

Article

Understanding Reverse Mortgage Acceptance in Spain with Explainable Machine Learning and Importance–Performance Map Analysis

Jorge de Andrés-Sánchez ^{1,*}  and Laura González-Vila Puchades ² 

¹ Social and Business Research Laboratory, Business and Management Department, Rovira i Virgili University, Av. de la Universitat 1, 43204 Reus, Spain

² Department of Economic, Financial and Actuarial Mathematics & Observatory of European Systems of Complementary Social Pension Plans, University of Barcelona, Av. Diagonal 690, 08034 Barcelona, Spain; lgonzalezv@ub.edu

* Correspondence: jorge.deandres@urv.cat

Abstract

In developed countries such as Spain, where the population is increasingly aging, retirement planning and longevity risk represent major societal challenges. In Spain, in particular, a significant proportion of household wealth is concentrated in real estate, primarily in the form of owner-occupied housing. For this reason, one emerging financial product in the retirement savings space is the reverse mortgage (RM). This study examines the determinants of acceptance of this financial product using survey data collected from Spanish individuals. The intention to take out an RM is explained through performance expectancy (PE), effort expectancy (EE), social influence (SI), bequest motive (BM), financial literacy (FL), and risk (RK). The analysis applies machine learning techniques: decision tree regression is used to visualize variable interactions that lead to acceptance; random forest to improve predictive capability; and Shapley Additive Explanations (SHAP) to estimate the relative importance of predictors. Finally, Importance–Performance Map Analysis (IPMA) is employed to identify the variables that merit greater attention in the acceptance of RMs. SHAP values indicate that PE and SI are the most influential predictors of intention to use RMs, followed by BM and EE with moderate importance, whereas the positive influence of RK and FL is more reduced. The IPMA highlights PE and SI as the most strategic drivers, and RK and BM act as relevant barriers to the widespread adoption of RMs.

Keywords: reverse mortgages; longevity risk; theory of planned behavior; decision tree regression; random forest; Shapley additive explanations; importance–performance map analysis



Academic Editors: Nan Zhu and Richard MacMinn

Received: 13 September 2025

Revised: 10 October 2025

Accepted: 14 October 2025

Published: 2 November 2025

Citation: Andrés-Sánchez, Jorge de, and Laura González-Vila Puchades. 2025. Understanding Reverse Mortgage Acceptance in Spain with Explainable Machine Learning and Importance–Performance Map Analysis. *Risks* 13: 212. <https://doi.org/10.3390/risks13110212>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

In Western countries, public social security systems are under revision, driven by demographic, economic, and social pressures. The rising share of retirees compared to the working-age population threatens the financial sustainability of these systems. Added to this are concerns about intergenerational equity and the need to adapt these systems to longer life expectancy. As a result, debates have emerged on reforms to ensure the long-term viability, adequacy, and fairness of pension systems (Helmdag and Väänänen 2025).

In Spain, the problem is particularly acute given the demographic and structural characteristics of its social security system. The population pyramid is flat, the result of

persistently low birth rates and one of the highest life expectancies worldwide (De Andrés Sánchez and González-Vila Puchades 2020). This has created a growing imbalance between contributors and pensioners (Banco de España 2024). Moreover, coverage is very broad, with many retirees relying almost exclusively on public benefits. This context creates serious challenges for the sustainability of the pension system, making reforms to secure its medium- and long-term viability an urgent priority (De Andrés Sánchez and González-Vila Puchades 2020).

One common measure to improve sustainability is reducing the replacement rate relative to pre-retirement earnings, which in Spain is around 80% (OECD 2023). Such measures increase the need for complementary private mechanisms. Unlocking housing wealth through a reverse mortgage (RM) emerges as a rational and appealing strategy for older adults. This instrument enables homeowners to release part of their property's value as liquid income while continuing to live in it, which is particularly relevant for asset-rich but cash-poor individuals (Rania 2025; Kwong et al. 2024).

Thus, RMs can improve quality of life in retirement, especially in countries like Spain, where 89.1% of those aged 65 or older own their homes (Instituto Nacional de Estadística 2024). Real estate represents a large share of household wealth, while savings in pension plans and other financial instruments remain low (De Andrés-Sánchez and González-Vila Puchades 2025). In this context of demographic aging and pressure on the public pension system, RMs offer a flexible solution to diversify income sources and adapt to individual needs, thereby strengthening retirees' financial autonomy (Boj et al. 2022; González-Vila Puchades et al. 2025).

Despite their potential as a retirement planning tool and their relatively reasonable actuarial cost (Davidoff 2015), RMs remain a niche product with limited uptake. This pattern has been documented across multiple countries (Bartsch et al. 2021; Hanewald et al. 2020; Hoekstra and Dol 2021; Kwong et al. 2025; Meneses Cerón et al. 2024) and also in Spain (Atance et al. 2021).

Several factors explain this low adoption. First, limited financial literacy (Ilan and Mugerman 2025), product complexity (Hanewald et al. 2020), and distrust toward financial institutions (Whait et al. 2019) discourage potential borrowers. Second, cultural barriers play an important role: in many contexts, particularly in Southern Europe, there is a strong preference for leaving housing assets to heirs, which reduces willingness to monetize property during retirement (Hoekstra and Dol 2021). Third, regulatory conditions and an underdeveloped market restrict access. In Spain, supply remains limited, with providers showing little interest due in part to their high exposure to longevity risk (Atance et al. 2024; Chen and Chen 2024).

These barriers have constrained the development of RM markets worldwide, despite their potential to improve retirement security. In countries like Spain, characterized by strained public pension systems and very high homeownership rates, RMs could provide a valuable complement to existing retirement income sources (Gavilán 2023).

These reflections motivate the present study, which analyzes the influence of the main drivers and barriers identified in the literature on the acceptance of RMs in Spain. The analysis of such adoption needs a conceptual ground to make a systematic examination. This paper adopts the Theory of Planned Behavior (TPB) that recognizes three groups of dimensions that explain an individual's intention to perform a specific action: attitude, perceived behavioral control, and subjective norms (Ajzen 1991). The model used, shown in Figure 1, will serve to address the following research questions (RQs):

- RQ1: What is the explanatory and predictive capacity of the TPB-based model developed in this paper?

- RQ2: What are the constructs or variables that require greater attention for the successful development of RMs in Spain?

Unlike most of the existing literature on financial decisions, which typically employs behavioral models estimated through structural equation modeling (Ashok and Vij 2020) or logistic regression (Bongini and Cucinelli 2019), this study applies machine learning techniques derived from decision trees, specifically decision tree regression (DTR) and its generalization, random forests (RF). Whereas traditional regression models require the specification of predefined (often linear) relationships between constructs, DTR offers a data-driven approach capable of identifying decision thresholds and complex interactions that linear models cannot easily capture. In addition, decision trees provide an intuitive visualization of how explanatory variables relate to behavioral intention (BI), making them particularly valuable in contexts where social phenomena are nonlinear and heterogeneous (Loh 2011). This methodological approach has been increasingly employed in studies of consumer behavior (Chung et al. 2023; Cuc et al. 2025; Imani et al. 2025; Richter and Tudoran 2024) and, though less frequently, in research on investment decisions (Rad et al. 2025).

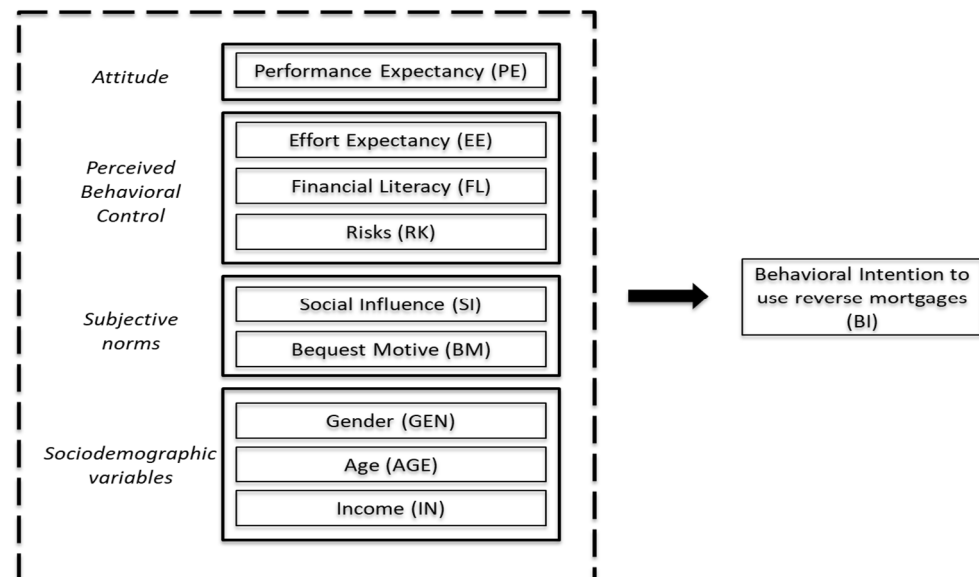


Figure 1. Conceptual framework of this paper. Source: Own elaboration.

The original formulation of TPB acknowledges the possibility of interactions among its three main dimensions, i.e., attitude, perceived behavioral control, and subjective norms, captured indirectly through correlations (Ajzen 1991). However, DTR eliminates the need for predefined hypotheses about such interactions. Instead, it allows the data itself to reveal patterns of variable interplay within the tree architecture. While RF further improves predictive accuracy by aggregating results across multiple trees, it does so at the expense of some interpretability (Breiman 2001). In this study, DTR serves as an interpretable representation of the average tree structure within the forest, whereas RF is used primarily to maximize predictive performance. Together, these methods are applied to address RQ1, concerning the explanatory and predictive capacity of TPB constructs in the context of RM acceptance.

To address RQ2, the study employs Shapley Additive Explanations (SHAP) (Lundberg and Lee 2017) to interpret the relative importance of each explanatory variable in the tree-based models, particularly the RF. These SHAP values are then incorporated into an Importance–Performance Map (IPM), adapting the methodology originally developed for Structural Equation Modeling (Ringle and Sarstedt 2016) by using SHAP-based importance

scores instead of path coefficients. The analysis is operationalized through the diagonal partition method (Abalo et al. 2007), enabling the construction of an IPM analysis (IPMA).

The value of IPMA lies in its ability to go beyond simple measures of impact. A variable with strong influence on BI may not warrant priority if its performance is already high. Conversely, focusing on variables with moderate importance but substantial room for improvement may yield greater overall gains. In this way, IPMA provides both a diagnostic and strategic tool, bridging predictive modeling with actionable insights for policymakers and financial institutions.

2. Literature Review

2.1. Life-Cycle Models and Theory of Planned Behavior in the Modelización of the Acceptance of Reverse Mortgages

An RM is primarily a financial product, the value of which can be assessed using quantitative parameters such as borrower age, home value, expected mortality, or sex. In this regard, Nakajima and Telyukova (2017) develop a life-cycle model that incorporates realistic risks associated with longevity, health, medical expenses, and housing price fluctuations. Their results show that, although RMs generate welfare gains for certain groups (particularly low-income households in poor health), take-up remains limited due to bequest motives, precautionary savings, and contractual costs. Similarly, Davidoff (2015), drawing on option pricing theory, concludes that despite the fact that RMs combine a credit line with a put option whose present value often exceeds closing costs, demand remains surprisingly weak.

Extending this financial–actuarial perspective to the Spanish context, Boj et al. (2022) develop a life-cycle economic–financial model that incorporates randomness in mortality and dependency. Their findings confirm that contracting an RM can improve the financial sustainability of older homeowners, increasing available income and reducing the probability of illiquidity, especially among single-person households. This evidence reinforces the idea that, from a purely actuarial standpoint, RMs often represent a rational strategy to enhance financial well-being in old age.

Although the abovementioned papers show that RMs are financially advisable from an actuarial perspective, they also confirm that actual use remains below expectations. This paradox is largely attributed to behavioral, social, and emotional factors (Davidoff 2015; Nakajima and Telyukova 2017). This highlights the need to complement financial approaches with behavioral frameworks that account for the psychological, cultural, and social determinants of decision-making. In this regard, the TPB (Ajzen 1991) offers a robust and flexible lens to analyze RM acceptance from a behavioral standpoint, shedding light on how attitudes, social influences, and perceived control shape intentions to adopt the product.

An RM is, in any case, a financial product that potential consumers may choose to use or not, and its adoption can therefore also be analyzed through behavioral frameworks of consumer behavior. TPB has been widely applied across diverse domains due to its explanatory versatility, and it includes consumer behavior in a great variety of settings (Rozenkowska 2023). Its three core dimensions, i.e., attitude toward the behavior, subjective norms, and perceived behavioral control, facilitate a systematic assessment of consumer perceptions, social pressures, and perceived barriers. Moreover, the adaptability of TPB enables the integration of additional elements such as values, emotions, or habits, broadening its explanatory capacity.

This theory has been extensively used in financial decision-making research, particularly in financial inclusion (Musa et al. 2024) and retirement financial planning (Bongini and Cucinelli 2019; Griffin et al. 2012). It has also served as the analytical basis in the few

studies specifically addressing RM acceptance, such as those conducted in India ([Ashok and Vij 2020](#)) and Malaysia ([Mohammed and Sulaiman 2018](#)).

The novelty of this paper lies in a TPB-based theoretical framework that integrates both the rationale of RMs and the influence of social and family expectations. While the framework can be implemented using conventional statistical methods, its second contribution is the use of machine learning techniques, which capture nonlinearities and complex interactions among explanatory factors. In this way, the study advances the theoretical understanding of RM acceptance while also offering a methodological contribution that expands the analytical tools available to researchers in consumer behavior research. A panoramic overview of the proposed model is presented in the following subsection.

2.2. A TPB Modeling of Reverse Mortgage Acceptance

A commonly used response variable in TPB studies is behavioral intention (BI), defined as an individual's predisposition to engage in a specific behavior ([Ajzen 1991](#)). In this study, BI refers to the intention to consider an RM as a viable option for retirement planning. Focusing on BI rather than actual usage is justified because the RM market in Spain remains in its early stages ([González-Vila Puchades et al. 2025](#)). When analyzing the acceptance of products with very limited penetration, BI provides a more reliable basis for comparison ([Arias-Oliva et al. 2023](#)).

Within the TPB framework, BI is explained by three dimensions: attitude, perceived behavioral control, and subjective norm. The first, attitude, reflects individuals' positive or negative evaluation of a specific action ([Ajzen 1991](#)). In the RM context, this evaluation is strictly tied to retirement planning, excluding other considerations such as leaving an inheritance. Positive aspects include mobilizing housing assets to prepare for longevity and supplement public pensions, while negative aspects involve the relatively low amounts received compared to property appraisals and the higher cost of the product relative to conventional mortgages ([Knaack et al. 2020](#)).

Within this attitudinal dimension, we consider performance expectancy (PE) to be a relevant variable. Life-cycle models, such as [Nakajima and Telyukova \(2017\)](#), and the related work by [Davidoff \(2015\)](#), which adopts a life-cycle logic, should not be regarded as disconnected from behavioral models, since a favorable or unfavorable actuarial evaluation is a key factor shaping attitudes toward these products. From this perspective, [Davidoff \(2015\)](#) shows that the actuarial value of RMs varies substantially across markets depending on housing price dynamics. For instance, borrowers in highly cyclical states such as Florida (where home prices rose rapidly before the financial crisis and then collapsed) would have obtained contracts that ex post proved highly valuable, whereas borrowers in more stable markets, such as Kansas, would have found fewer financial advantages. Interpreted within a TPB-grounded framework, such differences in perceived financial outcomes could contribute to more favorable attitudes among the former and less favorable attitudes among the latter.

Second dimension, perceived behavioral control, refers to the perception about the capability to carry out a given behavior, i.e., the extent to which an individual perceives having control over the inner and outer variables needed to perform that action ([Ajzen 1991](#)). This concept is not crisply defined, as it may encompass both self-efficacy and control over outcomes ([Sparks et al. 1997](#)). In this study, both meanings are considered. We include variables related to the perceived ease of contracting and understanding the product (effort expectancy, EE), as well as the respondent's ability to make financial decisions (financial literacy, FL). We also incorporate an external variable, risk (RK), which largely depends on the type of benefits chosen in the RM and the final contractual specifications. Depending on the contract, risk may include longevity risk, insurer insolvency in the case

of annuity payments, property value depreciation without a non-negative equity guarantee, uncertainty about rising healthcare costs due to unexpected illness, and interest rate risk (Alai et al. 2014).

The third dimension is subjective norms, defined as the perceived social pressure to engage in a specific behavior (Ajzen 1991). In the context of RMs, this includes both social influence (SI), i.e., the perceived interest of one's close social circle in financial planning, and the bequest motive (BM), referring to the intention to leave an inheritance to heirs. The latter is a key factor in retirement consumption decisions, a stage marked by the decumulation of wealth (Hoekstra and Dol 2021).

These three dimensions are also shaped by sociodemographic variables such as gender (GEN), age (AGE), and income (IN), which have been shown to influence the propensity to consider RMs. Their relevance has been confirmed not only in regression models, where demographic controls are standard (Choinière-Crèvecoeur and Michaud 2023; Costa-Font et al. 2010; Fornero et al. 2016), but also in life-cycle financial valuation models, where age and gender determine mortality patterns and income shapes household wealth. In the U.S. market, Nakajima and Telyukova (2017) found that older households (aged 80–90+) with low income are the most likely to adopt RMs. Since these are treated as control variables in our study, we do not formulate hypotheses about them.

2.3. Attitude Factor: Performance Expectancy

Performance expectancy (PE) should be understood as the utility that a potential user perceives in RMs for retirement planning. Designed primarily for retirees who own their home, an RM allows access to liquidity without selling or leaving the property. Its main advantages include supplementing retirement income while retaining lifelong use of the home, thereby improving financial well-being by increasing expected consumption and smoothing its trajectory (Rania 2025). In Spain, funds obtained through an RM are not taxed as income under personal income tax, and repayment is not required while the homeowner is alive (unless the property is transferred or otherwise stipulated in the contract), which provides stability during periods of economic vulnerability (Boj et al. 2022; Simón-Moreno 2019).

Nevertheless, important drawbacks must be considered. The amount received is typically much lower than the property's market value due to the risks assumed by the lender and the long repayment horizon. Moreover, interest accrues over time at rates higher than conventional mortgages, and transaction costs are substantial (Knaack et al. 2020), all of which can significantly reduce the residual value of the home for heirs (Moulton et al. 2017). From a strictly financial–actuarial perspective, several studies suggest that RMs often appear advisable, both in the United States (Davidoff 2015; Nakajima and Telyukova 2017) and in Spain (Boj et al. 2022), as the benefits in terms of income gains, liquidity protection, or option value frequently outweigh the associated costs.

De Andrés-Sánchez et al. (2023) and De Andrés-Sánchez and González-Vila Puchades (2023) show that PE is the most relevant variable in explaining the acceptance of life settlements. Consistent with these findings, the attitude dimension of the TPB has been shown to be significant in the acceptance of longevity-related financial products, such as life annuities (Nosi et al. 2017). In the more specific field of RM acceptance, studies conducted in India (Ashok and Vij 2020; Muralidharan and Soundara Raja 2022) and Malaysia (Mohammed and Sulaiman 2018) show that items related to the performance expectancy of such operations are the most relevant predictors of BI. Accordingly, we propose:

Hypothesis 1. *Performance expectancy is positively linked with the behavioral intention to use RMs for retirement planning.*

2.4. Perceived Behavioral Control Factors: Effort Expectancy, Financial Literacy and Risks

Effort expectancy (EE) can be understood as the ease of contracting and the comprehensibility of the scope and implications of the financial product being acquired. In general terms, the contracting process is relatively straightforward: the homeowner must prove ownership of the property, their age (usually over 65), and compliance with certain basic requirements. After the property is appraised and the contract is signed before a notary, they begin to receive the agreed-upon funds, either as periodic payments, a lump sum, or a combination of both ([Banco de España 2023](#)).

However, although its operational use is simple (it does not require the repayment or ongoing management), it can be difficult to understand, especially for older adults without financial training ([Knaack et al. 2020](#)). Terms such as “interest capitalization,” “residual value,” or “heirs’ rights” can be confusing. In Spain, only 13% of older adults fully understand the product, which largely explains its low uptake despite 61% being aware of its existence ([Caser 2024](#)).

Therefore, for an RM to be truly user-friendly, it is essential that applicants receive clear and accessible explanations ([Daptardar and Dasgupta 2014](#)). This is consistent with empirical findings showing that the general population is usually unfamiliar with how RMs operate, unless they have previously taken the initiative to learn about retirement planning instruments ([Davidoff et al. 2017](#); [Moulton et al. 2017](#)). In this regard, evidence from China, where RM adoption has been extremely low, indicates that well-designed and clearly explained products significantly improve receptivity among potential users ([Hanewald et al. 2020](#)).

On the other hand, it should not be overlooked that the difficulty of access is also present on the supply side, which has traditionally been reluctant to offer this product due to the high risks involved in its management ([Simón-Moreno 2019](#)). The supply of equity release products may take the form of RMs or other alternative reversion schemes, depending on factors such as the prevailing regulatory framework (e.g., maximum loan-to-value ratios), the expected profitability for providers, the level of risk assumed, and the maturity of the financial market in each country ([Alai et al. 2014](#)).

Financial literacy (FL) plays a crucial role in retirement planning, as it enables individuals to better understand the available products, assess risks, and make informed decisions to ensure their economic well-being in old age ([Gallego-Losada et al. 2022](#)). Individuals with higher levels of financial literacy tend to anticipate their future needs more clearly and plan more effectively for retirement ([Bongini and Cucinelli 2019](#); [She et al. 2024](#)). This reduces the likelihood of mistakes such as unnecessary indebtedness, excessive consumption, exclusive reliance on the public pension system, and poor decision-making in the selection of investment alternatives during the accumulation phase ([Lusardi and Mitchell 2017](#)).

Moreover, higher FL is associated with greater concern for retirement ([She et al. 2024](#)) and increased awareness of products such as annuities ([Nosi et al. 2017](#)), retirement savings plans ([Dragos et al. 2020](#)), and even RMs ([Davidoff et al. 2017](#); [Rania 2025](#)). In this sense, FL emerges as a key enabling factor for future retirees to regard RMs as a viable option ([Choinière-Crèvecoeur and Michaud 2023](#)). Moreover, in the RM setting, FL helps borrowers rely on long-term inflation expectations rather than anchoring on current rates, making them more likely to evaluate RMs in an informed way and to reduce cognitive biases and suboptimal choices ([Ilan and Mugerma 2025](#)).

RMs entail *risk* (RK) for clients from several sources that must be carefully evaluated before contracting. A primary concern is asset decapitalization, as loan interest accrues over time, particularly under variable interest rates ([Atance et al. 2021](#)). Longevity risk is another key factor: if the RM does not include a whole life annuity, beneficiaries may outlive the funds, creating economic vulnerability ([Dillingh et al. 2017](#)). Conversely, incorporating

a lifetime annuity introduces the opposite problem, i.e., premature death relative to life expectancy, making the product less attractive, especially for individuals whose expected longevity is below average (De Andrés Sánchez and González-Vila Puchades 2020). Health-related uncertainties also discourage homeowners from committing to their property, as they may anticipate future expenses (Hanewald et al. 2020).

Within RK, lack of trust in financial institutions and regulatory bodies is critical (Hoekstra and Dol 2021; Whait et al. 2019). Even when homeowners are open to using their property to supplement retirement income, distrust may drive them to alternatives such as selling their home and purchasing a less expensive one. Both quantitative evidence from India (Muralidharan and Soundara Raja 2022) and qualitative findings from Australia (Whait et al. 2019) confirm that RK remains a significant barrier to the development of RMs. Accordingly, we propose:

Hypothesis 2. *Effort expectancy is positively linked with the behavioral intention to use RMs for retirement planning.*

Hypothesis 3. *Financial Literacy is positively linked with the behavioral intention to use RMs for retirement planning.*

Hypothesis 4. *Risk is negatively linked with the behavioral intention to use RMs for retirement planning.*

2.5. Subjective Norms Factors: Social Influence and Bequest Motive

Social influence (SI) refers to the extent to which individuals feel that significant others support or encourage them to adopt a new product (De Andrés-Sánchez and González-Vila Puchades 2023). The TPB posits that others' expectations regarding a person's actions can shape their intentions, either positively or negatively. In the context of RMs, SI refers to the influence that close individuals, such as family members, friends, and trusted financial advisors, can exert on the borrower's intention to take out an RM, from the perspective that it is an appropriate product for planning the potential user's retirement (Mohammed and Sulaiman 2017).

Taking out an RM is often a complex decision, as this financial product can be difficult to understand, especially for seniors without financial education. For this reason, the opinions of trusted financial advisors are often highly relevant when making financial decisions or purchasing insurance products (Moulton et al. 2017). Given the complexity of RMs, independent professional advice is recommended in various instances (Banco de España 2023). Positive evaluations of these financial products by advisors can foster a more favorable attitude and a more positive perception among borrowers (Moulton et al. 2017; Muralidharan and Soundara Raja 2022). Young advisors with high incomes, strong financial knowledge, and specialization in retirement or wealth management are the most likely to recommend RMs, whereas older advisors with mental accounting biases tend to be more reluctant (Baulkaran and Jain 2024).

The opinions of family members and close acquaintances can be particularly significant in the acceptance of RMs (Ashok and Vij 2020; Mohammed and Sulaiman 2017, 2018). If relatives or close individuals believe that RMs are an appropriate tool to improve the borrower's financial well-being, they are likely to encourage them to take one out. Likewise, government actions (such as the introduction of tax incentives and educational programs aimed at increasing individuals' awareness of retirement planning) can influence their attitude toward various financial products (Hauff et al. 2020).

The importance of SI has been demonstrated in various contexts related to retirement planning, such as the predisposition to plan for retirement from an early age (Bongini and

Cucinelli 2019; She et al. 2024), the purchase of products such as life annuities (Nosi et al. 2017), life settlement agreements (De Andrés-Sánchez et al. 2023; De Andrés-Sánchez and González-Vila Puchades 2023), and a favorable attitude toward RMs (Ashok and Vij 2020; Mohammed and Sulaiman 2018).

Beyond findings showing that RMs can be a financially reasonable choice from an actuarial standpoint, life-cycle models acknowledge that behavioral factors, such as the stigma of incurring debt in old age or the *bequest motive* (BM) that is, the desire to leave assets to heirs, can discourage demand despite a favorable financial evaluation (Davidoff 2015; Nakajima and Telyukova 2017). This latter behavioral factor is a significant barrier to taking out an RM (Hoekstra and Dol 2021; Whait et al. 2019). In Spain, in particular, there is a strong cultural tendency to leave an inheritance to one's successors (Costa-Font et al. 2010).

SI refers to pressures originating outside the borrower (opinions in one's close circle that steer choices for the borrower's own benefit), whereas BM captures an inward orientation: the intention to leave an inheritance grounded in personal values such as altruism or a self-imposed duty (Gotman 2011). In practice, BM is operationalized via behaviors linked to inheritance-focused financial planning, while SI is gauged through perceived pressure in the proximate social environment. Although SI can affect BM, not everyone who plans to bequeath their home does so due to external pressure; such plans often reflect personal conviction. Consistent with Mohammed et al. (2018), we therefore treat SI and BM as distinct, not redundant, constructs that shed light on different drivers of RM adoption.

Evidence aligns with this view. Dillingh et al. (2013) report a significant negative association between BM and BI, particularly among individuals with children. Nakajima and Telyukova (2017) indicate that BM discourages the liquidation of the home. Davidoff et al. (2017) likewise find that a stronger desire to bequeath lowers the likelihood of considering RMs, whereas weaker BM corresponds to greater openness to these products. Similar findings are documented by Mohammed and Sulaiman (2018) and by Ashok and Vij (2020). Taken together, the literature identifies BM as a key determinant in RM decisions, with higher BM generally associated with reduced demand for RMs.

Therefore, this study tests the following hypotheses:

Hypothesis 5. *Social influence is positively linked with the behavioral intention to use RMs for retirement planning.*

Hypothesis 6. *Bequest motive is negatively linked with the behavioral intention to use RMs for retirement planning.*

3. Results

3.1. Analysis of Research Question 1

Table 1 displays the descriptive statistics of the responses to the questions comprising the scales, as well as the measures of internal validity. It can be observed that, although one of the items measuring acceptance is slightly above 5, the other is slightly below. Likewise, the overall acceptance score is below 50 out of 100, suggesting that the general perception is essentially neutral but closer to rejection than to acceptance.

Regarding the facilitators, PE, EE, and FL show scores notably higher than 50, while SI is clearly below that threshold. As for the barriers or inhibitors, both RK and BM reach high levels, exceeding 60.

The scales demonstrate internal consistency (Cronbach's alpha and composite reliability index > 0.7) and convergent validity, since the standardized factor loadings are >0.7 and the AVE exceeds 0.5 in all cases. Table 2 shows that the constructs meet discriminant

validity requirements, as correlations between constructs never exceed the square root of the extracted variance and, in no case, exceed 0.85 (Cheung et al. 2024).

Table 1. Descriptive statistics and measures of scale reliability.

	Mean (Item)	Median (Item)	SD (Item)	Factor Loading	CA	CR	AVE	Mean (Construct)
Behavioral intention (BI)					0.92	0.96	0.92	48
BI1	5.1	5	3.0	0.96				
BI2	4.6	5	3.0	0.96				
Performance expectancy (PE)					0.89	0.92	0.75	61
PE1	6.5	7	2.2	0.73				
PE2	5.9	6	2.5	0.91				
PE3	5.7	6	2.5	0.93				
PE4	6.4	7	2.4	0.89				
Effort expectancy (EE)					0.84	0.89	0.67	58
EE1	6.0	6	2.3	0.80				
EE2	5.4	5	2.1	0.78				
EE3	5.2	5	2.5	0.88				
EE4	6.7	7	2.5	0.83				
Financial literacy (FL)					0.91	0.96	0.92	72
FL1	7.2	8	2.1	0.96				
FL2	7.2	7	2.0	0.96				
Risk (RK)					0.85	0.91	0.77	61
RK1	5.8	6	2.5	0.88				
RK2	6.0	6	2.4	0.87				
RK3	6.6	7	2.4	0.88				
Social influence (SI)					0.79	0.90	0.82	47
SI1	4.6	5	2.8	0.90				
SI2	4.7	5	2.5	0.91				
Bequest motive (BM)					0.80	0.88	0.70	69
BM1	7.9	9	2.4	0.85				
BM2	5.6	6	2.7	0.81				
BM3	6.7	7	2.8	0.86				

Note: SD stands for standard deviation, CA refers to Cronbach's alpha, and CR to composite reliability. The construct mean has been calculated as indicated in Step 2. Source: Own elaboration.

Table 2. Matrix to assess discriminant validity of variables.

	BI	PE	EE	FL	RK	SI	BM	GEN	AGE	INC
BI	0.96									
PE	0.70 **	0.87								
EE	0.46 **	0.42 **	0.82							
FL	0.17 *	0.20 **	0.39 **	0.96						
RK	−0.40 **	−0.32 **	−0.49 **	−0.19 **	0.88					
SI	0.67 **	0.55 **	0.59 **	0.29 **	−0.48 **	0.908				
BM	−0.25 **	0.00	−0.04	0.10	0.19 **	−0.25 **	0.84			
GEN	0.08	0.18	0.01	0.16	−0.08	0.01	−0.03	1		
AGE	−0.14 *	−0.03	0.03	−0.11	−0.01	−0.01	0.04	0.07	1	
INC	0.04	0.04	0.04	0.12	−0.02	0.13 *	0.05	0.08	−0.15 *	1

Note: (1) The square root of the AVE is presented on the diagonal. (2) “**” indicates significance at $p < 0.05$; “***” indicates significance at $p < 0.01$. Source: Own elaboration.

Table 2 also shows that the hypotheses regarding the positive relationships of PE, EE, FL, and SI with BI (H1, H2, H3 and H5) are supported by Pearson correlations, which are positive and statistically significant. Likewise, the hypothesized negative correlations of RK and BM with BI are statistically significant and consistent with hypotheses H4 and H6.

Among the sociodemographic factors, only the negative correlation between AGE and BI is significant.

Figure 2 graphically displays the results of the DTR model. It can be seen that only PE (four times), SI (three times), BM (two times), and RK (once) act as primary splitters. In all cases, their role is consistent with the hypothesized sign of their relationship with BI. PE and SI function as upper thresholds for observations located in nodes with lower acceptance levels, while BM and RK act as lower thresholds. In particular, PE allows classification of participants across the entire acceptance spectrum, and SI does so for almost the entire sample (except for the 6% most reluctant to accept RMs). BM is relevant for discriminating respondents within ranges associated with low acceptance (BI scores between 21 and 53), whereas RK does so in ranges linked to indifference or moderate acceptance (between 48 and 65). Overall, the primary splitters confirm hypotheses H1, H4, H5 and H6.

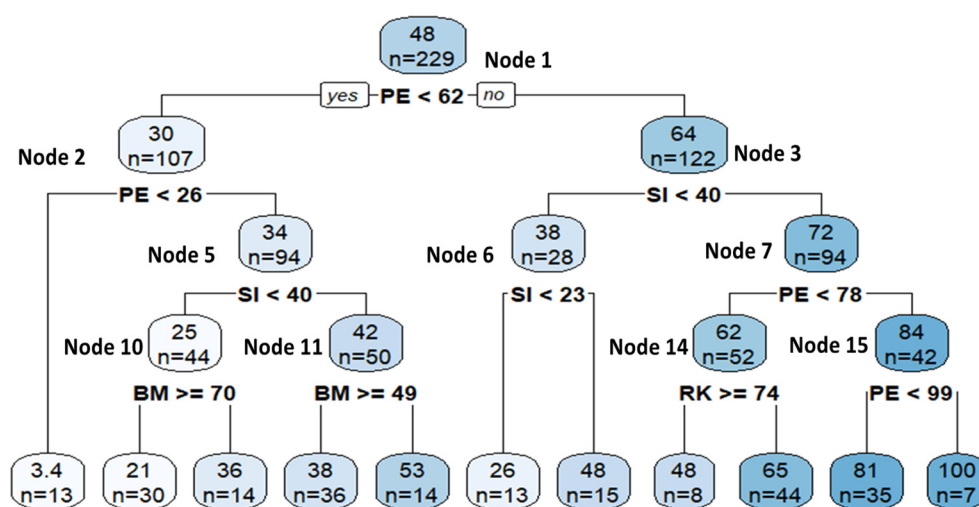


Figure 2. Results of DTR. Note: $R^2 = 69.3\%$. Source: Own elaboration. In the boxes, the upper part shows the average value of BI, and in the lower part, “n” stands for number of observations in each group.

Table 3 presents principal splits and surrogate splits as well. The analysis of these surrogate splits provides additional information on the relationship between explanatory variables and BI. Thus, PE appears in two surrogate splits, maintaining its role as an upper threshold in classes with lower acceptance, which remains consistent with hypothesis H1. The same pattern is observed for SI, which appears in three additional nodes (N1, N7 and N15) with the expected sign, thus confirming H5. As for EE, it appears in six surrogate splits, always acting consistently as an upper threshold for classes with lower acceptance, in accordance with H2.

Table 3. Principal splits (first row) and surrogate splits in the decision tree nodes (Figure 2).

N1	N2	N3	N5	N6	N7	N10	N11	N14	N15
PE < 62	PE < 26	SI < 40	SI < 40	SI < 23	PE < 78	BM ≥ 70	BM ≥ 49	RK ≥ 74	PE < 99
EE < 55	EE < 20	EE < 48	PE < 45	PE < 65	EE < 75	FL ≥ 45		BM ≥ 94	RK ≥ 5
FL < 70	BM < 24	FL < 32	EE < 64	EE < 32	FL < 83				SI < 97
RK ≥ 58		RK ≥ 81	RK ≥ 74	FL ≥ 85	RK ≥ 50				
SI < 50			BM ≥ 72	RK < 75	SI < 70				
GEN < 1			INC < 1	BM ≥ 80	BM ≥ 8				

Note: N1 stands for node 1 and so on. Source: Own elaboration.

Meanwhile, FL, RK, and BM also appear in several surrogate splits, although not always with the same sign. In the case of FL, it appears five times, but in three instances,

contradicting hypothesis H3, it acts as a lower threshold in classes with lower acceptance. Likewise, RK and BM appear as surrogate splits six and five times, respectively. However, in one instance each, they define an upper threshold rather than a lower one for observations associated with lower BI levels, which contradicts H4 and H6.

The involvement of sociodemographic factors is very limited (H7). GEN and IN appear in only one surrogate split each, and AGE does not appear at all. In the first case, the split suggests that women may have a greater predisposition to accept RMs, while higher-income individuals may show slightly more reluctance toward their use.

Figure 2 displays 11 terminal nodes that can be interpreted as different respondent profiles in the way they reach a positive or negative judgment about RMs. For example, the nodes with the highest predicted scores for taking out an RM (scores 81 and 100) are reached through a path involving SI, but their final split is determined exclusively by PE. The node with a score of 65 reflects a decision path based on evaluations of both PE and RK. Other nodes involve successive consideration of PE, SI, and BM.

Figure 2 also shows that the coefficient of determination for the DTR model is 69.30%, which can be considered substantial (Hair et al. 2019). Nevertheless, both the goodness of fit and the predictive capacity of the DTR can be enhanced through the application of the Random Forest (RF) algorithm. The optimal RF model was obtained by tuning three hyperparameters: the number of variables randomly selected at each split ($mtry = 3$), the total number of trees in the ensemble ($ntree = 300$), and the minimum number of observations per terminal node ($nodesize = 5$). This configuration yielded an RMSE of 18.41, with a very small standard deviation of 0.37, indicating high model stability.

Table 4 shows that RF achieves higher R^2 values and substantially lower error metrics compared to the DTR in the fitting phase. Moreover, the results of the Monte Carlo cross-validation presented in Table 4 indicate that RF exhibits the best generalization performance, with all measures being significantly different. Notably, for RF, Q^2 values exceed 50%, indicating a high level of predictive capacity in this context (Hair et al. 2019).

Table 4. Performance of the fit and predictive accuracy of DTR and RF.

Method	Fit Accuracy			Predictive Accuracy		
	R^2	RMSE	MAE	Q^2	RMSE	MAE
DTR	69.3%	15.969	12.312	41.3%	21.7	17.2
RF	91.7%	8.307	6.727	55.7%	18.9	15.4
Difference (RF-DTR)	22.4%	−7.662	−5.585	14.4% **	−2.8 **	−1.8 **

Note: “***” stands for a difference significantly different from zero at $p < 0.001$. Source: Own elaboration.

3.2. Analysis of Research Question 2

The SHAP analysis is performed on the RF generalization of the DTR, since, as shown in Table 4, RF generalizes much better than DTR. Figure 3 presents a SHAP beeswarm plot illustrating how high values (warm colors) and low values (cool colors) of each variable affect the model’s predictions. PE stands out as the most influential variable, followed by SI and EE, with slightly less intense but consistent positive effects, and by BM, whose influence is similar in magnitude to that of EE but with the opposite sign. RK and FL show much more moderate influence. In contrast, the sociodemographic factors (AGE, INC, and GEN) exhibit very limited contribution, with SHAP values close to zero in most cases.

Table 5 presents the mean absolute SHAP values for the nine explanatory variables, along with the results of Student’s t -test for their pairwise differences. PE has the highest value, followed by SI, BM, and EE. The least relevant latent variables are RK and FL, which are more important than the sociodemographic variables. The hierarchy of importance

based on SHAP values is statistically significant in all cases except for the comparison between BM and EE, whose difference is not significant.



Figure 3. Beeswarm plot of the RF adjustment of the conceptual framework in Figure 1. Source: Own elaboration.

Table 5. Mean of absolute SHAP and difference in mean absolute SHAP between variables.

		Differences in SHAPs (Row Minus Column)								
	Mean Absolute SHAP		EE	FL	RK	SI	BM	GEN	AGE	INC
PE	9.72	PE	7.42	8.59	8.02	2.46	7.22	9.56	8.99	9.52
EE	2.29	EE		1.17	0.60	−4.96	−0.20	2.13	1.57	2.09
FL	1.13	FL			−0.57	−6.13	−1.37	0.97	0.40	0.93
RK	1.69	RK				−5.56	−0.80	1.53	0.97	1.50
SI	7.25	SI					4.76	7.09	6.53	7.06
BM	2.49	BM						2.34	1.77	2.30
GEN	0.16	GEN							−0.56	−0.04
AGE	0.72	AGE								0.52
INC	0.20	INC								

Note: (1) The differences are calculated as the mean absolute SHAP of the variable in the row minus the mean absolute SHAP of the variable in the column. (2) All differences, except that of EE with BM, have statistical significance at $p < 0.01$. Source: Own elaboration.

Figure 4 presents the Importance–Performance Map constructed according to Step 7 in Section 3, using the SHAP values shown in Table 5 (for importance) and the mean construct values from Table 1 (for performance). Note that while the performance of facilitators (PE, EE, FL and SI) corresponds to the mean construct value in Table 1 (e.g., 61 for PE), for barriers (RK and BM), it is 100 minus the mean construct value (e.g., $100 - 69 = 31$ for BM).

The variables that deserve the greatest improvement efforts are PE, SI, and BM. For PE, although its performance level is high (and therefore improvements may be harder to achieve), its clear relevance for acceptance justifies attention, as even small enhancements could have a significant impact. BM lies at the opposite extreme: despite its relatively limited importance, it is, along with RK, the variable with the lowest performance level. SI falls in an intermediate position, with average performance and comparatively high importance. By contrast, RK, EE, and FL occupy areas of the map, suggesting that these constructs do not require special strategic attention.

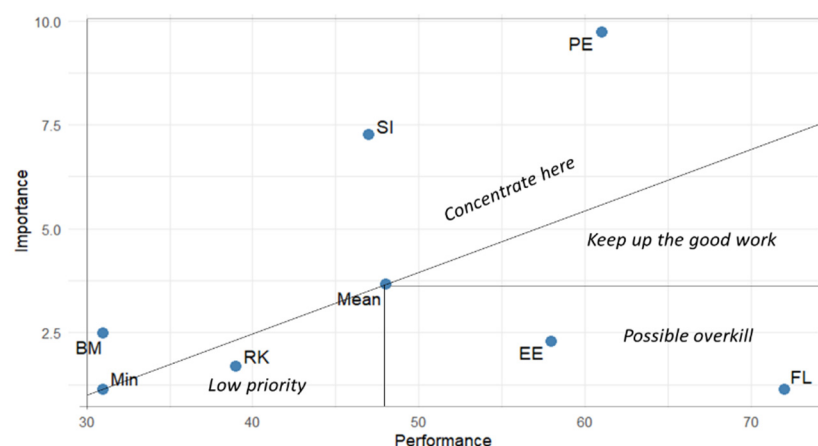


Figure 4. Importance–Performance Map of the assessed variables to produce acceptance of RMs. Source: Own elaboration.

4. Discussion

4.1. General Considerations

This study analyzes the determinants of RM acceptance as a financial planning tool for retirement in Spain, using an integrative framework that combines the TPB with explainable machine learning techniques. Two research questions guide the analysis: RQ1 examines the explanatory and predictive validity of the proposed model, while RQ2 evaluates the degree of attention that each construct requires for the successful development of RMs in Spain.

Regarding RQ1, the results are strong. The DTR model achieves an R^2 of 69.3%, and its enhanced version with RF increases explanatory capacity to 91.7%, with solid predictive validity ($Q^2 = 55.7\%$). According to [Hair et al. \(2019\)](#), these results indicate substantial explanatory power and high predictive capacity. This confirms both the theoretical relevance of the TPB and the ability of tree-based algorithms to model complex behaviors without assuming linear or additive relationships.

A key strength of the DTR approach is its ability to identify and visualize interactions. For example, nodes in the decision tree show that PE and SI act as primary splits across multiple branches, confirming their consistent and positive effect on BI across different user profiles. In contrast, variables such as BM and RK define user segments reluctant to adopt RMs, acting as thresholds that hinder higher acceptance. These patterns empirically support hypotheses H1, H4, H5, and H6.

EE does not appear as a primary split but consistently emerges as a surrogate split, indicating a solid positive association with BI and supporting H2. FL is also absent from primary splits but appears as a surrogate split in five branches. In two cases, it exerts the expected positive influence, while in three it shows a negative association, suggesting that FL can also function as a lower bound for groups with lower acceptance. This mixed evidence creates ambiguity regarding H3. Finally, sociodemographic variables (GEN, AGE, IN) exert only marginal influence on BI.

RQ2 is addressed through SHAP values and IPMA. SHAP results reveal a clear hierarchy: PE is the most influential predictor, followed by SI, BM, and EE. FL and RK exert moderate influence, while sociodemographic factors are virtually irrelevant. This suggests that the TPB framework adequately captures the core dimensions of the decision-making process.

The IPMA complements these findings by highlighting three strategic action zones. First, PE stands out as a high priority due to its strong importance, despite already having above-average performance. Second, SI appears as a consolidated variable, with high relevance and average performance, pointing to the need for continued attention. Third,

BM is identified as a barrier, with medium importance but low performance. Given its underperformance, BM may represent an opportunity for improvement, though its deep-seated value-driven nature suggests that interventions may require more nuanced strategies. Together, these insights offer practical guidance for financial institutions, regulators, and product designers in determining which variables demand immediate action and which can be addressed through gradual structural measures.

The central role of PE is consistent with prior TPB-based research on financial planning predispositions, which emphasizes the importance of attitudinal factors in financial inclusion (Musa et al. 2024), retirement planning (Bongini and Cucinelli 2019; She et al. 2024), and actuarial products such as life annuities (Nosi et al. 2017) and life settlements (De Andrés-Sánchez et al. 2023). In the RM field, similar evidence has mainly emerged from Asian contexts, such as Malaysia and India (Ashok and Vij 2020; Mohammed and Sulaiman 2018; Muralidharan and Soundara Raja 2022).

Variables related to subjective norms, especially SI, also show a significant influence on BI. This finding is consistent with prior studies in Italy (Bongini and Cucinelli 2019), Malaysia (She et al. 2024), and Australia (Griffin et al. 2012), some of which even suggest a greater role for SI than attitudinal variables. SI has likewise been identified as central in the adoption of annuities (Nosi et al. 2017) and life settlements (De Andrés-Sánchez and González-Vila Puchades 2023). In the specific context of RMs, the present findings align with results from Malaysia (Mohammed and Sulaiman 2018) and India (Ashok and Vij 2020; Muralidharan and Soundara Raja 2022).

Regarding BM, its relevance is consistent with previous findings in various European Union countries (Hoekstra and Dol 2021), Australia (Whait et al. 2019), India (Ashok and Vij 2020), and Malaysia (Mohammed and Sulaiman 2018). These results are also recognized in the explanation of why strictly financial–actuarial valuations appear somewhat contradictory to the persistently low adoption of RMs (Davidoff 2015). The fact that in one surrogate node it exceptionally acts as a ceiling threshold for profiles associated with lower acceptance would be consistent with Rasmussen et al. (1995), who note that, for certain profiles, BM could actually increase the demand for RMs, as older adults might view them as a means of transferring wealth to the next generation, allowing their homes to be retained by their children after their death.

The constructs related to the perceived behavioral control dimension (EE, FL and RK) are, in general, those with the lowest relevance in explaining BI, and none of them require special attention according to the IPMA. In the field of retirement planning, although this dimension has been shown to be relevant (Bongini and Cucinelli 2019; She et al. 2024), its influence is always lower than that of the attitude or subjective norms dimensions. In fact, authors such as Griffin et al. (2012) find no significant influence of this dimension on BI toward financial planning for retirement.

In regard to EE, in studies that explicitly consider it in contexts of products comparable to RMs, such as life settlements, EE appears as a relatively insignificant variable (De Andrés-Sánchez and González-Vila Puchades 2023).

The low relevance of FL in the intention to use RMs and its participation with different signs in the surrogate splits is noteworthy. This finding contradicts previous studies that have shown that this construct can be significant in shaping attitudes toward financial planning for retirement, albeit primarily through mediation by perceived behavioral control (She et al. 2024), and in the decision to take out RMs (Mohammed and Sulaiman 2018). However, while Bongini and Cucinelli (2019) report that the significance of FL is highly sensitive to the covariates included in their regression model, Choinière-Crèvecoeur and Michaud (2023) indicate that FL contributes to greater product knowledge as a complementary alternative to public pensions, but not necessarily to a greater willingness to contract it.

In fact, [Fornero et al. \(2016\)](#) find a negative relationship between FL and the propensity to use RMs.

RK, although it participates in a primary split in line with the expected sign, does not always maintain this pattern in surrogate splits. Likewise, its relevance is significantly lower than that of PE, EE, SI, and BM. This result could reconcile the findings of [Whait et al. \(2019\)](#), who identify risk aversion as a barrier to taking out RMs, with those of [Fornero et al. \(2016\)](#) and [Moulton et al. \(2017\)](#), who observe that RM borrowers tend to be more prone to risk.

In sum, this study demonstrates that RM acceptance in Spain can be robustly modeled using TPB constructs enriched by explainable machine learning. The combination of DTR, RF, SHAP, and IPMA allows not only for accurate prediction but also for the strategic prioritization of determinants. Attitudinal variables, especially PE, and social influences, particularly SI, emerge as the most relevant factors, while barriers such as BM and RK highlight the constraints that must be addressed. Effort-related factors (EE) and FL provide additional nuance, though their effects are less consistent. Socio-demographics appear to play only a marginal role. These insights advance the theoretical understanding of RM acceptance and provide actionable guidance for the design and regulation of equity release markets in Spain.

4.2. Theoretical and Analytical Implications

This study offers important theoretical implications in two dimensions: the suitability of the TPB to explain complex financial decisions, and the incorporation of explainable machine learning methods to enrich existing theoretical models.

First, it confirms the usefulness of the TPB for studying the acceptance of financial planning products in old age, such as RMs. The tripartite structure of the model into attitude (PE), perceived behavioral control (EE, FL, RK), and subjective norms (SI, BM) adequately captures the motivations, abilities, and perceived constraints of users. Previous literature has employed the TPB in the study of decisions such as saving for retirement ([Bongini and Cucinelli 2019](#); [Griffin et al. 2012](#)), insurance demand ([Dragos et al. 2020](#)) or predisposition toward financial inclusion ([Mussa et al. 2023](#)) and, in Asia, the use of RMs ([Ashok and Vij 2020](#); [Mohammed and Sulaiman 2018](#); [Muralidharan and Soundara Raja 2022](#)).

Secondly, this study highlights the value of explainable machine learning techniques for analyzing theoretical models of financial decision-making. Unlike traditional regression approaches such as Structural Equation Modeling, which require specifying causal relationships in advance, tree-based methods like DTR and RF uncover empirical patterns directly from the data. This is particularly relevant in complex, nonlinear contexts such as financial products, where decisions often deviate from rational, linear models ([Rad et al. 2025](#)). DTR makes it possible to identify respondent profiles and variable interactions in the evaluation of RMs, while SHAP values provide a robust measure of predictor importance that, when combined with performance metrics, enables IPMA and deepens theoretical interpretation.

Overall, this research suggests that the TPB, complemented with relevant variables such as BM and explainable machine learning methods, constitutes an appropriate theoretical–methodological framework for understanding the acceptance of complex, low-familiarity financial products among the general public.

4.3. Practical Findings of This Paper

In our survey, BI items average around 5 points, indicating moderate acceptance and falling short of the high levels reported by [Hanewald et al. \(2020\)](#) (89% interest). Nevertheless, this average value points to a significant potential market if appropriate

measures are implemented. The combined use of SHAP and IPMA identifies PE, SI, and BM as variables of high strategic interest.

Although PE is more difficult to improve than other variables, its high importance means that even small increases in performance could produce significant gains in behavioral intention. Possible measures include:

- Information campaigns should emphasize how RMs can enhance quality of life in old age, maintain consumption levels, reduce dependence on family or public assistance, and provide financial stability without leaving the home. While generic financial literacy has not proven especially relevant for product acceptance, a deeper understanding of the relationship between inflation, interest rates, and housing values can ultimately help contextualize the usefulness of RMs (Ilan and Mugerman 2025).
- Online tools that allow users to simulate how their disposable income would vary according to RM type, age, and property value can help translate the product's theoretical benefits into tangible personal advantages. In this regard, robo-advisors supported by artificial intelligence represent a particularly promising tool (Ilan and Mugerman 2025).
- Designing more flexible and user-friendly RM products could help increase demand by reducing contractual complexity, offering payout options better aligned with diverse household needs, and enhancing transparency in costs and risks (Hanewald et al. 2020).
- Market frictions need to be reduced to attain more appealing prices for borrowers and lenders. For example, in the United States, provisions such as the limited liability rules embedded in RM contracts and the uniform pricing applied regardless of regional housing risks act as significant barriers both for borrowers (who may perceive a lower net value) and for the sustainability of the program itself (Davidoff 2015). Similar barriers are also present in the Spanish context, particularly through inheritance laws.

SI emerges as the second most important variable, with a substantially above-average importance and slightly below-average performance, making it a priority strategic target. Enhancing SI involves shaping the potential user's social environment. Possible actions include:

- Sharing experiences of individuals who have successfully used RMs can demystify the product and strengthen confidence in its utility, particularly among older adults who value relatable, concrete examples. Such narratives emphasize the usefulness of RMs in addressing liquidity constraints during retirement and covering medical or care-related expenses (Hanewald et al. 2020).
- Awareness campaigns targeting subjective norms could be particularly effective if backed by trusted advisors. To ensure this trust, training programs for financial advisors and notaries are essential, providing continuous education on RM functioning, advantages, limitations, and suitable client profiles so they can offer accurate and reliable guidance (Baulkaran and Jain 2024; Ilan and Mugerman 2025).
- Institutional endorsement initiatives, such as the involvement of public institutions or consumer associations as guarantors of RM transparency, could legitimize the product and help counteract social skepticism (Hanewald et al. 2020).

BM is a barrier that, while moderately important and difficult to modify directly due to its deep personal and cultural roots, shows a very low performance score. This suggests that strategies aimed at reconciling BM with RM adoption could have a significant impact. Designing more flexible products that facilitate the transfer of housing to descendants may reduce the strength of this barrier (Kwong et al. 2025). Such measures should also

promote intergenerational dialogue to ease tensions around inheritance and family transfers (Hanewald et al. 2020). Possible actions in this regard may include:

- Designing hybrid products that allow for partial repayment options or clauses guaranteeing a minimum residual value for heirs, making the product more acceptable for those who prioritize inheritance.
- Promoting intergenerational financial planning incentives: Regulations could grant tax benefits if part of the RM proceeds is allocated to investment funds or life insurance policies in the heirs' names.
- Intergenerational campaigns: Because RM adoption decisions often involve family members, campaigns aimed at children and heirs (framing the RM as a family planning solution rather than a threat to inheritance) could reduce resistance.
- Reframing the concept of legacy: Campaigns could broaden the notion of legacy to include not only material inheritance but also emotional well-being, independence, and the absence of a financial burden on children. This more holistic perspective may help soften psychological resistance to using housing wealth.

5. Materials and Methods

5.1. Sampling

Data collection was carried out through a structured online survey administered to Spanish participants who are at least 40 years old. The survey was conducted between May and July 2025. A mixed sampling method was employed, combining purposive and snowball sampling techniques. The questionnaire was distributed through company mailing lists and social networks such as LinkedIn, among other channels. Participants were also encouraged to share the survey link with acquaintances who met the specified criterion.

5.2. Sample and Sociodemographic Profile

The total number of valid responses obtained was 229. It is common in the use of DTR and RF to apply the heuristic rule of “ten observations per explanatory variable” in regression analysis (Stupak 2024), which would imply a minimum recommended size of 90 observations since Figure 1 suggests nine explanatory variables. In this context, the available sample size, while tight, can be considered reasonable. This consideration applies to both DTR and RF models. In fact, Breiman (2001) shows that, with proper hyperparameter tuning, RF models can generalize correctly even with samples of 200 observations and 10 explanatory variables.

Another common approach is to analyze the statistical power of the machine learning method, using statistical effect sizes as a reference (Stupak 2024). In this case, using G*Power 3.1 (Faul et al. 2009), it is verified that a regression model with nine explanatory variables and a sample of 229 observations achieves a power of 80% assuming a significance level of 5%, provided that the effect size required to this end is at least 0.075 (between small and medium), which corresponds to an $R^2 = 6.98\%$.

The sample profile is presented in Table 6. It is composed of 55.15% men and 44.85% women. Regarding age, 24.89% are 50 years old or younger, 48.47% are between 51 and 60 years old, 14.85% are between 61 and 65 years old, and 11.79% are 66 years old or older. With respect to net monthly income level, 22.27% reported earning less than €3000, 32.75% between €3000 and €4999, 36.68% at least €5000, and 8.30% did not respond.

As for educational level, 16.16% have primary or secondary education, while 83.84% have a university education. A total of 73.36% of respondents are married or in a civil partnership, 25.33% reported being single, divorced, or widowed, and 1.31% did not respond. As for the number of children, 20.96% have no children, 16.16% have one child, 51.53% have two children, and 10.92% have three children.

Table 6. Sociodemographic profile (N = 229).

Variable	Responses
Gender	Men (55.15%), Female (44.85%)
Age	≤50 years (24.89%); ≥51 and ≤60 years (48.47%); ≥61 and ≤65 years (14.85%); ≥66 years (11.79%)
Monthly income	Less than €3000 (22.27%); Between €3000 and €4999 (32.75%); At least €5000 (36.68%); Not answered (8.30%)
Academic degree	Primary or secondary education (16.16%); University education (83.84%)
Marital status	Married or in a civil partnership (73.36%); Never married, divorced, or widowed (25.33%); Not answered (1.31%)
Number of children	No child (20.96%); one child (16.16%); two children (51.53%); three or more children (10.92%)

Source: Own elaboration.

5.3. Factors Measurement

An initial draft of the questionnaire was revised and tested by a group of university professors specializing in finance and insurance. Although their suggestions did not imply substantial modifications of the questionnaire, they enhanced its clarity, comprehensibility, and the wording of the introductory text.

The survey begins with a concise description of what RMs entail, followed by questions on sociodemographic variables. Next, the questions linked to the latent factors included in the conceptual ground in Section 2 are introduced. The questionnaire is written in Spanish. The English wording of the items corresponding to BI, PE, EE, FL, RK, SI, and BM is provided in Appendix A.

BI is based on [Ashok and Vij \(2020\)](#) and [Muralidharan and Soundara Raja \(2022\)](#), and the items of PE, in the attitude dimension, are grounded in [Pahuja and Sanjeev \(2016\)](#) and [Mohammed et al. \(2018\)](#). With regard to the dimension perceived behavioral control, the items of EE are inspired by [Pahuja and Sanjeev \(2016\)](#) and [Mohammed et al. \(2018\)](#); those of FL by [Hastings et al. \(2013\)](#) and [De Andrés-Sánchez and González-Vila Puchades \(2023\)](#); and those of RK by [Dillingh et al. \(2013\)](#), [Faqih \(2016\)](#) and [Ashok and Vij \(2020\)](#). Regarding the dimension of subjective norms, while SI items are grounded in [Ashok and Vij \(2020\)](#) and [Muralidharan and Soundara Raja \(2022\)](#), BM items are based on [Dillingh et al. \(2013\)](#) and [Ashok and Vij \(2020\)](#).

The items are responded to using an 11-point Likert scale ranging from 0 (“strongly disagree”) to 10 (“strongly agree”). Some authors recommend using slightly broader scales than the traditional 5- or 7-point formats (such as the 11-point scale) since humans have greater sensitivity in their perceptions. Furthermore, this approach is consistent with the grading system widely used in Spain, which is based on a scale from 0 to 10 ([Bisquerra Alzina and Pérez-Escoda 2015](#)).

Sociodemographic factors are modeled dichotomously for gender, age and net monthly income. In the case of age, respondents who are 60 years or older at the time of the survey, corresponding to the “Baby Boomer” generation, are differentiated from younger respondents, who belong to Generation X. Regarding income level, participants with high monthly earnings (at least €5000) are distinguished from the rest of the sample.

5.4. Data Analysis

Revised literature evaluates the acceptability and use of RMs through financial pricing models, both from the lenders’ perspective (e.g., [Alai et al. 2014](#)) and from the borrowers’ point of view (e.g., [Davidoff 2015](#)). On the borrowers’ side, econometric approaches are also common, including discrete choice regression ([Costa-Font et al. 2010](#); [Fornero et al. 2016](#)) and structural equation modeling ([Ashok and Vij 2020](#); [Bongini and Cucinelli 2019](#);

Griffin et al. 2012; Mohammed and Sulaiman 2018). By contrast, our study applies two machine learning methods, DTR and RF, in a way comparable to regression methods, with their use justified for several reasons.

First, tree-based machine learning methods capture nonlinear relationships and interactions without imposing restrictive a priori assumptions typical of behavioral modeling, and they do not require conditions such as error normality or homoscedasticity, which are rarely met in survey data. While regression models are attractive because they estimate coefficients that indicate the direction of relationships, decision trees allow us to examine whether variable thresholds at primary or surrogate nodes act as upper or lower bounds shaping the intention to use, offering an alternative and intuitive way of interpreting relationships.

Second, DTR and RF are complementary. Decision trees provide transparent visualizations of how variables interact to generate respondent profiles according to their propensity to contract RMs. RF, as ensembles of multiple trees built from bootstrap samples, achieves higher predictive power and reduces overfitting. In this sense, DTR can be seen as a simplified, interpretable version, while RF provides a more robust and accurate approach.

Finally, predictive power is crucial not only for theory development and validation but also for selecting models that can inform managerial and policy decisions (Liengard et al. 2021). In this regard, our focus is on identifying the variables with the greatest explanatory capacity for intention to use through the method with the strongest predictive performance, most likely RF. This method has emerged as a particularly useful predictive instrument in business and consumer behavior studies (Richter and Tudoran 2024). The relative importance of the variables (PE, EE, FL, RK, SI, BM) is estimated using SHAP values (Lundberg and Lee 2017), which offer a transparent and consistent interpretation of the model's outcomes.

The data analysis is structured into seven sequential phases designed to address RQ1 and RQ2. Each of these steps is carried out entirely using tools in R 4.5.0 (R Development Core Team 2025).

Step 1: Since the model is based on latent variables, the process begins by assessing the internal consistency and discriminant validity of the scales used, as recommended by Hair et al. (2019). This assessment includes calculating Cronbach's alpha, composite reliability, average variance extracted (AVE), and identifying factors through exploratory factor analysis. In addition, the correlation matrix among variables is examined to verify the consistency of the formulated hypotheses regarding the expected direction of the relationships between these variables. This phase is conducted using the *psych* package in R.

Step 2: Next, the final construct scores are generated by calculating a weighted average of the items, based on their factor loadings, and rescaling the results to a 0–100-point scale. This procedure follows the guidelines proposed by Ringle and Sarstedt (2016) for measuring the performance of latent variables. This stage is implemented with the *psych* and *dplyr* packages. Sociodemographic variables are coded dichotomously: a value of 1 is assigned to men (0 otherwise), to individuals belonging to Generation X (0 otherwise), and to those reporting net monthly income equal to or greater than €5000 (0 otherwise).

Step 3: DTR is then fitted. The fact that the variables are expressed on a common 100-point scale, rather than as standardized factor scores, facilitates the interpretation of cut-off points in the tree nodes. To determine the sign of the relationship between an explanatory variable X and BI, we analyze how observations are distributed in the nodes where that variable appears. If a threshold X_a limits access to nodes with low acceptance ($X < X_a$), a positive relationship is inferred; if the opposite occurs ($X \geq X_a$), the relationship is considered negative. This phase considers both primary and surrogate splits, the latter

being relevant when information on the primary splitting variable is missing. Although primary splits take precedence, surrogate splits enrich the tree's interpretation. This phase is executed with the *rpart* and *rpart.plot* packages.

Step 4: To optimize the model's accuracy and predictive performance, a random forest (RF) algorithm is employed, acknowledging that this approach sacrifices some interpretability compared to individual decision trees. RF fitting requires careful hyperparameter calibration to maximize predictive power, particularly when working with moderate sample sizes (Probst et al. 2019). In this study, a 5-fold cross-validation procedure is used—a technique widely recommended for model selection (Kuhn and Johnson 2013)—to identify the parameter combination that minimizes the root mean squared error (RMSE). The number of repeats was set to one beyond the 5-fold cross-validation, and a fixed random seed (123) was used to ensure reproducibility.

Following Alhazeem et al. (2024), three key parameters are tuned: (1) *mtry*, which specifies the number of predictors randomly sampled at each split; (2) *ntree*, the total number of trees in the forest; and (3) *nodesize*, the minimum number of observations per terminal node. To systematically explore their optimal configuration, a medium-sized grid search is conducted, evaluating multiple combinations of parameter values.

Specifically, *mtry* is tested in the range {2, 3, 4, 5}, *nodesize* in {1, 5, 10}, and *ntree* in {300, 500, 1000}. These ranges are consistent with established guidelines for RF tuning in small-to-moderate datasets, ensuring sufficient model diversity while avoiding excessive computational cost. In total, 36 parameter combinations are evaluated using 5-fold cross-validation, selecting the configuration that minimizes RMSE and maximizes the model's explanatory capacity. This optimization phase is implemented using the *caret* package in combination with *randomForest* in R.

Step 5: The performance of the RF model is then compared with that of the DTR to evaluate potential improvements. Model fit is assessed using metrics such as R^2 , RMSE, and mean absolute error (MAE) over the entire sample. For predictive capacity, Stone–Geisser's Q^2 is used, along with RMSE and MAE derived from Monte Carlo cross-validation based on repeated random resampling. This phase is implemented using the *caret*, *rsample*, and *randomForest* packages.

The results of these evaluations allow RQ1 to be answered by providing a robust estimate of both the explanatory and predictive ability of the groundwork, as well as identifying relevant interaction patterns in RM acceptance, thereby contributing to the empirical testing of hypotheses H1 through H9.

Step 6: To address RQ2, SHAP values (Lundberg and Lee 2017) are calculated for all observations and variables, using the model with the best predictive performance (either DTR or, more likely, RF). From these values, mean absolute SHAP values are computed to estimate the average contribution of each variable to the predictions, thus establishing a hierarchical order of explanatory importance with respect to BI. This analysis is performed with the *fastshap* package.

Step 7: Finally, to complete the approach to RQ2, an IPMA focused on the TPB model is carried out. The performance of each construct is estimated from the sample mean of the constructs, which is rescaled to a 100-point scale. For theoretical facilitators (PE, EE, FL, SI), performance corresponds to the direct mean; for inhibitors (RK and BM), the inverted mean is used (100 minus the average value). Variable importance is measured using their mean absolute SHAP values. IPMA interpretation is based on the diagonal partitioning scheme proposed by Abalo et al. (2007) and is illustrated in Figure 5.

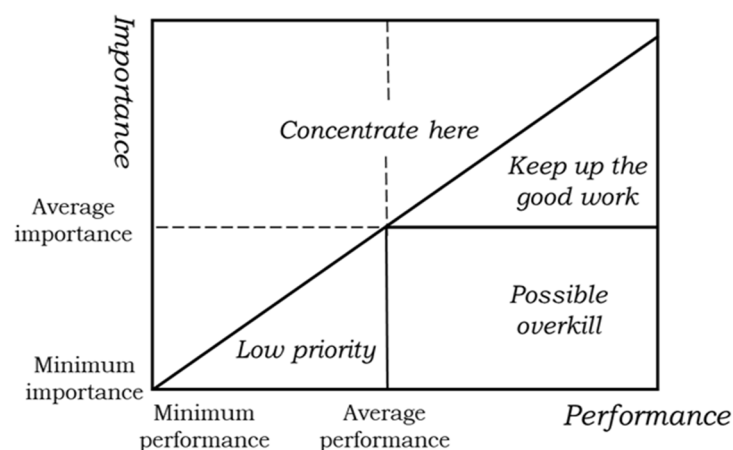


Figure 5. Importance–Performance Map interpretation used in this study. Source: Own elaboration adapted from [Abalo et al. \(2007\)](#).

6. Conclusions

6.1. Principal Takeaways

This study analyzes the acceptance of RMs using the TPB, extended with constructs considered relevant to product adoption, including FL, RK, and BM, and evaluated through decision tree–based machine learning techniques.

The first finding is that the proposed model is both theoretically sound and empirically robust. With DTR, the model explains around 69% of the variability in BI to use RMs, while ensemble methods such as RF raise explanatory power to nearly 90%. DTR highlights how variables interact to generate acceptance, whereas RF provides strong predictive capacity, confirming the suitability of combining TPB with tree-based algorithms.

The second finding relates to the hierarchy of explanatory variables. SHAP analysis identifies PE and SI as the most influential determinants of RM acceptance. A second tier comprises EE and BM, whose contributions are comparable. In contrast, FL and RK show lower importance and, in some cases, inconsistent effects. Sociodemographic variables exert only marginal influence, confirming that acceptance is mainly driven by attitudinal and normative constructs rather than background characteristics.

The third finding arises from IPMA. PE emerges as a factor of high importance and relatively strong performance, implying that improvements could be costly but still yield significant gains. SI is also highly important but with moderate performance, making it a strategic priority for intervention. BM, by contrast, presents very low performance, suggesting that targeted efforts to reduce this barrier could have a disproportionately positive effect on BI.

Overall, the study demonstrates the value of combining machine learning and explainability methods such as SHAP with managerial tools like IPMA. This integrated approach not only improves predictive accuracy but also offers actionable insights into how drivers and barriers interact to influence acceptance of RMs. For the effective deployment of RMs as a retirement planning instrument in the decumulation phase, strategies should focus on enhancing PE, reinforcing the product’s social legitimacy, and mitigating reluctance associated with BM.

6.2. Limitations and Future Research Directions

We acknowledge several limitations of this empirical research that should be considered when interpreting the findings. The study has been conducted in Spain using a convenience sample mainly recruited through platforms such as LinkedIn and mailing lists of individuals interested in the topic, which resulted in a respondent profile char-

acterized by high educational attainment and professional experience, often in mid- or senior-management positions. Such characteristics may have influenced the results regarding behavioral intention to use RMs, since education has been shown to affect financial decisions such as the purchase of life annuities (Dragos et al. 2020; Nosi et al. 2017).

Consequently, the sample is skewed toward well-educated and higher-income individuals and may not fully reflect the perspectives of lower-income retirees, who could display different preferences and constraints. Furthermore, the study assesses behavioral intention rather than actual usage, which, although reasonable given the very limited market penetration of RMs in Spain, weakens the scope of the policy implications. Expressed intentions do not always translate into actual behavior, since adoption is also shaped by product availability, contractual features, and market pricing. This gap between interest and actual behavior has been observed in other countries; for instance, Hanewald et al. (2020) report high survey interest in RMs in China but caution that real-world adoption may be considerably lower.

For this reason, caution is advised when generalizing the results to potential borrowers from other cultural contexts or with different educational and professional backgrounds. To reach broader conclusions, future research should include a more diverse set of countries and socioeconomic profiles.

Another limitation is the focus on a single retirement planning product. While insights are valuable for understanding RM acceptance, extrapolation to other products (e.g., life settlements or annuities) or to broader personal finance decisions should be undertaken cautiously.

In methodological terms, the analysis relies on a cross-sectional survey, which prevents conclusions about long-term dynamics. Furthermore, the study has been carried out at a time when pension systems across Europe are under active debate regarding reform. Measures designed to mobilize private resources to complement public pensions are evolving, particularly given expectations of declining generosity. A more comprehensive picture would require longitudinal designs or repeated cross-sectional studies at different stages of the pension reform process in Spain.

Overall, while this research provides valuable insights into the determinants of RM acceptance, the contextual, methodological, and product-specific limitations highlight the need for broader, more diverse, and longitudinal evidence to strengthen the external validity of the findings.

Author Contributions: Conceptualization, J.d.A.-S. and L.G.-V.P.; Methodology, J.d.A.-S. and L.G.-V.P.; Software, J.d.A.-S. and L.G.-V.P.; Validation, J.d.A.-S. and L.G.-V.P.; Formal analysis, J.d.A.-S. and L.G.-V.P.; Investigation, J.d.A.-S. and L.G.-V.P.; Writing—original draft, J.d.A.-S. and L.G.-V.P.; Writing—review & editing, J.d.A.-S. and L.G.-V.P.; Visualization, J.d.A.-S. and L.G.-V.P.; Supervision, J.d.A.-S. and L.G.-V.P.; Project administration, J.d.A.-S. and L.G.-V.P. All authors have read and agreed to the published version of the manuscript.

Funding: Jorge de Andrés-Sánchez recognizes the support of Telefonica and the Telefonica Chair on Smart Cities of the Universitat Rovira i Virgili and Universitat de Barcelona (project number: 42.DB.00.18.00).

Institutional Review Board Statement: (1) All participants received detailed written information about the study and procedure; (2) no data directly or indirectly related to the health of the subjects were collected, and therefore the Declaration of Helsinki was not mentioned when informing the subjects; (3) the anonymity of the collected data was ensured at all times; (4) the research received a favorable evaluation from the Ethics Committee of the researchers' institution (CEIPSA-2022-PR-0005).

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AGE	Age
BI	Behavioral Intention
BM	Bequest Motive
DTR	Decision Tree Regression
EE	Effort Expectancy
FL	Financial Literacy
GEN	Gender
IPMA	Importance–Performance Map Analysis
IN	Income
PE	Performance Expectancy
RF	Random Forest
RK	Risk
RM	Reverse Mortgage
SHAP	Shapley Additive Explanations
SI	Social Influence
TPB	Theory of Planned Behavior

Appendix A. English Wording of Items Used in This Paper

Behavioral Intention (BI)

- BI1: I would consider the possibility of applying for a reverse mortgage in the future if circumstances require it.
- BI2: I am receptive to incorporating a reverse mortgage into my long-term retirement planning.

Performance Expectancy (PE)

- PE1: I regard reverse mortgages as a valuable financial resource for individuals in retirement.
- PE2: I believe that obtaining a reverse mortgage could assist in preserving my lifestyle throughout retirement.
- PE3: I think reverse mortgages offer effective support for managing personal finances during later life.
- PE4: In my view, a reverse mortgage would enhance my access to financial resources during retirement.

Effort Expectancy (EE)

- EE1: I find reverse mortgages to be relatively simple to grasp and operate.
- EE2: The application procedure for a reverse mortgage appears to be clear and manageable.
- EE3: I feel confident in my ability to oversee the process involved in using a reverse mortgage.
- EE4: I am assured of my capacity to handle a reverse mortgage without major complications.

Financial Literacy (FL)

- FL1: I consider myself to be well-informed in financial matters.
- FL2: I am capable of making sound financial decisions with confidence.

Risk (RK)

- RK1: I associate reverse mortgages with considerable financial risk.

- RK2: I view reverse mortgages as involving excessive uncertainty.
- RK3: I am uneasy about the possible negative outcomes linked to reverse mortgages.

Social Influence (SI)

- SI1: My social circle would likely support my decision to pursue a reverse mortgage.
- SI2: Individuals whose perspectives I respect consider reverse mortgages to be a beneficial option for retirees.

Bequest Motive (BM)

- BM1: I feel a strong desire to pass on assets to my descendants.
- BM2: Ensuring that I leave an inheritance is a central goal in my life.
- BM3: I perceive that utilizing a reverse mortgage might interfere with my intention to leave wealth to my heirs.

References

- Abalo, Javier, Jesús Varela, and Vicente Manzano. 2007. Importance values for Importance–Performance Analysis: A formula for spreading out values derived from preference rankings. *Journal of Business Research* 60: 115–21. [\[CrossRef\]](#)
- Ajzen, Icek. 1991. The theory of planned behavior. *Organizational Behavior and Human Decision Processes* 50: 179–211. [\[CrossRef\]](#)
- Alai, Daniel H., Hua Chen, Daniel Cho, Katja Hanewald, and Michael Sherris. 2014. Developing Equity Release Markets: Risk Analysis for Reverse Mortgages and Home Reversions. *North American Actuarial Journal* 18: 217–41. [\[CrossRef\]](#)
- Alhazeem, Ensaf, Anas Alsobeh, and Bilal Al-Ahmad. 2024. Enhancing Software Engineering Education through AI: An Empirical Study of Tree-Based Machine Learning for Defect Prediction. Paper presented at the 25th Annual Conference on Information Technology Education, New York, NY, USA, October 10–12; pp. 153–56. [\[CrossRef\]](#)
- Arias-Oliva, Mario, Jorge Pelegrín-Borondo, Kiyoshi Murata, and Stéphanie Gauttier. 2023. Conventional vs. disruptive products: A wearables and insideables acceptance analysis: Understanding emerging technological products. *Technology Analysis and Strategic Management* 35: 12. [\[CrossRef\]](#)
- Ashok, Shruthi, and Madhu Vij. 2020. Exploring the determinants of reverse mortgage purchase decision: Evidence from India. *Journal of Internet Banking and Commerce* 25: 369.
- Atance, David, Ana Debón, and Iván De La Fuente. 2021. *Hipoteca Inversa: Impacto del Riesgo de Longevidad en el Caso Español*. Madrid: Anales del Instituto de Actuarios Españoles, pp. 135–59. [\[CrossRef\]](#)
- Atance, David, Ana Debón, and Iván De La Fuente. 2024. Valuation of reverse mortgages in the Spanish market for foreign residents. *Technological and Economic Development of Economy* 30: 46–73. [\[CrossRef\]](#)
- Banco de España. 2023. Guía Sobre la Hipoteca Inversa. Available online: <https://www.bde.es/f/webbde/Secciones/Publicaciones/Folleto/Ficheros/GUIA.pdf> (accessed on 10 September 2025).
- Banco de España. 2024. Informe Anual 2023. Available online: https://www.bde.es/f/webbe/SES/Secciones/Publicaciones/PublicacionesAnuales/InformesAnuales/23/Fich/InfAnual_2023.pdf (accessed on 10 September 2025).
- Bartsch, Florian, Florian Buhlmann, Karolin Kirschenmann, and Carolin Schmidt. 2021. Is There a Need for Reverse Mortgages in Germany? Empirical Evidence and Policy Implications. Discussion Paper Series, No. 31. Available online: <https://hdl.handle.net/10419/236738> (accessed on 10 September 2025).
- Baulkaran, Vishaal, and Pawan Jain. 2024. Home equity and retirement funding: Challenges and opportunities. *Global Finance Journal* 61: 100969. [\[CrossRef\]](#)
- Bisquerra Alzina, Rafel, and Núria Pérez-Escoda. 2015. Les escales de Likert poden augmentar en sensibilitat? *REIRE Revista d'Innovació i Recerca en Educació* 8: 129–47. [\[CrossRef\]](#)
- Boj, Eva, Maria Mercè Claramunt, and Xavier Varea. 2022. Reverse mortgage and financial sustainability. *Technological and Economic Development of Economy* 28: 872–92. [\[CrossRef\]](#)
- Bongini, Paola, and Doriana Cucinelli. 2019. University students and retirement planning: Never too early. *International Journal of Bank Marketing* 37: 775–97. [\[CrossRef\]](#)
- Breiman, Leo. 2001. Random forests. *Machine Learning* 45: 5–32. [\[CrossRef\]](#)
- Caser. 2024. Situación del Ahorro y la Inversión en España: Informe Ejecutivo. Available online: https://www.caser.es/documents/473773/16053307/1732183763860_caser%20pensiones%202024%20low.pdf (accessed on 10 September 2025).
- Chen, Hong-Ming, and Jing-Yi Chen. 2024. Structural analysis of reverse mortgages in Taiwan. *Humanities and Social Sciences Communications* 11: 1204. [\[CrossRef\]](#)

- Cheung, Gordon W, Helena D. Cooper-Thomas, Rebecca S. Lau, and Linda C. Wang. 2024. Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations. *Asia Pacific Journal of Management* 41: 745–83. [CrossRef]
- Choinière-Crèvecoeur, Ismael, and Pierre-Carl Michaud. 2023. Reverse mortgages and financial literacy. *Journal of Financial Literacy and Wellbeing* 1: 79–102. [CrossRef]
- Chung, Doohee, Pilwon Jeong, Donghwan Kwon, and Hyunsoo Han. 2023. Technology acceptance prediction of robo-advisors by machine learning. *Intelligent Systems with Applications* 18: 200197. [CrossRef]
- Costa-Font, Joan, Joan Gil, and Oscar Mascarilla. 2010. Housing wealth and housing decisions in old age: Sale and reversion. *Housing Studies* 25: 375–95. [CrossRef]
- Cuc, Lavinia Denisa, Dana Rad, Teodor Florin Cilan, Bogdan Cosmin Gomoii, Cristina Nicolaescu, Robert Almași, Simona Dzitac, Florin Lucian Isac, and Ionut Pandelica. 2025. From AI Knowledge to AI Usage Intention in the Managerial Accounting Profession and the Role of Personality Traits—A Decision Tree Regression Approach. *Electronics* 14: 1107. [CrossRef]
- Daptardar, Ashish, and Chandan Dasgupta. 2014. Reverse mortgage in the Indian housing market: A review. *International Journal of Management & Business Studies* 4: 18–20.
- Davidoff, Thomas. 2015. Can ‘High Costs’ Justify Weak Demand for the Home Equity Conversion Mortgage? *Review of Financial Studies* 28: 2364–98. [CrossRef]
- Davidoff, Thomas, Patrick Gerhard, and Thomas Post. 2017. Reverse mortgages: What homeowners (don’t) know and how it matters. *Journal of Economic Behavior & Organization* 133: 151–71. [CrossRef]
- De Andrés Sánchez, Jorge, and Laura González-Vila Puchades. 2020. Enhanced annuities as a complement to the public retirement pension: Analysis of their implementation in Spain. *Revista Galega de Economía* 29: 1–19. [CrossRef]
- De Andrés-Sánchez, Jorge, and Laura González-Vila Puchades. 2023. Combining fsQCA and PLS-SEM to assess policyholders’ attitude towards life settlements. *European Research on Management and Business Economics* 29: 100220. [CrossRef]
- De Andrés-Sánchez, Jorge, and Laura González-Vila Puchades. 2025. Longevity risk and annuitisation decisions in the absence of special-rate life annuities. *Risks* 13: 37. [CrossRef]
- De Andrés-Sánchez, Jorge, Laura González-Vila Puchades, and Mario Arias-Oliva. 2023. Factors influencing policyholders’ acceptance of life settlements: A technology acceptance model. *Geneva Papers on Risk and Insurance—Issues and Practice* 48: 941–67. [CrossRef]
- Dillingh, Rik, Henriëtte Prast, Mariacristina Rossi, and Cesira Urzi Brancati. 2013. The Psychology and Economics of Reverse Mortgage Attitudes: Evidence from the Netherlands. CentER Discussion Paper Series, No. 135. Available online: <https://ideas.repec.org/p/crp/wpaper/135.html> (accessed on 10 September 2025).
- Dillingh, Rik, Henriëtte Prast, Mariacristina Rossi, and Cesira Urzi Brancati. 2017. Who wants to have their home and eat it too? Interest in reverse mortgages in the Netherlands. *Journal of Housing Economics* 38: 25–37. [CrossRef]
- Dragos, Simona Laura, Cristian Mihai Dragos, and Gabriela Mihaela Muresan. 2020. From intention to decision in purchasing life insurance and private pensions: Different effects of knowledge and behavioural factors. *Journal of Behavioral and Experimental Economics* 87: 101555. [CrossRef]
- Faqih, Khaled M. S. 2016. An empirical analysis of factors predicting the behavioral intention to adopt Internet shopping technology among non-shoppers in a developing country context: Does gender matter? *Journal of Retailing and Consumer Services* 30: 140–64. [CrossRef]
- Faul, Franz, Edgard Erdfelder, Axel Buchner, and Albert-Georg Lang. 2009. Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods* 41: 1149–60. [CrossRef] [PubMed]
- Fornero, Elsa, Mariacristina Rossi, and Maria Cesira Urzi Brancati. 2016. Explaining why, right or wrong, (Italian) households do not like reverse mortgages. *Journal of Pension Economics & Finance* 15: 180–202. [CrossRef]
- Gallego-Losada, Rocío, Antonio Montero-Navarro, José-Luis Rodríguez-Sánchez, and Thais González-Torres. 2022. Retirement planning and financial literacy, at the crossroads: A bibliometric analysis. *Finance Research Letters* 44: 102109. [CrossRef]
- Gavilán, Ángel. 2023. El Sistema Público de Pensiones y los Principales Retos del Envejecimiento Poblacional. Banco de España. Available online: <https://www.bde.es/f/webbe/GAP/Secciones/SalaPrensa/IntervencionesPublicas/DirectoresGenerales/economia/Arc/IIPP-2023-05-25-gavilan.pdf> (accessed on 10 September 2025).
- González-Vila Puchades, Laura, Maite Mármol Jiménez, Sara Solanilla Blanco, and Xavier Varea Soler. 2025. Do reverse mortgages reduce poverty rates among older adults living alone in Spain? Analysing their overall and gender-specific effects. *Social Indicators Research*. [CrossRef]
- Gotman, Anne. 2011. Towards the end of bequest? The life cycle hypothesis sold to seniors. *Civitas: Journal of Social Sciences* 11: 93–114. [CrossRef]
- Griffin, Barbara, David Loe, and Beryl Hesketh. 2012. Using proactivity, time discounting, and the theory of planned behavior to identify predictors of retirement planning. *Educational Gerontology* 38: 877–89. [CrossRef]
- Hair, Joseph F., Jeffrey J. Risher, Marko Sarstedt, and Christian M. Ringle. 2019. When to use and how to report the results of PLS-SEM. *European Business Review* 31: 2–24. [CrossRef]

- Hanewald, Katja, Hazel Bateman, Hanming Fang, and Shang Wu. 2020. Is there a demand for reverse mortgages in China? Evidence from two online surveys. *Journal of Economic Behavior and Organization* 178: 29–55. [\[CrossRef\]](#)
- Hastings, Justine, Brigitte C. Madrian, and William L. Skimmyhorn. 2013. Financial literacy, financial education, and economic outcomes. *Annual Review of Economics* 5: 347–73. [\[CrossRef\]](#) [\[PubMed\]](#)
- Hauff, Jeanette C., Anders Carlander, Tommy Gärling, and Giani Nicolini. 2020. Retirement financial behaviour: How important is being financially literate? *Journal of Consumer Policy* 43: 543–64. [\[CrossRef\]](#)
- Helmdag, Jan, and Niko Väänänen. 2025. Financial sustainability above all else? Drivers and types of pension reform recommendations in EU socio-economic governance. *JCMS: Journal of Common Market Studies* 63: 1236–58. [\[CrossRef\]](#)
- Hoekstra, Joris, and Kess Dol. 2021. Attitudes towards housing equity release strategies among older home owners: A European comparison. *Journal of Housing and the Built Environment* 36: 1347–66. [\[CrossRef\]](#)
- Ilan, Mordechai, and Yevgeny Mugerman. 2025. Misguided mortgage choices: Financial literacy, inflation expectations, and borrowing decisions. *Journal of Behavioral and Experimental Finance* 35: 100740. [\[CrossRef\]](#)
- Imani, Mehdi, Ali Beikmohammadi, and Hamid Reza Arabnia. 2025. Comprehensive analysis of Random Forest and XGBoost performance with SMOTE, ADASYN, and GNUS under varying imbalance levels. *Technologies* 13: 88. [\[CrossRef\]](#)
- Instituto Nacional de Estadística. 2024. Encuesta de Condiciones de Vida. Base 2004. Vivienda. Hogares por Régimen de Tenencia de la Vivienda y Edad y Sexo de la Persona de Referencia. Available online: <https://www.ine.es/jaxiT3/Tabla.htm?t=4583&L=0> (accessed on 10 September 2025).
- Knaack, Peter, Margaret Miller, and Fiona Stewart. 2020. Reverse Mortgages, Financial Inclusion, and Economic Development: Potential Benefit and Risks. *World Bank Policy Research Working Paper Series*. No. 9134. Available online: <https://hdl.handle.net/10986/33290> (accessed on 10 September 2025).
- Kuhn, Max, and Kjell Johnson. 2013. Over-fitting and model tuning. In *Applied Predictive Modeling*. New York: Springer, pp. 61–92. [\[CrossRef\]](#)
- Kwong, Koon Shing, Jing Rong Goh, and Ting Lin Collin Chua. 2024. Enhancing sell-type home reversion products for retirement financing. *Risks* 12: 22. [\[CrossRef\]](#)
- Kwong, Koon Shing, Jing Rong Goh, Jordan Jie Xin Lee, and Ting Lin Collin Chua. 2025. Redesigning home reversion products to empower retirement for Singapore's public flat owners. *Risks* 13: 23. [\[CrossRef\]](#)
- Liengard, Benjamin Dybro, Pratyush Nidhi Sharma, G. Tomas M. Hult, Morten Berg Jensen, Marko Sarstedt, Joseph F. Hair, and Christian M. Ringle. 2021. Prediction: Coveted, yet forsaken? Introducing a cross-validated predictive ability test in partial least squares path modeling. *Decision Sciences* 52: 362–92. [\[CrossRef\]](#)
- Loh, Wei-Yin. 2011. Classification and regression trees. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery* 1: 14–23. [\[CrossRef\]](#)
- Lundberg, Scott M., and Su-In Lee. 2017. A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems* 30: 4765–74.
- Lusardi, Annamaria, and Olivia S. Mitchell. 2017. How ordinary consumers make complex economic decisions: Financial literacy and retirement readiness. *Quarterly Journal of Finance* 7: 1750008. [\[CrossRef\]](#)
- Meneses Cerón, Luis Ángel, Jaime Andrés Carabalí Mosquera, Jorge Eduardo Frías Navarrete, Zoraida Ramírez Gutiérrez, and Jefferson Muñoz Vargas. 2024. Analysis, modelling, and financial perspectives of reverse mortgage implementation in Colombia. *Heliyon* 10: e31214. [\[CrossRef\]](#)
- Mohammed, Mohammed Ishaq, and Noralfishah Sulaiman. 2017. Determinants of reverse mortgage use intention: A theoretical framework. *International Research Journal of Management and Commerce* 4: 153–178.
- Mohammed, Mohammed Ishaq, and Noralfishah Sulaiman. 2018. Determinants of reverse mortgage usage in Malaysia. *Real Estate Management and Valuation* 26: 5–23. [\[CrossRef\]](#)
- Mohammed, Mohammed Ishaq, Noralfishah Sulaiman, and Dahiru Adamu. 2018. Dimensionality and reliability of the determinants of reverse mortgage use intention. *Path of Science* 4: 1013–23. [\[CrossRef\]](#)
- Moulton, Sharron, Carla Loibl, and Daniel Haurin. 2017. Reverse mortgage motivations and outcomes: Insights from survey data. *Cityscape* 19: 73–98.
- Muralidharan, D. R., and R. Soundara Raja. 2022. Impact of perception and attitude on behavioural intention towards reverse mortgage loans: A study on senior citizens in Bangalore City. *Journal of Emerging Technologies and Innovative Research* 9: 67–76.
- Musa, Haruna, Nor Hayati Binti Ahmad, and Alias Mat Nor. 2024. Extending the Theory of Planned Behavior in financial inclusion participation model—evidence from an emerging economy. *Cogent Economics & Finance* 12: 2306536. [\[CrossRef\]](#)
- Mussa, Abeba, Meeghan Rogers, and Xu Zhang. 2023. Financial capability across generations and technology. *Financial Services Review* 30: 4. [\[CrossRef\]](#)
- Nakajima, Makoto, and Irina Telyukova. 2017. Reverse mortgage loans: A quantitative analysis. *The Journal of Finance* 72: 911–50. [\[CrossRef\]](#)

- Nosi, Costanza, Antonella D'Agostino, Margherita Pagliuca, and Carlo Alberto Pratesi. 2017. Securing retirement at a young age: Exploring the intention to buy longevity annuities through an extended version of the theory of planned behavior. *Sustainability* 9: 1069. [CrossRef]
- OECD. 2023. *Pensions at a Glance 2023: OECD and G20 Indicators*. Paris: OECD Publishing. [CrossRef]
- Pahuja, Anuraj, and Rinku Sanjeev. 2016. Reverse mortgage: An empirical study in Indian perspective. *International Journal of Banking, Risk and Insurance* 4: 2.
- Probst, Philipp, Marvin N. Wright, and Anne-Laure Boulesteix. 2019. Hyperparameters and tuning strategies for random forest. *WIREs Data Mining and Knowledge Discovery* 9: e1301. [CrossRef]
- Rad, Dana, Lavinia Denisia Cuc, Gabriel Croitoru, Bogdan Cosmin Gomo, Luminita Mazuru, Raluca Simina Bilti, Sergiu Rusu, Maria Sinaci, and Florentina Simona Barbu. 2025. Modeling investment decisions through decision tree regression—A behavioral finance theory approach. *Electronics* 14: 1505. [CrossRef]
- Rania, Francesco. 2025. Reverse mortgages and pension sustainability: An agent-based and actuarial approach. *Risks* 13: 147. [CrossRef]
- Rasmussen, David W., Isaac F. Megbolugbe, and Barbara A. Morgan. 1995. Using the 1990 Public Use Microdata Sample to estimate potential demand for reverse mortgage products. *Journal of Housing Research* 6: 1–23.
- R Development Core Team. 2025. R: A Language and Environment for Statistical Computing. Vienna. Available online: <http://www.R-project.org/> (accessed on 10 September 2025).
- Richter, Nikole Franziska, and Ana Alina Tudoran. 2024. Elevating theoretical insight and predictive accuracy in business research: Combining PLS-SEM and selected machine learning algorithms. *Journal of Business Research* 173: 114453. [CrossRef]
- Ringle, Christian M., and Marko Sarstedt. 2016. Gain more insight from your PLS-SEM results. *Industrial Management & Data Systems* 116: 1865–86. [CrossRef]
- Rozenkowska, Katarzyna. 2023. Theory of planned behavior in consumer behavior research: A systematic literature review. *International Journal of Consumer Studies* 47: 2670–700. [CrossRef]
- She, Long, Ratneswary Rasiah, Marc Aul Weissmann, and Harpaljit Kaur. 2024. Using the Theory of Planned Behaviour to explore predictors of financial behaviour among working adults in Malaysia. *FIIB Business Review* 13: 118–35. [CrossRef]
- Simón-Moreno, Héctor. 2019. The regulation of reverse mortgages as a source of income in retirement: Policy options and legal drivers. *Journal of Housing and the Built Environment* 34: 1005–22. [CrossRef]
- Sparks, Paul, Carol A. Guthrie, and Richard Shepherd. 1997. The dimensional structure of the perceived behavioral control construct. *Journal of Applied Social Psychology* 27: 418–38. [CrossRef]
- Stupak, Thompson. 2024. How Much Data Is Required to Train ML Models in 2024? Available online: <https://www.akkio.com/post/how-much-data-is-required-to-train-ml> (accessed on 10 September 2025).
- Whait, Robert B., Braam Lowies, Peter Rossini, Stanley McGreal, and Bill Dimovski. 2019. The reverse mortgage conundrum: Perspectives of older households in Australia. *Habitat International* 94: 102073. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.