İstanbul İktisat Dergisi - Istanbul Journal of Economics
74, 2024/1, s. 281-314
E-ISSN: 2602-3954

RESEARCH ARTICLE

Exploring the Impact of Behavioural Factors and Personality Traits on Private Pension System Participation: A Machine Learning Approach*

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ABSTRACT

This study aims to investigate the effects of personality traits, in addition to basic financial literacy, private pension literacy and behavioural factors on Private Pension System (PPS) participation using machine learning algorithms. The PPS participation model was trained using both random forest and LightGBM algorithms, and the contributions of model inputs in the prediction of pension participation were interpreted using the Tree SHAP algorithms with swarmplots. The data employed in the empirical analysis is survey data collected from the Şırnak province of Türkiye with a sample size of 449. The findings of the study shows that: (i) PPS participation is more likely for females and middle-aged people; (ii) High basic financial literacy has a negative impact on PPS participation; (iii) Extraversion is the key personality trait affecting PPS participation; (iv) Advanced pension literacy has more impact on participation than simple pension literacy: (v) Present-fatalistic tendency is key behavioural factor and it negatively affects PPS; (vi) Present-hedonistic, conscientiousness, future-time orientation, and locus of control tendencies increase PPS participation. Furthermore, the distribution of colours in LightGBM has a greater degree of uniformity in both directions compared with the random forest algorithm. Finally, to increase PPS participation, the results of the study suggest the implementation of the following policy measures: Tailored pension literacy programmes can help to increase pension participation rates. Incentives should be created to prevent narrow-minded behaviour and establish a sense of protection and control around PPS, targeting middle-aged individuals and women.

Keywords: Private pension system, Behavioural factors, Personality traits, Machine learning algorithms, Tree SHAP
JEL Classification: C60, G41, J32

DOI: 10.26650/ISTJECON2023-1360545

* This article is the part of the PhD thesis prepared at Istanbul University by Can Verberi.

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Submitted: 20.09.2023
Revision Requested: 06.01.2024
Last Revision Received: 20.03.2024
Accepted: 22.04.2024

Citation: Verberi, C., & Kaplan, M. (2024). Exploring the impact of behavioural factors and personality traits on private pension system participation: a machine learning approach. *İstanbul İktisat Dergisi - Istanbul Journal of Economics 74*(1), 281-314. https://doi.org/10.26650/ISTJECON2023-1360545

Introduction

For many reasons, increasing social security expenditures has caused social security system-related government budget deficits to increase over time. Since the 1980s, governments have striven to transform their social security systems into a market-based structure as well as establishing the Private Pension System (PPS) to cope with the burden of the system on government budgets.

Chile was the pioneering country that devised its social security system as a two-pillar structure through the establishment of the PPS in 1981. Within this two-pillar pension system, the first pillar corresponds to the public social security system, while the second pillar entails the PPS. The PPS converts the Social Security System into a market-oriented framework and aids in alleviating the social security burden via the implementation of its three primary functions: (i) the augmentation of savings in the economy by means of collecting pension contributions and channelling the under-pillow savings towards the PPS. In the PPS, the more participants are encompassed within the system, the greater the accumulation of pension contributions; (ii) the promotion of investment by directing the pension contributions towards the capital markets; (iii) PPS also leads to the conversion of investment returns to benefits. Consequently, in addition to social security benefits, PPS participants enjoy supplementary advantages. The benefit is computed by subtracting the expenses and management fees of the private pension company from the investment returns. As such, all these aspects underscore the direct correlation between PPS and savings as well as investment, thus underscoring its pivotal role in mitigating the social security burden. Because of these reasons, numerous governments perceive the PPS as a valuable policy instrument for generating funds for financial markets and savings, which in turn leads to its expanding prevalence and encouragement.

The establishment of the Turkish PPS in 2003 aimed to capitalise on the advantages of PPS. Its formation closely mirrored that of its counterparts in developed countries: it incorporated tax incentives and a 25% state contribution and adopted the Automatic Enrollment System (AES). However, the Turkish PPS has failed to attain satisfactory growth in the contribution per participant and has faced challenges in attaining the necessary level of funding since its establishment (Ertuğrul, Gebeşoğlu, & Atasoy, 2018). Moreover, it cannot reach enough participants compared with the working population (see appendix for details). Consequently, additional effective policy measures and institutional changes must be implemented to realise the anticipated benefits of PPS in Türkiye.

Although a limited number of studies are available, several examine the underlying factors that contribute to the low levels of participation and the observed failure in establishing a strong PPS in Türkiye (Türkmen, & Kılıç, 2022; Canöz, & Baş, 2020; Özbek, 2020; Özer, & Çınar, 2012). A concise analysis of the existing literature reveals significant aspects related to the determinants of the Turkish PPS. Firstly, behavioural factors and personality traits are utilised as determinants of private pension participation. However, these factors only address certain dimensions of behavioural factors and personality traits, such as risk and future considerations. Second, there is a noticeable lack of studies that explore the relationship between PPS participation and private pension literacy in Türkiye. Third, there is also a scarcity of studies that thoroughly examine the determinants of PPS participation, considering basic financial literacy, private pension literacy, behavioural factors, and personality traits, utilising machine learning algorithms. Fourth, none of the studies reviewed employ machine learning algorithms to analyse the impact of behavioural factors, personality traits, pension literacy, and basic financial literacy on PPS. Finally, a limited number of studies compare the performance of the random forest and light gradient boosting machine (LightGBM) algorithms in training their models.

Considering these facts, this study aims to analyse and evaluate the determinants of private pension participation using survey data collected from the Şırnak province of Türkiye. Pension participation is modelled as a function of financial literacy, private pension literacy, behavioural factors, and personality traits and analysed using machine learning algorithms. This study contributes to the existing literature mainly in two ways. First, in addition to basic financial literacy, the private pension participation model includes pension financial literacy, many personality traits, and behavioural factors such as the Big Five personality traits, pessimism, procrastination, time perspective, compulsive buying, and locus of control in the analysis. Second, it employs random forest, LightGBM, and Tree SHAP, which is a variant of SHapley Additive exPlanation (SHAP), as a machine learning algorithm to estimate the importance of the variables subject to empirical analysis and to interpret and compare the estimated results.

The rest of the study is organised as follows. A theoretical literature review of pension participation is presented in Section 2. Section 3 reviews the empirical literature on pension participation and its determinants. Section 4 introduces the dataset and the methodology. The results obtained from the empirical analysis of the data are given in Section 5. Section 6 concludes the study with policy recommendations.

1. Review of the Theoretical Literature on the Determinants of Pension Participation

This section provides the theoretical basis for the determinants of private pension participation. Individuals have a growing desire for greater economic security in their old age, leading to an increasing interest in private complementary provident arrangements (Barr, & Diamond, 2009; Holzmann, & Hinz, 2005). In other words, they accumulate savings from their incomes to ensure economic security in the future. This viewpoint asserts that the factors influencing savings are identical to those influencing retirement savings (or participation in private pension systems). A brief review of the theoretical discussions on the subject shows that the theoretical factors that make people participate in a PPS involve income, institutional factors, behavioural factors, and personal traits.

Income: Income seems to be the most obvious and well-known factor that determines private pension participation and the size of pension contributions. The importance of income factor in pension participation can be explained by referring to theories on savings. The larger the income, the more people save, and these people are more reluctant to participate in PPS because it provides an alternative institutional framework for saving. Numerous economic theories assert that saving behaviour is contingent on income and consumption patterns, with an increase in income levels leading to a higher propensity to save. Consequently, it can be contended that a higher income level positively influences the rates of participation in PPS.

Keynes (1936) defines saving as the proportion of income that exceeds the portion allocated to consumption. However, Friedman (1957) posits in his permanent income hypothesis that the primary determinant of savings is permanent income. Consequently, he concludes that the age of the population has significant implications for consumption and saving, prioritising it over temporary income. The life cycle hypothesis, developed by Modigliani and Brumberg (1954), postulates that long-term income is the main driver of saving. In contrast to the permanent income hypothesis, this theory recognises the longevity of life and advocates the consideration of life resources and current income. Like the permanent income hypothesis, the life cycle hypothesis acknowledges the influence of individual age on consumption and saving, while also asserting that consumption is contingent on long-term income. Duesenberry (1967) elucidates saving behaviour through the lens of the relative income hypothesis. According to this hypothesis, households make consumption decisions based on their relative income. Consequently, current consumption is influenced by past savings. Thus, an increase in income triggers a more substantial change in consumption than a decrease in income. In contrast to other savings theories, the relative income hypothesis assumes a correlation between income distribution and savings. It posits that savings are influenced by interest rates, the relationship between current and expected future incomes, income distribution, age distribution of the population, and income growth (Duesenberry, 1967).

Institutional Factors: Theories regarding institutional saving posit that both individuals and institutional processes impact households' savings. Consequently, individual behaviour is influenced by social institutions. As stated by Sherraden (1991), the mechanisms of institution encompass rules, incentives, implicit connections, and subsidies. He refers to the incentives within the PPS as institutional subsidies. Accordingly, individuals accumulate wealth through the incentives provided by the PPS.

Behavioural Factors: A limited range of behavioural theories examine the determinants of savings. Behavioural savings theories differ from economic theories in their assumptions about preferences for saving and consumption. Unlike economic theories, behavioural savings theories posit that saving and consumption preferences, as well as individual economic behaviours, are not influenced by preferences and economic resources (Beverly, 1997). These theories propose that individuals are subject to behavioural constraints and incentives. One well-known behavioural savings theory is the behavioural life-cycle hypothesis (Shefrin, & Thaler, 1988). According to this theory, individuals can be categorised as either planners or doers. Planners and doers make different decisions regarding saving and consumption on the basis of the time periods they consider. While planners base their consumption and savings decisions on lifetime utility, doers make economic decisions for a single period (Thaler, & Shefrin, 1981). However, if the preferences and incentives of doers change and become more restricted, they will exhibit greater self-control. According to this theory, individuals often accept rules that limit their behaviour as doers. Therefore, it is concluded that planners are more inclined to participate in PPS than doers. Furthermore, a mandatory pension plan could increase overall savings (Thaler, & Shefrin, 1981).

This study considers procrastination, locus of control, time perspective, pessimism, and compulsive buying as behavioural variables. Procrastination is defined as the voluntary postponement of an intended event that is expected to have negative consequences (Piotrowska, 2019). Locus of control is a psychological notion that includes individuals' beliefs regarding the degree to which they can control the events that impact them. Time perspective is examined under three subheadings: future (expectations), present-hedonistic, and present-fatalistic. Present-hedonistic individuals avoid long-term work and focus on pleasure in their lives. Present-fatalistic individuals believe that an external force is dominant in their lives and not in their actions. Pessimism is defined as the negative bias of expectations and perceptions in life (Burke, Joyner, Czech and Wilson, 2000). Compulsive buying is the uncontrollable urge to buy or use a substance or activity (O'Guinn, & Faber, 1989).

Behavioural factors play a pivotal role in determining savings. Hence, they have a close association with PPS. The relationship between pessimism and retirement savings is mediated through various channels. Individuals with a pessimistic outlook tend to have shorter life expectancies, resulting in negative decisions regarding retirement savings (O'Dea, & Sturrock, 2019). Furthermore, pessimism may interact with retirement savings through other behavioural factors, such as locus of control and procrastination (Burke et al., 2000; Piotrowska, 2019). Procrastination, due to its consequences such as anxiety, depression, and stress, exhibits a positive correlation with pessimism (Van Eerde, 2003). Pessimists, owing to their external locus of control (such as fate), display a lack of motivation to save for retirement (Piotrowska, 2019). Nevertheless, pessimism can have a positive impact on retirement savings, as it is positively associated with individualism, thereby positively influencing financial comfort (Bengtson, Biblarz, & Roberts, 2002). Consequently, it encourages individuals to consider their financial conditions during retirement, leading to increased retirement savings. According to Personality Plus (Littauer, 1995), pessimists possess a unique ability to identify problems that optimists may overlook. This phenomenon is known as defensive pessimism, which involves preparing for negative outcomes and harbouring negative expectations (Burke et al., 2000). Consequently, pessimism may positively influence savings through this mechanism. Procrastination exhibits a negative relationship with retirement planning, as it prioritises short-term actions over long-term consequences and is prone to postponement (Piotrowska, 2019). The locus of control is closely linked to self-control, which in turn has a positive impact on savings. Hence, it is a critical behavioural factor in the context of retirement savings.

According to the theory of planned behaviour (Ajzen, 1991), future time perspective can influence retirement savings by affecting the attitudes, subjective norms, and perceived behavioural control of individuals regarding saving and investing for retirement. Individuals who have a strong future time perspective may have more positive attitudes towards saving and investing for retirement because they value the long-term benefits and consequences of their actions. Empirical evidence is scarce on the causality of compulsive buying, future (expectations), present-fatalistic, and present-hedonistic to retirement savings. However, some studies have suggested a negative relationship between compulsive buying and retirement savings. For example, Asebedo and Browning (2020) found that compulsive buyers had lower levels of retirement saving adequacy than non-compulsive buyers. They also found that compulsive buyers had lower levels of future time perspective than non-compulsive buyers. Another study by Donnelly, Iyer, and Howell (2012) found that compulsive buyers had lower levels of financial well-being than non-compulsive buyers. They also found that compulsive buyers had higher levels of present-hedonistic time perspective than non-compulsive buyers. The causal factor behind compulsive buying is theoretically attributed to hedonism, as posited by O'Guinn and Faber (1989). Piotrowska (2019) deduced that hedonism, fatalism, and present-fatalistic and present-hedonistic tendencies manifest a positive influence on compulsive buying. Moreover, she contends that the impact of compulsive buying on retirement savings can be elucidated through the mechanisms of status consumption and a deficiency in self-assurance. Finally, it is determined that the indirect consequence of present-fatalistic attitudes, mediated through procrastination, has a detrimental effect on retirement savings.

Personality traits play a crucial role in determining retirement savings, making them closely linked to PPS. This investigation focuses on the Big Five personality traits, which were established by Costa and McCrae (1992) and serve as the foundation for identifying personality traits (Piotrowska, 2019). The Big Five encompasses extraversion, agreeableness, conscientiousness, neuroticism, and openness. Extraversion is a personality trait that is responsive to rewards, socially oriented, positive, and willing to take risks (Balasuriya, & Yang, 2019). Agreeableness is defined as a personality trait that is cooperative, friendly, inclined towards volunteering, and nonviolent (Rentfrow, Jokela, & Lamb, 2015). Conscientiousness can be described as a personality trait that is oriented towards success and characterised by diligence (Piotrowska, 2019). Neuroticism encompasses anxiety, aversion to risk, depression, instability, and avoidance of harm (Rentfrow, Jokela, & Lamb, 2015; Balasuriya, & Yang, 2019). Lastly, openness is a personality trait associated with being receptive to new experiences and ideas (Costa, & McCrae, 1992).

The life span theory of control can explain how personality traits influence retirement savings by affecting the level of perceived control over financial outcomes. For example, individuals who score high on conscientiousness may have a higher sense of control over their finances because they are more organised, disciplined, and responsible. They may also have more positive attitudes towards saving and investing for retirement and may be more likely to follow a financial plan (Heckhausen, & Schulz, 1995). Individuals with high extraversion have greater net worth (wealth) levels and may have an increased ability to adjust to retirement (Asebedo, & Browning, 2020). Conversely, individuals who score high on neuroticism may have a lower sense of control over their finances because they are more anxious, worried, and emotional. They may also have more negative attitudes towards saving and investing for retirement and may be more likely to avoid or procrastinate financial decisions (Heckhausen, & Schulz, 1995). The theory of planned behaviour can explain how personality traits influence retirement savings by affecting the three factors that shape behavioural intentions. For example, individuals who score high on openness to experience may have more positive attitudes towards saving and investing for retirement because they are more curious, creative, and adventurous (Ajzen & Schmidt, 2020). Conversely, individuals who score low on agreeableness may have more negative attitudes towards saving and investing for retirement because they are more competitive, selfish, and distrustful (Asebedo & Browning, 2020).

2. Empirical Review of the Literature on the Determinants of PPS Participation

Having reviewed the theoretical literature above, this section reviews the findings of the empirical studies on the factors that affect private pension participation rates. Numerous studies empirically explore the causal relationship between PPS participation and its determinants, personality traits, behavioural factors, pension literacy, and so on. They usually conclude that personality traits, financial literacy, pension literacy, behavioural factors, and demographic variables affect participation in PPS. Furthermore, several other studies employ variables such as retirement preparation, participation probability in pension plans, and participation in pension plans as explanatory variables of PPS participation.

Niu, Zhou, and Gan (2020) investigated the correlation between financial literacy and retirement preparation in China. They utilised a longitudinal dataset and applied multivariate regression analysis. The findings reveal a positive association between financial literacy and retirement preparation. In a similar vein, Brown and Graf (2013) explored the link between financial literacy and retirement planning. Their study employs the probit model and utilises survey data from 1500 households in Switzerland. The results demonstrate a robust relationship between financial literacy and voluntary retirement savings. Unlike Niu, Zhou, and Gan (2020), Fornero and Monticone (2011) incorporate the possibility of participating in retirement plans as a dependent variable. They analysed the relationship between financial literacy and retirement plan participation in Italy in 2006 using SHIW survey data (covering 7,768 households and 19,551 individuals in the year 2015) and OLS and IV estimators. The findings indicate that financial literacy positively impacts the probability of participating in retirement plans.

Furthermore, few international studies analyse the causality between financial literacy and PPS based on savings. Landerretche and Martínez (2013) tested the relationship between retirement financial literacy and voluntary retirement savings in Chile using cross-sectional data analysis and a probit model. The analysis results show that employees with higher retirement literacy participate more in the retirement system. Diaz, Ruiz, and Tapia (2021) concentrate on Chile, employing clustering algorithms and probit regression to analyse the impact of pension literacy on voluntary pension and banking savings. They discovered a positive and significant connection between pension literacy and voluntary pension savings. Furthermore, a higher level of pension literacy positively influences the likelihood of voluntary banking savings, with conscientiousness emerging as a significant predictor of voluntary banking savings.

Salleh, Wahab, Karim, and Lim (2022) centred their study on the level of preparedness exhibited by employees in relation to a fully Defined Contribution Retirement scheme. Their findings highlight the importance of higher financial literacy and positive behavioural, normative, and controlled beliefs in informed financial decision-making, particularly concerning retirement savings, within a sample of 350. In a similar vein, Fang, Hao, and Reyers (2022) investigated the effects of financial advice, financial literacy, and social interaction on the decisions made by households regarding retirement savings in New Zealand. Analysing data from the 2018–2019 wave of the Financial Capability Barometer survey with a probit model, they determined that financial advice and financial literacy complemented each other, jointly leading to improved retirement savings decisions among 3,629 individuals. Finally, Tomar, Baker, Kumar, and Hoffman (2021) delved into how the interplay between financial literacy and psychological traits such as retirement goal clarity, future time perspective, attitude towards retirement, risk tolerance, and social group support influenced women's retirement planning behaviour in India. Using partial least squares regression with multi group analysis on a sample of 485, they found positive associations between future time perspective, retirement goal clarity, and social group support with retirement planning behaviour, moderated by financial literacy.

In previous studies, the effect of personality and behavioural factors on PPS is usually analysed by variables such as purchase decision, purchase intention, PPS savings level, and PPS participation level as dependent variables. Dragos, Dragos, and Muresan (2020) studied the effect of behavioural and socio-demographic factors on purchasing private pension plans in Romania by using a logit regression and sampling 1579 individuals. The results indicate that the decision to purchase PPS is positively affected by investing through specialised institutions and seeking financial consultancy, while perceiving PPS as an investment and viewing the public pension system as adequate are negatively associated with the decision to purchase PPS. The findings suggest that behavioural factors and knowledge about private pensions are associated with the purchase decision but not with the purchase intention. Piotrowska (2019) investigated retirement savings behaviours among 826 participants aged 25-45 in Poland, employing logistic, multiple, and mediation models to examine the influence of personality and behavioural constraints. The results show that procrastination negatively impacts retirement savings, whereas compulsive buying is positively associated with retirement savings. Furthermore, introversion, undirectedness, locus of control, and future orientation positively affect participation in private pension plans.

Balasuriya and Yang (2019) explored the relationship between personal traits and retirement decisions in England using longitudinal data analysis and several statistical models, including Ordinary Least Squares (OLS), probit, and random-effects models. The findings reveal that extraversion and openness exhibit a negative association with participation in PPS, whereas conscientiousness positively impacts both participation in PPS and the amount contributed. Moreover, agreeableness and extraversion are negatively associated with the PPS contribution amount. Previous studies include retirement expectations as an explanatory variable. Bottazzi, Japelli, and Padula (2006) investigated the influence of Italian reform on retirement wealth accumulation and household expectations on retirement outcomes. The results show that the reforms revise workers' retirement expectations and that more knowledgeable workers increase their retirement wealth savings through the reforms.

Many studies have investigated the correlation between PPS and financial literacy, personality traits and behavioural factors in Türkiye. They concluded that financial knowledge, individual characteristics, and behavioural aspects are commonly linked to PPS. Furthermore, the analysis incorporates participation, withdrawal, and fund preferences in PPS as dependent variables. These studies typically identify basic financial knowledge as an explanatory variable for financial literacy, as well as risk factors, future anxiety, and security as representations of personality traits and behavioural factors. In contrast to studies conducted in other countries, limited attention is given to personality traits, behavioural factors, pension literacy, and the big five personality traits as explanatory variables. Doğan (2016) examined the association between investment fund preferences in PPS and behavioural finance tendency by including 400 bank personnel in the analysis. The study employed ANOVA, Chi-square, T-test, and correlation methods. The findings indicate that risk perception, risk-taking attitude, emotional intelligence, and basic and advanced financial literacy levels significantly impact individual pension fund preferences.

Canöz and Baş (2020) studied participation factors in private pension plans using the binary logit model. The findings demonstrate that saving habits and investment, financial literacy, future anxiety and security, gender, and tenure affect the decisions to enter PPS for state university academicians. According to the results for foundation university academicians, savings and investment habits, financial literacy level, and age affect academicians' participation decision for PPS. Özbek (2020) analysed whether the financial literacy level of individuals, depending on their financial attitudes and behaviours affect their participation in the PPS by using randomly selected 405 participants as a sample and the Structural Equation Model. The findings indicate that financial literacy has a positive effect on participation in PPS.

Bayar, Gündüz, Öztürk, and Şaşmaz (2020) investigated the effect of financial literacy on participation in the private pension system in a sample of Uşak University personnel using factor analysis and logistic regression. The results indicate that basic and medium levels of financial literacy do not significantly influence participation in PPS. However, advanced financial literacy has a negative effect. Similarly, Türkmen and Kılıc (2022) examined the role of financial literacy and perceived consumer risks in elucidating the ownership of individual pension plans among workers in Türkiye. The study employs T-tests, ANOVA, and Chi-Square tests on a sample of 651 individuals. The findings reveal that financial literacy does not exhibit a significant correlation with involvement in the individual pension system, whereas perceived consumer risks vary depending on the ownership of individual pension plans.

In the existing studies, numerous studies have been undertaken with the aim of examining the correlation between demographic factors and PPS in Türkiye. These investigations consistently reveal that demographic indicators are usually associated with PPS. One such study by Özer and Çınar (2012) surveyed 289 faculty members from a foundation university to determine their perspectives on PPS. The findings demonstrate a notable relationship between various variables such as age, gender, length of employment, income level, and individuals' perspective on PPS. Similarly, Yemez and Akdoğan (2019) analyse the impact of demographic factors on the purchasing behaviour of private pensions. In this particular study, a survey was administered to 430 bank customers aged 18 and above in Sivas city, employing the t-test and One-way ANOVA tests for the subsequent analysis. In contrast to the findings of Özer and Çınar (2012), the results indicate that variables such as age, education level, average monthly income, gender, and marital status were not significantly important in the decision to purchase a private pension plan. Instead, private pension purchasing behaviour increases in tandem with higher income levels. Furthermore, the type of bank is discovered to have an impact on purchasing behaviour. Interestingly, it is observed that the intention to purchase a private pension plan does not affect the actual decision to purchase, while the behaviour surrounding private pension plans varies according to an individual's occupation.

Some studies have tested the views and reasons for leaving the Turkish PPS. Şataf and Yıldırım (2019) studied the awareness of PPS and the opinions of individuals about it in Ordu by a randomly selected sample of 371 people in the workforce. Participants think they need a lower retirement age, and they do not fully trust PPS. Moreover, most registered participants are in the 25-44 age range, at least a university graduate, and have a high monthly income. Kocabıyık and Küçükçakal (2018) investigated the reasons for leaving and staying in the Automatic Enrollment System in Isparta by surveying 463 public and private sector employees and the Crosstabs Test. The results demonstrate that state contribution is the most important factor in the Automatic Enrollment System. Other ideas include receiving lump sum money in the future and the usefulness of AES. The main reasons for leaving are that the 10-year period is too long, 3% of the earnings are deducted, and the savings are directed to other investment instruments.

To summarise, previous studies employing various methodologies arrive at a consensus that a connection exists between personality traits, financial literacy, pension literacy, behavioural factors, demographic variables, and PPS. This study aims to address the gaps in the existing literature identified earlier by examining the factors that determine participation in PPS under the constraints of financial literacy, private pension literacy, behavioural factors, and personality traits. In addition, we employ random forest, LightGBM, and Tree SHAP as machine learning algorithms. Moreover, we compare the performance of the random forest algorithm and the light gradient boosting machine (LightGBM) to address another gap in the existing literature.

3. Dataset, Methodology, and Model

3.1. Dataset

The data employed in the empirical analysis is survey data independently collected from the Şırnak province of Türkiye, involving 449 participants, without being tied to any project or funding. In this context, the survey consists of 33 questions (see appendix for details). Advanced pension literacy and big five personality traits consist of multiple items; therefore, the empirical counterpart of these variables is obtained by aggregating these items. The sample consists of the working age (and mostly employed) population, between the ages of 15 and 52. During the data collection process, a face-to-face survey is conducted. Similar to previous studies, Rentfrow et al. (2015) (the personality scale consists of 44 items (The Big Five Inventory)), Piotrowska (2019) (the 10-item question set adapted from Gosling, Rentfrow and Swan Jr (2003)), and Oishi et al. (2015) (which use the 25-item scale from Brody and Ehrlichman (1998)) are applied as personality trait survey sets. We utilise a personality trait survey set from Rentfrow et al. (2015) personality inventory (The Big Five Inventory) in the analysis because the scope of the question set is wider in this study. Furthermore, we adapted a behavioural factor survey set from Piotrowska (2019). A 7-point Likert scale ((1) strongly disagree-... - strongly agree (7)) is employed in the personality scale and behavioural factor question sets. The questions by Dragos, Dragos, and Muresan (2020) are used to assess PPS perceptions and the adequacy of the public pension system. Finally, the pension literacy question set is provided by Landerretche and Martínez (2013), and the question sets by Lusardi and Mitchell (2011) are applied to measure basic financial literacy.

3.2. Model and Methodology

To investigate the determinants of PPS participation, we employed basic financial literacy, private pension literacy, behavioural factors, and personality traits as independent variables in the empirical model of PPS participation. The model is also extended with sociodemographic variables (individuals' age, gender, income, education level). Details of variables are presented in the Appendix.

In the empirical analysis of the participation model, this study uses machine learning algorithms utilising Python programming language. Moreover, the dataset is randomly separated into 80% and 20% as the training and testing datasets, respectively, because this ratio is a common heuristic in the field, supported by its alignment with the Pareto principle (Joseph, 2022). In recent years, the importance of machine learning algorithms has sharply increased in empirical analysis. This is because it has been argued that traditional methodologies used in empirical analyses can lead to arbitrary and non-robust estimation and might not be efficient for non-linear situations (Salas-Rojo, & Rodríguez, 2022). Biases and model selection problems limit parameter-based analyses, and non-parametric tests have inefficiencies due to arbitrary segmentation (Han, 2022). Tree classification algorithms are bias-free and have no model selection problems. Thus, machine learning algorithms are preferred to solve the inefficiencies observed in traditional methodologies.[1]

[1] The methodology and terminology of machine learning models differ from those of econometric models. As the relationship between dependent and independent variables is estimated in econometrics, the relationships between the inputs and outputs of ML models are found by training the ML model using optimisation techniques and model evaluation criteria (Mullainathan, & Spiess, 2017).

Machine learning algorithms used in this study include random forest, LightGBM, and Tree SHAP, which are variants of SHAP. Random forest and LightGBM regressors are employed in the dataset training process. After the model is trained, the Tree SHAP is used to interpret the contributions of the inputs of the model (determinants of pension participation-features, inputs of the model) in predicting the output of the model (pension participation variable-output of the model).[2] The random forest algorithm is a technique of machine learning that uses numerous decision trees to perform classification or regression tasks. It is founded on the concept of ensemble learning, in which the predictions of numerous models are combined to enhance the overall precision and diminish the possibility of overfitting (Breiman, 2001).

The random forest algorithm consists of the following steps:

Bootstrap sampling: A random sample of the original dataset is drawn with replacement, meaning that some observations may be repeated. This process is repeated several times to create different bootstrap samples, each of which will be used to train a separate decision tree (Schonlau, & Zou, 2020).

Feature selection: For each split in the decision tree, a random subset of features (or predictors) is selected as candidates. This adds randomness and diversity to the tree because different features may be used in different trees. The optimal feature for each split is selected on the basis of criterion, such as Gini impurity, information gain, or mean squared error (Savargiv, Masoumi, & Keyvanpour, 2021).

Tree construction: Each bootstrap sample is used to grow a fully developed decision tree without pruning or regularisation. The trees are allowed to reach their maximum depth, which may vary depending on the data (Schonlau, & Zou, 2020).

Prediction: For classification tasks, the random forest predicts the class that receives the majority vote from the individual trees. For regression tasks, the random forest predicts the average or median of the individual trees' predictions (Breiman, 2001).

2 We employ Tree SHAP because machine learning algorithms are not directly interpreted for causal inference.

The random forest algorithm has several advantages over single decision trees. First, it reduces the variance and improves the generalisation ability of the model, as it averages out the errors and biases of the individual trees (Breiman, 2001). Second, it handles high-dimensional and complex data well, as it can capture non-linear and interactive effects among features (Schonlau, & Zou, 2020). Third, it is robust to outliers and noise because it relies on multiple samples and features (Savargiv, Masoumi, & Keyvanpour, 2021). Finally, it provides measures of variable importance and feature selection, as it can rank features based on how often they are used in splits or how much they decrease the error (Breiman, 2001).

However, the random forest algorithm also has some limitations and challenges: It may still overfit or underperform in some cases, depending on the data characteristics and hyperparameters, such as the number of trees, the number of features, and the splitting criterion (Breiman, 2001). It may lose some interpretability and transparency compared with single decision trees, as it is harder to visualise and explain the logic behind many trees (Savargiv, Masoumi, & Keyvanpour, 2021). It requires more computational resources and time than single decision trees because it involves building and storing many trees (Schonlau, & Zou, 2020). The random forest algorithm can be described as follows (Breiman, 2001):

$$\hat{f}_B(x) = \frac{1}{B}\sum_{b=1}^{B} T_b(x).$$

where $\hat{f}_B(x)$ is the predicted output of the random forest for input x;B is the number of trees in the random forest; $T_b(x)$ is the predicted output of the b-th tree for input x. The idea behind this formula is that by averaging the predictions of many trees, we can reduce the variance and noise of each tree and obtain a more stable and accurate prediction.

LightGBM (Light Gradient Boosting Machine) is a framework for gradient boosting that employs algorithms for learning based on trees. Given a dataset $D = \{(x_i, y_i)\}_{i=1}^{n}$ of n instances with p features and one target variable, the objective function of LightGBM is as follows (Ke et al., 2017):

$$\mathcal{L}(\phi) = \sum_{i=1}^{n} l(y_i, \phi(x_i)) + \sum_{j=1}^{J} \Omega(f_j)$$

where $\phi(x) = \sum_{j=1}^{J} f_j(x)$ is the prediction score for *x*, *l* is a differentiable loss function, f_j is a decision tree, and $\Omega(f_j)$ is a regularisation term for the complexity of the tree. LightGBM possesses several advantages over random forest and other decision tree algorithms. These advantages include faster training speed and higher efficiency, lower memory usage, better accuracy, support of parallel and distributed and GPU learning, and the capability to handle large-scale data (Ke et al., 2017).

SHAP (Shapley Additive Explanations) is a machine learning method that is used to explain the output from different machine learning models. Tree SHAP is specially designed to explain the outputs of tree-based models. SHAP is consistent for estimating the importance degree of variables, and its results can be easily interpreted. It has a similar concept to the Shapley value approach (Han, 2022). It is proposed by Lundberg and Lee (2017) and provides interpretable estimation results. The explanation model consists of a linear function of a binary variable as follows:

$$g(z') = \phi_0 + \sum_{i=1}^{M} \phi_i \, z_i' \tag{1}$$

g(z') is a defined local surrogate model that enables interpretation of the original model under condition $z' = \{0,1\}^M$. M represents the number of independent variables and $\phi \in R$ (Han, 2022). z_i' takes the value of 1 in the observed variable and the other conditions take the value of 0. The estimation equation is as follows:

$$\Phi i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(M - |S| - 1)!}{M!} \left(f_x(S \cup \{i\}) - f_x(S)\right) \tag{2}$$

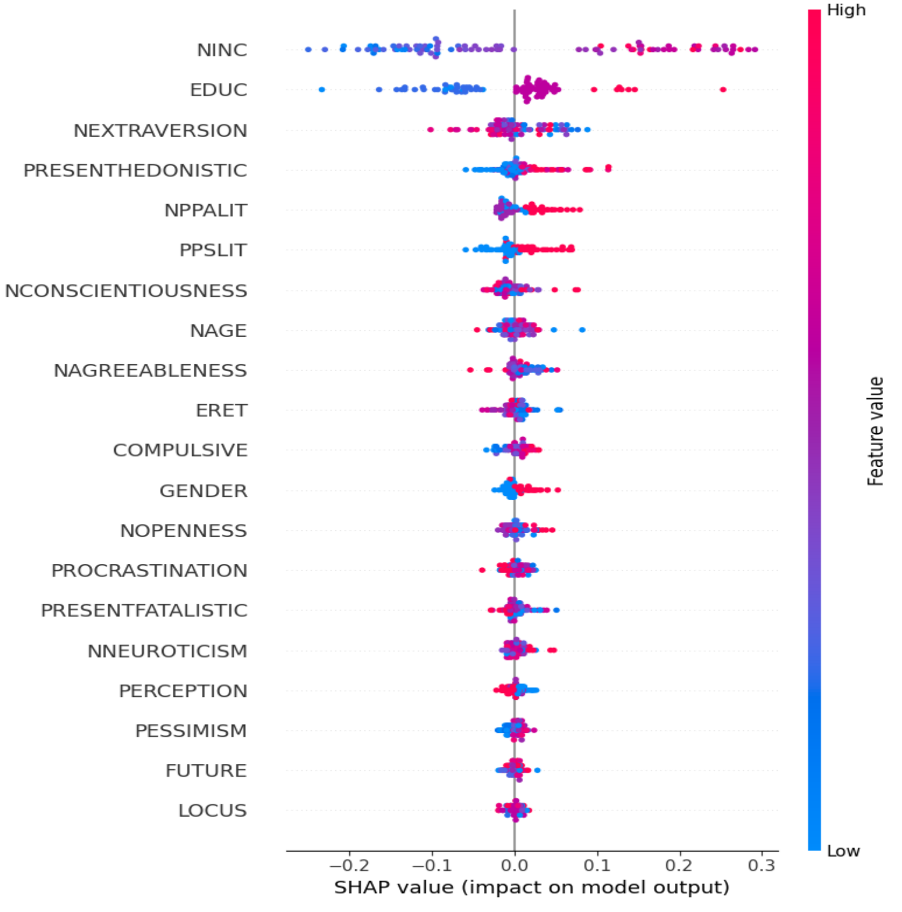
where N is a set of independent variables; S is a subset of variables from N, S⊂N, excluding i; (|S|!(M — |S| — 1)!)/M! is a weighting factor; $f_x(S)$ is the expected output of subset S.

4. Results

This section presents the findings derived from the empirical analysis of the PPS participation model using machine learning algorithms. Initially, the estimation results of the random forest and LightGBM are illustrated and interpreted, followed by an analysis of the significance of the variables. The SHAP summary plot displayed in Figure 1 shows the estimated results of the random forest algorithm. In Figure 1, the SHAP values are represented on the horizontal axis (x-axis), whereas the determinants of PPS participation features are presented on the vertical axis (y-axis). As the model output variable (PPS participation) assumes a value of one for participation and zero for non-participation, positive SHAP values correspond to participation, whereas negative SHAP values correspond to non-participation. In Figure 1, blue (red) signifies low (high) values of participation features. Leveraging this information, we interpret Figure 1 as follows. A decrease in income level decreases the SHAP value. This suggests a positive correlation between private participation and income levels. Similarly, higher values of EDUC, PRESENTHEDONISTIC, NPPALIT, PPSLIT, and GENDER (females) are associated with high SHAP values, indicating that these features contribute to the prediction of pension participation. Conversely, higher values of PERCEPTION and GENDER (males) correspond to negative SHAP values, implying that an increase in the values of these variables increases the likelihood of non-participation.

However, as seen in Fig. 1, it is difficult to clearly distinguish between the variables. This makes it difficult to interpret and analyse the results in the random forest SHAP plot (Fig. 1). This is due to the unstable nature of the decision tree algorithm, which limits interpretation. To clarify the effects of features on the model output of PPS, the PPS model is also trained with LightGBM. The following SHAP summary plot in Fig. Figure 2 shows the estimated results of LightGBM.

Figure 1: Random Forest SHAP summary plot

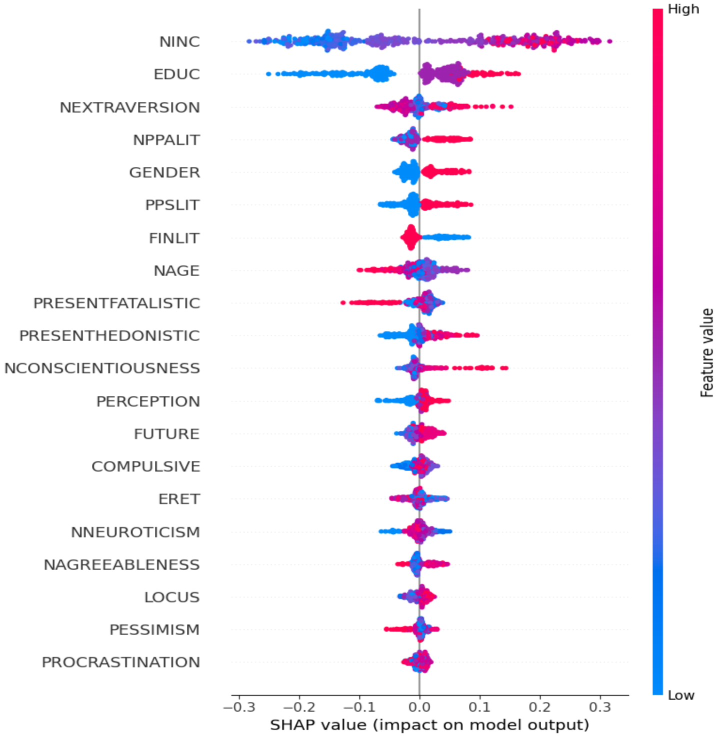


Note: (1) The vertical order signifies the relative significance of the variable. (2) The red colour denotes a high value, while the blue colour signifies a low value of the variable. (3) The horizontal axis represents the influence of the variable's value on the output. (4) The density exhibited by the dots displays their intensity. (5) The output (dependent) variable, PPS Participation (PPS), is accompanied by several independent variables. These include PPS Perception (PERCEPTION), which reflects an individual's view of PPS; Financial literacy (FINLIT), representing basic financial literacy; Normalised pension literacy (NPPALIT); Normalised monthly individual income (NINC); Gender (GENDER); Education level (EDUC); and Normalised age (NAGE). Additionally, ERET measures the adequacy of the Public Pension System. Personality traits encompass normalised extraversion (NEXTRAVERSION), agreeableness (NAGREEABLENESS), conscientiousness (NCONSCIENTIOUSNESS), neuroticism (NNEUROCRITICISM), and openness (NOPENNESS). Behavioural factors include procrastination (PROCRASTINATION), time preferences such as future orientation (FUTURE), present-hedonistic (PRESENTHEDONISTIC), and present-fatalistic (PRESENTFATALISTIC) attitudes, locus of control (LOCUS), pessimism (PESSIMISM), and compulsive buying (COMPULSIVE).

Examination of Figure 1 reveals that income (NINC) plays the most crucial role in determining private pension participation, while the variable of PROCRASTINATION appears to be the least influential. In the case of INC, similar to the random forest algorithm, INC's impact on the output and degree of intensity is much greater than that of the other variables. In other words, the individuals 'income contribute the most in participating in PPS. Regarding all variables, the division of colour in LightGBM is more uniform in both directions compared with the random forest algorithm. It is worth mentioning again that positive SHAP values correspond to participation, while negative SHAP values represent non-participation in the pension system. High education works in a strongly positive direction, whereas low education levels work in a strongly negative direction. This implies that the more educated person prefers to participate in pension more. The other variables can be interpreted in the same way.

Table 1 presents the evaluation results based on the evaluation metrics for each model. Upon comparing the two models, the evaluation values exhibit a significant increase in all evaluation metrics for LightGBM compared with the random forest algorithm. The interpretation and analysis of the SHAP are summarised as follows: For the random forest algorithm, although the importance of variables can be estimated through the SHAP, it is difficult to interpret the results accurately because of the unstable characteristics of the algorithm. Conversely, LightGBM demonstrated greater stability by sequentially updating multiple classification learners, as evident in the SHAP summary plot and evaluation results. Consequently, LightGBM appears to be more reliable and appropriate for the interpretation and analysis of variables of importance.

Figure 2. LightGBM SHAP summary plot.



Note: (1) The vertical order signifies the relative significance of the variable. (2) The red colour denotes a high value, while the blue colour signifies a low value of the variable. (3) The horizontal axis represents the influence of the variable's value on the output. (4) The density exhibited by the dots displays their intensity. (5) The output (dependent) variable, PPS Participation (PPS), is accompanied by several independent variables. These include PPS Perception (PERCEPTION), which reflects an individual's view of PPS; Financial literacy (FINLIT), representing basic financial literacy; Normalised pension literacy (NPPALIT); Normalised monthly individual income (NINC); Gender (GENDER); Education level (EDUC); and Normalised age (NAGE). Additionally, ERET measures the adequacy of the Public Pension System. Personality traits encompass normalised extraversion (NEXTRAVERSION), agreeableness (NAGREEABLENESS), conscientiousness (NCONSCIENTIOUSNESS), neuroticism (NNEUROCRITICISM), and openness (NOPENNESS). Behavioural factors include procrastination (PROCRASTINATION), time preferences such as future orientation (FUTURE), present-hedonistic (PRESENTHEDONISTIC), and present-fatalistic (PRESENTFATALISTIC) attitudes, locus of control (LOCUS), pessimism (PESSIMISM), and compulsive buying (COMPULSIVE).

Table 1: Evaluation results[3,4]

	Evaluation Metrics				
Algorithms	**Accurate**	**Precision**	**Recall**	**F1**	**ROC-AUC**
Random Forest	0.7667	0.7500	0.5455	0.6316	0.8570
LightGBM	0.9111	0.9310	0.8182	0.8710	0.9830

The findings of the Tree SHAP offer support for various methodologies that elucidate the correlation between participation in PPS, personality traits, behavioural factors, pension financial literacy, and sociodemographic variables. Extraversion emerges as the preeminent personality trait with a significant impact on participation, suggesting that individuals with higher net worth are more inclined to engage in PPS. Advanced pension literacy holds more sway than simple pension literacy, indicating that comprehensive knowledge of pension systems plays a pivotal role. Present-fatalistic tendencies exert a negative influence on participation as the most important behavioural factor, potentially indicating a connection with procrastination. Among sociodemographic groups, females and middle-aged individuals demonstrated a greater propensity to participate in PPS. High levels of basic financial literacy negatively affect PPS participation, possibly because financially literate individuals perceive PPS as an investment opportunity rather than a tool for retirement savings. Present-hedonistic tendencies are associated with an increased likelihood of participation, potentially because of compulsive buying behaviours. The trait of conscientiousness manifests as a favourable impact, which corresponds to the theory of planned behaviour. This suggests that individuals possessing a strong sense of responsibility and self-control are more likely to engage in participation. Individuals with a strong future-time orientation demonstrate a greater likelihood of engaging in PPS, which aligns with the theory of planned behaviour. Individuals with a heightened locus of control, indicating a sense of self-control, are more inclined to participate in PPS.

[3] The hyperparameters for the LightGBM classifier are as follows: the number of leaves is 8, the learning rate is 0.05, and the number of estimators is 100. For the Random Forest classifier, the maximum depth is 10 and the number of estimators is 50.

[4] The LightGBM and Random Forest algorithms are trained using various hyperparameters and yield comparable results.

This implies that fostering a sense of personal responsibility and control over one's financial future can foster participation. Perception of protection emerges as a pivotal factor in PPS participation. Individuals who view PPS as a means of financial security are more likely to participate. Finally, when comparing machine learning algorithms, LightGBM proves to be a more robust and dependable algorithm for interpreting variable importance compared to the random forest algorithm.

5. Conclusions and Policy Recommendations

This study investigates the determinants of participation in PPS under various sociodemographic, personality traits, behavioural factors, pension literacy, and basic financial literacy constraints and provides valuable insights into the factors influencing individuals' decisions to participate in PPS. These findings have several significant conclusions and implications for economic policy makers. Individual income is identified as the most critical sociodemographic factor influencing PPS participation. Extraversion stands out as the most crucial personality trait that affects participation, indicating that individuals with higher net worth (wealth) levels are more likely to participate. Advanced pension literacy is more influential than simple pension literacy, suggesting that knowledge about pension systems plays a pivotal role. Present-fatalistic tendencies have a negative impact on participation as the most crucial behavioural factor, suggesting a potential link with procrastination. Among the sociodemographic groups, females and middle-aged individuals exhibit a higher likelihood of participating in PPS. This suggests that targeted policies and marketing efforts should focus on these demographics to increase participation rates. High basic financial literacy has a negative impact on PPS participation, possibly because financially literate individuals are aware of alternative investment tools for accumulating savings. This finding implies the need for tailored financial education efforts to clarify the role of PPS in retirement planning. Present-hedonistic tendencies are associated with an increased likelihood of participation, potentially due to compulsive buying behaviours. Conscientiousness exerts a favourable impact that coincides with the theory of planned behaviour, suggesting that individuals possessing a strong sense of responsibility and self-control tend to be more inclined to engage. Individuals with a strong future-time orientation are more likely to participate in PPS, which aligns with the theory of planned behaviour. This suggests that promoting a long-term perspective and emphasising the benefits of saving for retirement may boost participation. Individuals with a higher locus of control, indicating a sense of self-control, are more likely to participate in PPS. This implies that promoting a sense of personal responsibility and control over one's financial future can encourage participation. Protection perception is a crucial factor in PPS participation. Individuals who perceive PPS as a means of financial protection are more likely to participate. This highlights the importance of government incentives and marketing campaigns that emphasise the protective aspects of PPS. Finally, this study compares machine learning algorithms and demonstrates that LightGBM is a more stable and reliable machine learning algorithm for interpreting variable importance compared with the random forest algorithm.

Policymakers should consider these findings when designing strategies to promote PPS participation. Tailored financial education programmes, especially for those with high basic financial literacy, can help individuals better understand the benefits of PPS as a retirement saving tool. They should create incentives to act less present-oriented or by establishing rules that prevent narrow-minded behaviour. These incentives should yield benefits for participants in PPS in the long term and should encompass a wide array of personality traits and behavioural factors. In addition, efforts should be made to create a sense of protection and control around PPS, targeting middle-aged individuals and women as potential participants.

Ethics Committee Approval: Approval was received from the Istanbul University Rectorate Social and Humanities Research Ethics Committee. (Date and Number: 18.08.2022-1156898).
Author Contributions: Conception/Design of Study- C.V., M.K.; Data Acquisition- C.V., M.K.; Data Analysis/Interpretation- C.V., M.K.; Drafting Manuscript- C.V., M.K.; Critical Revision of Manuscript- C.V., M.K.; Final Approval and Accountability- C.V., M.K.
Peer-review: Externally peer-reviewed.
Conflict of Interest: The author has no conflict of interest to declare.
Grant Support: The author declared that this study has received no financial support.

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Appendix

Table 2: Comparison of PPS participants and working age population

Year	PPS Participants (% of population)	Working Age Population (% of population)
2004	0.47	65.63
2005	0.97	66.03
2006	1.49	66.38
2007	1.96	66.67
2008	2.28	66.70
2009	2.53	66.95
2010	2.83	67.09
2011	3.20	67.27
2012	3.70	67.47
2013	4.83	67.64
2014	5.80	67.74
2015	6.75	67.76
2016	7.33	67.86
2017	11.02	67.93
2018	12.47	67.88
2019	12.99	67.83
2020	13.34	67.75
2021	18.4	67.77
2022	20.34	67.99

Source: OECD; www.egm.org.tr

Table 3: Measures of variables

Variable	**Items**
Dependent variable	
PPS: PPS participation	Are you a member of the PPS? (Yes = 1 or No = 0)
Independent variables	
PERCEPTION: PPS perception by Dragos, Dragos, and Muresan (2020)	What do you think of PPS? 0. None 1. Investment (to provide a more secure financial future) 2. Protection (financial support in case of need, unexpected events) 3. Investment and Protection (Both financial support and investment for the future)
FINLIT: Basic financial literacy by Lusardi and Mitchell (2011)	Suppose you have 100 Turkish Lira (TL) in a saving account and the interest rate is 2% per year. How much do you think you will have in your account after 5 years? (1= More than 102 TL 0=102 TL 0= Less than 102 TL)
PPSLIT: Simple pension literacy by Landerretche and Martínez (2013)	What percentage of government contribution is added to your PPS contribution? (0= 15% 0= 20% 0= 25% 1= 30%)
NPPALIT: (Normalised) Advanced pension literacy by Landerretche and Martínez (2013)	How often can the PPS fund basket be changed? (0= 3 times a year 0= 6 times a year 0= 9 times a year 1= 12 times a year) There is an option to receive monthly payments for life when I retire from PPS. (1= True 0= False)
NINC: (Normalised) Income (Monthly)	What is your average monthly net income in TL? (..........................TL)
GENDER: Gender	1 = Male 2 = Female
EDUC: Education level	1 = Primary school 2 = Middle school 3 = High school 4 = University 5 = Master's / Doctorate
NAGE: (Normalised) Age	15-52 years
The questions about personality traits by Rentfrow et al. (2015)- seven point Likert scale of 1 = strongly disagree . . . 7 = strongly agree	I see myself as someone who:
NEXTRAVERSION: (Normalised) Extraversion	• Enthuse others • Is quiet • Outgoing and sociable
NAGREEABLENESS: (Normalised) Agreeableness	• Tend to find fault with others (reverse score) • Starts quarrelling with others (reverse score) • Is considerate and kind to almost everyone

Table 3: Continued

NCONSCIENTIOUSNESS: (Normalised) Conscientiousness	• Tends to be disorganised (reverse score) • perseveres until the task is completed • Easily distracted (reverse score)
NNEUROCRITICISM: (Normalised) Neuroticism	• Is anxious • Is emotionally stable and not easily upset (reverse score) • Remains calm in tense situations (reverse score) • Gets nervous easily
NOPENNESS: (Normalised) Openness	• Is curious about different things • prefers work that is routine (reverse score)
Behavioural Factors by adapted from Piotrowska (2019)	
1. PROCRASTINATION: Procrastination -seven point Likert scale 1 = strongly disagree . . . 7 = strongly agree	• I delay making difficult decisions
2. Time preferences -seven point Likert scale 1 = strongly disagree . . . 7 = strongly agree	
a) FUTURE: *Future*	• When I want to achieve something, I set goals and think of specific ways to achieve them.
b) PRESENTHEDONISTIC: *Present-Hedonistic*	• I like to play games of chance (lottery, six-horse racing, etc.) when I have money
c) PRESENTFATALISTIC: *Present-Fatalistic*	• There is no point in worrying about the future because there is nothing to do.
3. LOCUS: Locus of control	• I often feel that I have very little influence over what happens to me.
4. PESSIMISM: Pessimism	• I see myself as pessimistic.
5. COMPULSIVE: Compulsive buying	• You continue to buy things despite the financial and family problems caused by your purchases.
ERET: Adequacy of the Public Pension System—seven-point Likert scale 1 = strongly disagree . . . 7 = strongly agree	• The public pension system meets my financial needs