondent's age in years Highest level of education attained Presence of children and dependence status Current labor market status Self-reported income level		
Investment Questions	Do you invest currently (excluding KiwiSaver)? How do you currently manage your investments? Please select all that apply. Why don't you tend to invest? What is the biggest barrier to investing? Choose the top 3 reasons.		

This table outlines the measurement scales used in the analysis, including the items comprising each construct, the original sources from which the measures were adapted, and the scoring approach applied.

Appendix C. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.jbef.2026.101195.

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