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The impact of personality, behavior, and geography on participation in the private pension system in Türkiye: A machine learning approach☆

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ABSTRACT

This study examines regional disparities in the factors that affect participation in the Private Pension System (PPS) in Türkiye, focusing on sociodemographic characteristics, personality traits and behavior, and pension and financial literacy. The behavioral factors identified encompass procrastination, locus of control, pessimism, compulsive buying, and time perspective, and the personality traits include openness, agreeableness, extraversion, neuroticism, and conscientiousness. The study employs data on two provinces in Türkiye, Şırnak and Istanbul, and uses XGBoost and Tree SHAP algorithms and a probit model. Our findings indicate that personality traits such as openness, agreeableness, and conscientiousness have a positive influence on individual engagement in pension plans, whereas extraversion has a negative impact. Additionally, basic pension literacy is more influential than advanced pension literacy. The results also show that regional geography significantly influences personality and behavioral factors. Finally, a perception of protection is a critical factor in PPS participation.

1. Introduction

This study analyzes and evaluates the determinants of participation in the Private Pension System (PPS) in Türkiye under the constraints of financial literacy, private pension literacy, behavioral factors, and personality traits, considering the differentiation effect of regional geography. The empirical analysis uses data from Şırnak and Istanbul Provinces in Türkiye. PPS participation is modeled as a function of financial literacy, private pension literacy, behavioral factors, and personality traits and is analyzed with machine learning algorithms and a probit model. Particularly since the 1980s, governments have increasingly turned toward neoliberal principles in their economic decision-making, such as deregulation, limited government intervention, privatization, and balanced budgets, driven by a desire for fiscal restraint through reducing public expenditure. Consequently, they are considering a redesign of the social security system with two main objectives: reducing social security spending to achieve a balanced budget and transforming it to a market-based structure so as to shift the financial burden from the public to the private sector. The first to redesign policy in this way was in 1981 in Chile, where its PPS was established as part of its social security system. Chile's social security system was designed with two pillars: the first pillar is the public social security system, and the second pillar is the PPS. PPS contributes to the transformation of the social security system into a market-based structure. The Turkish PPS was established in 2003 on similar grounds.

Identifying the determinants of participation in the Turkish PPS is critical, as it does not have sufficient funds or participants. Since its establishment, the Turkish PPS has struggled to achieve satisfactory growth in the contribution per participant and to reach the necessary level of funding (Ertuğrul, Gebeşoğlu, & Atasoy, 2018). Additionally, it has not attracted enough participants relative to the working-age population and has one of the lowest ratios in OECD countries of private pension funding to the gross domestic product (GDP) (for details, see Appendix Tables A2 and A3).

The tax incentive designed to attract participants, which includes the state covering 25 percent of the contribution, along with the automatic enrollment system (AES) in Türkiye, have not resulted in a significant increase in the number of participants and funding. Consequently, effective policies that are not income-dependent are required to attract more participants and funding to the Private Pension System (PPS), such as promoting financial deepening. Financial deepening encompasses two critical elements: a broader selection of financial products and

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services, and improved access for various socioeconomic groups. In this context, diversification in private pension plans is achieved by maximizing benefits and ensuring extensive participation across different socioeconomic groups. To enhance PPS participation, an additional policy framework can be developed utilizing information on personality traits, behavioral factors, and financial literacy. In summary, public policy proposals must be formulated to encourage greater PPS participation.

Our review of the empirical literature on Turkish PPS shows a few trends. First, behavioral factors and personality traits are employed very little and often cover risk and future dimensions (Canöz & Baş, 2020; Doğan, 2016; Özbek, 2020; Türkmen and Kılıç, 2022). Second, no study analyzes the relationship between PPS participation and private pension literacy in Türkiye. Third, in studies that investigate the determinants of Turkish PPS, the effect of regional geography on personality traits is not included, and, in particular, no study analyzes the impact of personality traits and behavioral factors on participation in PPS, considering regional geographic differences. First, few studies thoroughly examine the determinants of PPS participation, including basic financial literacy, private pension literacy, behavioral factors, and personality traits, using machine learning algorithms. Fifth, few studies have compared the performance of CatBoost, Extreme Gradient Boosting (XGBoost), Random Forest, and LightGBM in training their models with traditional empirical methods.

This study fills gaps in the literature on the determinants of PPS as follows. First, we analyze the differentiating effect of regional geography on personality traits in Türkiye by examining Istanbul and Şırnak, two provinces that differ in terms of physical geography (mountainous versus flatlands), location direction (east-west, etc.), and urban population size (metropolitan and non-metropolitan). Second, many personality traits and behavioral factors other than basic financial literacy are considered, including pension financial literacy, Big Five personality traits, pessimism, procrastination, time perspective, compulsive buying, and locus of control. Third, we employ machine learning algorithms, such as CatBoost, Extreme Gradient Boosting (XGBoost), Random Forest, LightGBM, and TreeSHAP, to estimate the importance of the variables subject to empirical analysis and interpret and compare the estimated results and performance to those from the probit model, which is a traditional empirical method.

This study makes several theoretical contributions to understanding PPS participation. By combining geographic, behavioral, and psychological dimensions and employing innovative analytical techniques, this study sheds light on how geographic differences within a country can influence financial behaviors and decisions. In particular, the inclusion of psychological variables significantly enhances our understanding of how individual differences impact financial decision-making. Notably, this study reveals that basic pension literacy is more influential on PPS participation than advanced pension literacy. Additionally, the identification of protection perception as a critical factor shows the importance of perceived security and trust in financial systems in encouraging participation. Lastly, this study demonstrates the potential of machine learning with larger samples for creating more robust and accurate models that capture the factors influencing PPS participation in economic and finance research.

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

2. Review of the theoretical literature on the determinants of pension participation

This section gives the theoretical basis of the determinants of participation in private pensions. Over time, people have become more interested in greater economic security in their old age, encouraging them to invest more in private complementary provident arrangements (Barr & Diamond, 2009; Holzmann & Hinz, 2005). In other words, they ensure their future economic security by accumulating savings that come from their current income. This perspective argues that the factors that influence savings are identical to those that influence retirement savings (or participation in a private pension system). A brief review of the theoretical literature on the subject reveals that the factors that motivate people to participate in a PPS include income, institutional factors, behavioral factors, and personality traits.

2.1. Income

Many economic theories focus on the determinants of savings. Economic theories generally suggest that savings behavior depends on income and consumption. These theories advance different definitions of income. Keynes (1936) defined savings as the portion of income that remains after consumption; when disposable income increases, consumption increases as well, but at a lower rate. However, in his permanent income hypothesis, Friedman (1957) postulated that the main determinant of savings is permanent income. Thus, he concluded that a person's age is relevant to consumption and savings, rather than temporary income. The life-cycle hypothesis proposed by Modigliani and Brumberg (1954) assumes that long-term income is the main determinant of savings. In contrast to the permanent income hypothesis, this theory suggests that life is long; therefore, lifelong resources and current income should be considered. This theory, like the permanent income hypothesis, concludes that a person's age affects consumption and savings. Furthermore, they argue that consumption is dependent on long-term income. The life-cycle income hypothesis states that savings also depend on growth rates, wealth, and capital markets. Duesenberry (1967) explained savings behavior using the relative income hypothesis, which holds that households make consumption decisions based on relative income. Accordingly, current consumption is related to past savings. Thus, an increase in income leads to a change in consumption that is larger than the decrease in income. Unlike other savings theories, the relative income hypothesis assumes that income distribution is associated with savings. It states that savings depend on interest rates, the relationship between current and expected future income, income distribution, the age distribution of the population, and income growth (Duesenberry, 1967).

2.2. Institutional factors

Institutional savings theories hold that individual and institutional processes affect household savings. Thus, they usually assert that individual behavior is related to social institutions. According to Sherraden (1991), the institutional mechanisms consist of rules, incentives, implicit connections, and subsidies. He refers to incentives in PPS as institutional subsidies. Hence, PPS incentives enable individuals to accumulate wealth.

2.3. Behavioral factors and personal traits

A few behavioral theories have investigated the determinants of saving. Behavioral savings theories differ from economic savings theories in terms of assumptions about savings and consumption preferences. In contrast to economic theories, behavioral savings theories assume that unfixed savings and consumption preferences and individual economic behaviors are independent of preferences and economic resources (Beverly, 1997). They argue that individuals have behavioral constraints and incentives. The best-known behavioral savings theory is the behavioral life-cycle hypothesis (Shefrin & Thaler, 1988), which claims that people can be divided into planners and doers. Planners and doers make different decisions about savings and consumption in terms of the benefit periods considered. Whereas the planner bases decisions about consumption and savings on their lifetime utility, the doer makes economic decisions for one period (Thaler & Shefrin, 1981). If the doer's preferences and incentives change, and preferences are limited, the doer will have more self-control. According to this theory, people often accept rules that restrict a doer. So, a mandatory pension plan might increase overall savings (Thaler & Shefrin, 1981).

This study considers behavioral variables such as procrastination, locus of control, time perspective, pessimism, and compulsive buying. 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 concept that includes people's beliefs about the extent to which they can control the events that affect them. People with an external locus of control commonly ascribe the consequences of life to external circumstances (e.g., fate, luck, other individuals), whereas those who have an internal locus of control maintain the conviction that a majority of events in life evolve based on their own actions (Piotrowska, 2019). We examine the time perspective in terms of three subheadings: future (expectations), present hedonistic, and present fatalistic. Present hedonistic comprises people who avoid long-term work and focus on pleasure in their lives. Present-fatalistic people believe that an external force is dominant in their lives, not their actions. Pessimism is defined as having a negative bias in expectations and perceptions in life (Burke, Joyner, Czech, & Wilson, 2000). Compulsive buying is an uncontrollable urge to buy or use a substance or engage in an activity (O'Guinn & Faber, 1989).

Behavioral factors play a pivotal role in determining savings, so they are closely related. The relationship between pessimism and retirement savings is mediated through various channels. People with a pessimistic outlook tend to have shorter life expectancy, resulting in negative decisions about retirement savings (O'Dea & Sturrock, 2019). Furthermore, pessimism may interact with retirement savings through other behavioral factors, such as locus of control and procrastination (Burke et al., 2000; Piotrowska, 2019). Because of its consequences, such as anxiety, depression, and stress, procrastination is positively correlated with pessimism (Van Eerde, 2003). Pessimists, based on their external locus of control (e.g., fate), lack the motivation to save for retirement (Piotrowska, 2019). Nevertheless, pessimism can have a positive impact on retirement savings, as it is positively associated with individualism and thereby positively influences financial comfort (Bengtson, Biblarz, & Roberts, 2002). Consequently, it encourages people to consider their financial conditions in retirement, leading to an increase in retirement savings. According to Personality Plus (Littauer, 1995), pessimists have a unique ability to identify problems that optimists might overlook. This phenomenon is known as defensive pessimism, which involves preparing for negative outcomes and harboring negative expectations (Burke et al., 2000). Consequently, pessimism can positively influence savings through this mechanism. Procrastination is negatively related to retirement planning, as it prioritizes short-term actions over long-term consequences and leads to postponement (Piotrowska, 2019). The (internal) locus of control is closely linked to self-control, which, in turn, has a positive impact on savings. Hence, it is a critical behavioral factor in the context of retirement savings.

According to the theory of planned behavior (Ajzen, 1991), having a future time perspective can influence retirement savings by affecting people's attitudes, subjective norms, and perceived behavioral control regarding saving and investing for retirement. People with a strong future time perspective may have a more positive attitude toward saving and investing in retirement, because they value the long-term benefits and consequences of their actions. Little empirical evidence is available about the causal relation to retirement savings of compulsive buying, future (expectations), and being present fatalistic and present hedonistic. However, some studies have suggested that compulsive buying is negatively related to retirement savings. For example, Asebedo and Browning (2020) find that the retirement savings of compulsive buyers are relatively inadequate when compared with the savings of noncompulsive buyers. They also find that future time perspectives are greater among noncompulsive buyers than among compulsive buyers. Donnelly, Iyer, and Howell (2012) find that financial well-being is lower among compulsive buyers than among noncompulsive buyers and that compulsive buyers have higher levels of a present-hedonistic time perspective than noncompulsive buyers. O'Guinn and Faber (1989) theoretically attribute compulsive buying to hedonism. Piotrowska (2019) deduces that hedonism, fatalism, and present-fatalistic and present-hedonistic tendencies have a positive influence on compulsive buying. Moreover, she contends that the impact of compulsive buying on retirement savings can be explained through the mechanisms of status consumption and lower self-respect. Accordingly, compulsive buying increases retirement savings through the status consumption mechanism, and it decreases retirement savings through the absence of a self-respect mechanism. Finally, 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, and they are closely linked to the PPS. This investigation focuses on the Big Five personality traits, established by Costa and McCrae (1992), which serve as the foundation for identifying personality traits (Piotrowska, 2019). The Big Five encompass extraversion, agreeableness, conscientiousness, neuroticism, and openness (Exley, Doyle, Grable, & Campbell, 2022). Extraversion can be characterized as a personality trait that responds to rewards and is socially oriented, positive, and willing to take risks (Balasuriya & Yang, 2019). Agreeableness is defined as a personality trait that is cooperative, friendly, inclined toward volunteering, and nonviolent (Rentfrow, Jokela, & Lamb, 2015). Conscientiousness can be described as a personality trait that is oriented toward success and characterized by diligence (Piotrowska, 2019). Neuroticism encompasses anxiety, aversion to risk, depression, instability, and avoidance of harm (Balasuriya & Yang, 2019; Rentfrow et al., 2015). Lastly, openness is a personality trait associated with receptiveness to new experiences and ideas (Costa & McCrae, 1992).

The life-span theory of control explains how personality traits influence retirement savings by affecting 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 organized, disciplined, and responsible. They may also have more positive attitudes toward saving and investing for retirement and are more likely to follow a financial plan (Heckhausen & Schulz, 1995). Individuals with high extraversion have greater net worth levels and may have an increased ability to adjust to retirement (Asebedo & Browning, 2020). However, it could negatively affect retirement savings because extraverts like to socialize and follow the spending habits of others and tend to engage in hedonistic consumption (Balasuriya & Yang, 2019). However, 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 toward saving and investing for retirement and are more likely to avoid or procrastinate about making financial decisions (Heckhausen & Schulz, 1995). Nevertheless, neuroticism could positively affect retirement savings through compulsive buying (Piotrowska, 2019). The theory of planned behavior explains the impact of personality traits on retirement savings through their effect on the three factors that shape behavioral intentions. For example, individuals who score high on openness to experience may have more positive attitudes toward saving and investing for retirement because they are more curious, creative, and adventurous (Ajzen & Schmidt, 2020). But individuals who score low on agreeableness may have more negative attitudes toward saving and investing for retirement because they are more competitive, selfish, and distrustful (Asebedo & Browning, 2020).

3. Literature review

Many studies investigate the causal relationship among personality traits, behavioral factors, pension literacy, and PPS. They usually conclude that personality traits, financial literacy, pension literacy, behavioral factors, and demographic variables affect participation in PPS. In addition, many other studies analyze the relationship between geography and personality traits, frequently concluding that geography affects the distribution of personality traits. Several studies use retirement preparation, probability of participation in pension plans, and participation in pension plans as explanatory factors of PPS.

Niu, Zhou, and Gan (2020) investigate financial literacy and retirement preparation (e.g., financial necessities, long-term financial plans, and purchasing a pension plan) in China with a longitudinal dataset and multivariate regression. They find a positive relationship between financial literacy and retirement preparation. Similarly, Brown and Graf (2013) examine the relationship between financial literacy and retirement planning in Switzerland, using a probit model and survey data on 1500 households. The results show a strong relationship between financial literacy and voluntary retirement savings. Van Rooij, Lusardi, and Alessie (2011) examine the relationship between financial literacy and retirement planning in the Netherlands. Unlike Niu et al. (2020) and Fornero and Monticone (2011), they use ordinary least squares (OLS) and generalized method of moments (GMM) methodologies and find a negative link between basic financial literacy and retirement planning. Unlike Niu et al. (2020), Van Rooij et al. (2011), and Brown and Graf (2013), Fornero and Monticone (2011) include the possibility of participating in a retirement plan as a dependent variable. They analyze the relationship between financial literacy and participation in a retirement plan in Italy in 2006 and 2008 with SHIW (Survey on Household Income and Wealth) survey data (covering 7768 households and 19,551 individuals in 2006, and 7977 households and 19,907 individuals in 2008) and OLS and instrumental variable (IV) estimators. Their findings indicate that financial literacy has a positive effect on the probability of participation in a retirement plan.

Few international studies analyze the causality between financial literacy and PPS based on savings. Landerretche and Martínez (2013) test the relationship between retirement financial literacy and voluntary retirement savings in Chile, using cross-sectional data analysis and a probit model. Their 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 analyze the impact of pension literacy on voluntary pension and bank savings. They find a positive and significant connection between pension literacy and voluntary pension savings. Furthermore, higher pension literacy positively influences the likelihood of having voluntary bank savings, with conscientiousness emerging as a significant predictor of voluntary bank savings.

Salleh, Wahab, Karim, and Lim (2022) center their study on the level of preparedness by employees in relation to a fully defined contribution retirement scheme. Their findings highlight the importance of higher financial literacy and positive behavioral, normative, and controlled beliefs in informed financial decision-making, particularly concerning retirement savings, with a sample size of 200 workers. In a similar vein, Fang, Hao, and Reyers (2022) look at the effects of financial advice, financial literacy, and social interaction on decisions by households regarding retirement savings in New Zealand. Analyzing data from the 2018–2019 wave of the Financial Capability Barometer survey with a probit model, they determine that financial advice and financial literacy are complementary, leading 3629 people to make better decisions about saving for retirement. Finally, Tomar, Baker, Kumar, and Hoffman (2021) study the interplay between financial literacy and psychological traits, such as retirement goal clarity, future time perspective, attitude toward retirement, risk tolerance, and social group support, which influence women's retirement planning behavior in India. Using a partial least squares regression and multigroup analysis with a sample of 485 women, they find that retirement planning behavior has a positive association with future time perspective, retirement goal clarity, and social group support, moderated by financial literacy.

In prior studies, the effect of personality and behavioral factors on PPS is usually analyzed with dependent variables such as purchase decision, purchase intention, PPS savings level, and PPS participation level. Dragos, Dragos, and Muresan (2020) study the effect of behavioral and sociodemographic factors on purchasing private pension plans in Romania using a logit regression and a sample of 1579 people. The results indicate that investing through specialized institutions and financial consultants positively affects the decision to purchase a PPS, whereas regarding PPS as an investment and the public system as adequate is negatively related to the decision to purchase a PPS. The results lead to the conclusion that behavioral factors and private pension knowledge are related to the purchasing decision but not to the purchasing intention. Piotrowska (2019) examines retirement savings under personality and behavioral constraints among 826 participants in Poland ages 25–45 with logistic, multiple regression, and mediation models. The findings show that although procrastination negatively affects retirement savings, compulsive buying increases retirement savings, and introversion, lack of direction, locus of control, and future orientation positively affect participation in PPS.

Balasuriya and Yang (2019) investigate the effect of personal traits on retirement decisions in England, using longitudinal data analysis and an OLS, probit, and random-effects model. Their results indicate that extraversion and openness are negatively related to participation in PPS, conscientiousness positively affects participation in PPS and making larger PPS contributions, and agreeableness and extraversion are negatively related to the PPS contribution amount. Some studies include retirement expectations as an explanatory variable. Bottazzi, Jappelli, and Padula (2006) study the impact of Italian reforms on retirement wealth accumulation and household expectations in terms of retirement outcomes, using a sample of 9724 men and 5925 women. The results show that the reforms change workers' retirement expectations and that the reforms led more knowledgeable workers to increase their retirement savings.

Many studies analyze the relationship between PPS and financial literacy, personality traits, and behavioral factors in Türkiye. They conclude that financial literacy, personality traits, and behavioral factors are usually associated with PPS. Moreover, participation, exiting, and fund preferences in PPS are added to the analysis as dependent variables. In these studies, basic financial knowledge on financial literacy, risk variables, future anxiety, and security represent personality traits, and behavioral factors are used as explanatory variables. Unlike studies on other countries, they do not include many personality traits and behavioral factors, pension literacy, and the Big Five personality traits as explanatory variables. Doğan (2016) examines the relationship between investment fund preferences in the PPS and behavioral finance tendency among 400 bank personnel, using Analysis of Variance (ANOVA), chi-square, *t*-test, and correlation methods, and obtains results showing that risk perception, risk-taking attitude, emotional intelligence, and basic and advanced financial literacy levels affect individual pension fund preferences.

Canöz and Baş (2020) study the participation factor in private pension plans using the binary logit model. Their findings show that savings habits and investment, financial literacy, future anxiety and security, and gender and tenure affect decisions to participation in the PPS by scholars at state and foundation universities. The results indicate that savings and investment habits, financial literacy level, and age affect decisions about participation in PPS. Özbek (2020) analyzes whether the financial literacy level of people, depending on their financial attitudes and behaviors, affects their participation in the PPS, using a randomly selected sample of 405 participants and the structural equation model, and finds that financial literacy has a positive effect on participation in the PPS.

Bayar, Gündüz, Öztürk, and Şaşmaz (2020) investigate the effect of financial literacy on participation in the PPS with a sample of Uşak University personnel, using factor analysis and logistic regression. Their findings demonstrate that basic and moderate financial literacy do not significantly affect participation in the PPS. However, advanced financial literacy negatively affects it. Similarly, Türkmen and Kılıç (2022) examine the role of financial literacy and perceived consumer risks in explaining ownership of individual pension plans by workers in Türkiye. Their study employs *t*-tests, ANOVA, and chi-square tests with a sample of 651 workers. Their findings reveal that financial literacy does not have a significant correlation with involvement in the individual pension system, whereas perceived consumer risks vary, depending on ownership of individual pension plans.

Many prior studies study the association between demographic variables and PPS in Türkiye. They find that demographic indicators are usually associated with PPS. Özer and Çınar (2012) conduct a survey on the perspectives of 289 faculty members at a foundation university about the PPS. Their findings show a significant relationship between variables such as age, gender, work experience, income level, and the perspective on the PPS. Yemez and Akdoğan (2019) analyze the effect of demographic variables on private pension purchasing behavior. They conduct a survey of 430 bank customers in Sivas over age 18 and use a *t*-test and one-way ANOVA tests. Unlike Özer and Çınar (2012), they find that age, education level, average monthly income, gender, and marital status are not significant in purchasing a private pension plan, and private pension purchasing behavior increases as people's income level rises. Moreover, the type of bank affects the purchasing behavior. The intention to purchase a private pension plan does not affect purchasing, and behavior regarding the private pension plan varies by occupation.

Some studies discuss the views about and reasons for leaving the Turkish PPS. Using a sample of 371 randomly selected workers in Ordu, Şataf and Yıldırım (2019) study awareness of and opinions about the private pension system. The respondents believe that the retirement age should be lower, and they do not fully trust the PPS. Moreover, most registered participants are age 25–44, at least a university graduate, and have a high monthly income. Kocabıyık and Küçükçakal (2018) survey 463 public and private sector employees in Isparta and conduct a crosstabs test to investigate the reasons for leaving and remaining in the AES. The results demonstrate that the most important factor for remaining in the AES is the state contribution. Other factors are receiving a lump sum of money in the future and the usefulness of the AES. People mainly leave because they believe that the 10-year period is too long, that the 3 percent of the earnings deducted is too high, and that the savings could be directed to other kinds of investment.

Several papers examine the differences in personality traits by geography, considering factors such as physical geography (mountainous versus flatlands), location direction (e.g., east or west) or city population sizes (metropolitan and nonmetropolitan). These findings demonstrate a relationship between regional geography and personality traits and behavioral factors. Allik et al. (2009) investigate personality traits in Russia using the survey data on 7065 people in 33 regions. Their findings reveal the existence of geographic differences in personality traits. Using a sample of 619,397 respondent in all 50 US states, Oishi, Talhelm, and Lee (2015) test the hypothesis that people living in mountainous US states are more introverted than those in nonmountainous US states, and their results confirm this hypothesis. Using a sample of 286, 000 employees, Burger (2014) examines the regional structure of savings in the German occupational pension system and identifies differences in financial behavior among metropolitan versus nonmetropolitan cities and different geographic locations (east-west, etc.). Other studies hold that regional geography is not determinative in terms of differentiation of personality traits. Rentfrow et al. (2013) use a sample of 1,596, 704 participants in 49 US states to analyze regional variation in personality traits. Their results show no systemic differences in personality traits across geographic regions. Using a sample of approximately 400, 000 people in 380 Local Authority Districts, Rentfrow et al. (2015) investigate regional personality differences in Great Britain and do not find systemic regional personality differences.

To summarize, previous studies using various methodologies have achieved a consensus that a connection exists among personality traits, financial literacy, pension literacy, behavioral factors, demographic variables, and PPS. The goal of this study is to address gaps in the literature identified earlier by examining the factors that determine participation in PPS in Istanbul and Şırnak; these two areas differ in terms of physical geography (mountainous, flatlands), locational direction (east-west, etc.), and urban population size (metropolitan and nonmetropolitan) under the constraints of financial literacy, private pension literacy, behavioral factors, and personality traits. To do so, we employ CatBoost, extreme gradient boosting (XGBoost), random forest, LightGBM, and Tree SHAP (Shapley additive explanations) as machine learning algorithms and probit models, which are traditional empirical methods. We also compare the performance of CatBoost, extreme gradient boosting (XGBoost), random forest, LightGBM, and the probit model to address gaps in the literature.

4. Dataset, methodology, and model

4.1. Dataset

The data used in our empirical analysis comprise data collected through a face-to-face survey between September 2022 and March 2023 in the provinces of Istanbul and Şırnak in Türkiye.[1] The respondents included 990 participants in Istanbul and 415 in Şırnak of working age (and mostly employed), ages 16–67 (in Istanbul) and 15–54 (in Şırnak).[2] The survey consists of 33 questions (for details, see Appendix Table A1), with multiple items on advanced pension literacy and the Big Five personality traits; the empirical counterpart of these variables is obtained by aggregating these items.

In addition, we use personality trait survey sets, following previous studies, such as Rentfrow et al. (2015) (whose personality scale consists of 44 items, i.e., the Big Five Inventory), Piotrowska (2019) (whose 10-item question set is adapted from Gosling, Rentfrow, & Swann, 2003), and Oishi et al. (2015) (whose 25-item scale comes from Brody & Ehrlichman, 1998). Because our study requires a broader set of questions, we use the personality trait survey set from Rentfrow et al. (2015) and adapt the behavioral factors survey set from Piotrowska (2019). A seven-point Likert scale (from 1 = strongly disagree to 7 = strongly agree) is employed in the personality scale and behavioral factors question sets. We also use the questions by Dragos et al. (2020) to examine perceptions and the adequacy of the PPS. Finally, to measure basic financial literacy, we employ the pension literacy question set by Landerretche and Martínez (2013) and the question sets by Lusardi and Mitchell (2011).

4.2. Model and methodology

To investigate the determinants of PPS participation, we use independent variables, such as basic financial literacy, private pension literacy, behavioral factors, and personality traits, in the empirical model. The model also includes sociodemographic variables (age, gender, income, and education level). The variables are defined in Appendix Table A1.

In our empirical analysis of the model, we use machine learning algorithms and a probit model, which is a traditional empirical model. In recent years, machine learning algorithms has become more important

[1] Because of practical constraints, including cost and time limitations, we focus on just two cities in the survey. Prior studies also use samples from these two cities in conducting regional comparisons (Bosley, 2017; Godina, Sineva, Khafizova, Okushko, & Negasheva, 2020; Plaut, Markus, Treadway, & Fu, 2012; Shade, 1979).

[2] Several prior studies use cross-sectional survey data and sample sizes similar to ours: Dragos et al. (2020), which comprises 1579 participants in April–June 2016; Piotrowska (2019), which has 826 participants in November 2016; Tomar, Baker, Kumar, and Hoffmann (2021), with 485 participants; Türkmen and Kılıç (2022), with 651 participants.

for empirical analysis because traditional methodologies used in empirical analysis can lead to arbitrary and nonrobust estimation and might not be efficient under nonlinear conditions (Salas-Rojo & Rodríguez, 2022). Bias and model selection problems limit parameter-based analyses and nonparametric tests are inefficient because of arbitrary segmentation (Han, 2022). Tree classification algorithms are bias-free and have no model selection problems. Thus, machine learning algorithms are preferred for addressing the inefficiencies in traditional methodologies.[3] However, caution is warranted because machine learning algorithms are typically designed for large datasets and tend to perform better under those conditions (Rajula, Verlato, Manchia, Antonucci, & Fanos, 2020). As the number of variables and data per subject increases, classical statistical modeling, originally designed for smaller datasets, faces challenges. As input variables and associations grow, the boundary between statistical and ML approaches becomes less clear (Bzdok, Altman, & Krzywinski, 2018). In other words, with small sample sizes, traditional empirical models might perform better than machine learning methods.

The machine learning algorithms used in this study include CatBoost, extreme gradient boosting (XGBoost), random forest, LightGBM, and TreeSHAP, which is variant of SHAP. CatBoost, extreme gradient boosting (XGBoost), random forest, and LightGBM classifiers are employed in the training process. After the model is trained, 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).[4]

This study also compares the performance of four algorithms: CatBoost, XGBoost, LightGBM, and random forest. It shows that gradient boosting methods (GBMs), such as CatBoost, XGBoost, and LightGBM, are more flexible and have higher performance than random forest, which is simpler and more robust. CatBoost is a GBM developed by Yandex for both classification and regression problems (Prokhorenkova, Gusev, Vorobev, Dorogush, & Gulin, 2018). It uses a new ordered boosting technique that makes it faster and better than other boosting methods, such as XGBoost. CatBoost also handles categorical features well with its own encoding and loss functions (Prokhorenkova et al., 2018). CatBoost has achieved state-of-the-art results on many datasets, especially those with categorical features (Dorogush, Ershov, & Gulin, 2018). However, CatBoost is more complex than XGBoost/LightGBM, which affects the training speed. The prediction value of CatBoost is expressed as follows:

$$F(x) = F_0(x) + \sum_{t=1}^{T} \eta f_t(x)$$

where $F_0(x)$ is the initial approximation; T is the number of trees; η is the learning rate; and $f_t(x)$ is the prediction value of the t-th tree (Prokhorenkova et al., 2018). XGBoost is another popular and effective GBM that has won many machine learning competitions (Chen & Guestrin, 2016). It supports distributed gradient boosting, regularization to prevent overfitting, and tree pruning techniques to improve performance. It is an optimized distributed gradient boosting library that uses a more regularized model to control overfitting. XGBoost improves on tree learning algorithms, with sparsity-aware splits and more efficient tree growth strategies. Experiments have shown that XGBoost often beats other methods with many datasets (Gill et al., 2022; Shwartz-Ziv and Armon, 2022). The objective function of XGBoost during the t-th iteration is (Chen & Guestrin, 2016):

$$\phi^{(t)} = \arg\min_{\phi} L^{(t)}(\phi) = \arg\min_{\phi} \left[\sum_{i=1}^{n} l\left(y_i, \widehat{y}_i^{(t-1)} + f_t(x_i)\right) + \sum_{k=1}^{t} \Omega(f_k) \right]$$

where $\widehat{y}_i^{(t-1)}$ is the predicted value for the ith instance at the $(t-1)$-th iteration, and f_t is the tree added at the t-th iteration.

$$\sum\nolimits_{i=1}^{n} l\left(y_i, \widehat{y}_i^{(t-1)} + f_t(x_i)\right)$$

is a loss function that measures the difference between the predicted and actual values. $\sum_{k=1}^{t} \Omega(f_k)$ is a regularization term that determines the complexity of the XGBoost model.

The random forest algorithm is a machine learning technique 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 potential for overfitting (Breiman, 2001). This method employs many deep decision trees, each trained on a different subset of the same data, to reduce the variance. Random forests create a group of decision trees by randomly choosing features and data points from the training set. They are more resistant to noise and overfitting than single decision trees. The random forest method is easy, simple, and works well with default settings. However, it does not use gradient-based optimization such as GBMs (Probst et al., 2019). The random forest algorithm can be constructed as follows (Breiman, 2001):

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

where $\widehat{f}_B(x)$ is the predicted random forest output for input x; B is the number of trees in the random forest; $T_b(x)$ is the predicted output of the bth tree for input x. The idea behind this equation 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 is a framework for gradient boosting that employs algorithms for learning based on trees (Ke et al., 2017). It has some particular techniques, such as leaf-wise growth, which trains trees more quickly by expanding them leaf by leaf, and histogram-based algorithms, which handle sparse and skewed data better. LightGBM is designed to solve XGBoost's memory problems with new techniques, including leaf-wise growth, which expand trees layer by layer, and reducing the number of features for splits (Ke et al., 2017). It also uses histogram-based algorithms and improves data loading and caching. LightGBM has proven to be more accurate than XGBoost on large datasets while being up to 10 times faster (Bentéjac, Csörgő, & Martínez-Muñoz, 2021). However, LightGBM is less complex than XGBoost, which can affect performance with some problems. The objective function of LightGBM is (Ke et al., 2017):

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

where $\phi(x) = \sum_{j=1}^{J} f_j(x)$ is the prediction score for x, l is the differentiable loss function, f_j is a decision tree, and $\Omega\left(f_j\right)$ is a regularization term for the complexity of the tree. The data are split randomly into two parts: 80 percent for training and 20 percent for testing. Each algorithm is trained on the training part using the best hyperparameters found by a grid search (for details, see Table 1) and tested on the testing part using accurate, precision, recall, F1, and ROC-AUC (Receiver Operating Characteristic-Area Under the Curve) scores for classification problems.

SHAP is a machine learning method based on game theory that is used to explain the output from different machine learning models. SHAP values clarify the forecasts generated by complex models, relying

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

[4] We employ Tree SHAP since machine learning algorithms are not directly interpreted for causal inference.

Table 1
Hyperparameter optimization of machine learning algorithms.

Hyperparameter	CatBoost	XGBoost	LightGBM	Random forest
Tree depth	5 (5)	3 (5)	2 (4)	7 (10)
Alpha	–	–	–	–
Gamma	–	0.0001	–	–
Minimum samples leaf	–	–	–	–
Minimum sample split	–	–	–	–
Gamma	–	–	–	–
Learning rate	0.1	0.1	0.1	–
Reg_Alpha	–	0.0001	0.0001	–

Notes: The highlighted parameters are optimized through the use of a grid search technique, whereas the remaining parameters are assigned default values, denoted as –. The parameters in parentheses represent the optimized parameters in Şırnak Province, whereas the other parameters represent those in Istanbul Province.

on Shapley values derived from game theory. The use of model-agnostic and feature attribution has certain advantages over traditional econometric methods (Rodríguez-Pérez & Bajorath, 2020). The limitations of econometric methods often stem from the assumptions and specifications of the underlying models (LeSage & Pace, 2009). The model-agnostic property of Tree SHAP enables it to be applied to any machine learning model, regardless of its complexity or architecture. However, econometric methods might lack the ability to offer such detailed clarification, particularly for nonlinear or high-dimensional models (Rodríguez-Pérez & Bajorath, 2020). Feature attribution encompasses both global and local interpretation of machine learning models, which is achieved through the aggregation or visualization of the feature attributions across different instances. The explanation model comprises a linear function of a binary variable as follows:

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

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

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

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; and $f_x(S)$ is the expected output of subset S.

The probit model is a widely used traditional empirical method for analyzing binary outcomes. This methodology provides a framework for understanding the relationship between prediction variables and the probability of a specific event. The probit model assumes the existence of a latent variable Y^* that represents the underlying propensity for the event of interest to occur (Greene, 2018). This latent variable is assumed to follow a standard normal distribution. The observed binary variable Y is then determined by comparing Y^* w ith a threshold value. The probit model equation is as follows (Wooldridge, 2013):

$$P\left(Y = 1|X\right) = \Phi\left(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k\right) \tag{3}$$

where $P\left(Y = 1|X\right)$ is the probability of the event given the prediction variables X; $\Phi(.)$ is the cumulative distribution function of the standard normal distribution; and β is the coefficient associated with each prediction variable X.

5. Empirical results

This section presents the findings from the empirical analysis of the PPS participation model using machine learning algorithms and a probit model. First, we compare and interpret the evaluation results of the CatBoost, XGBoost, Random Forest, LightGBM and probit model, and then we analyze the significance of the variables. Table 2 compares the performance of four machine learning algorithms—CatBoost, XGBoost, random forest, and LightGBM—and a probit model across Istanbul and Şırnak Provinces, using various evaluation metrics. Among the probit model and the four algorithms, XGBoost has the best performance in many metrics for the Istanbul sample. The results also indicate that CatBoost and Random Forest perform slightly better than LightGBM in accuracy, recall, and ROC-AUC, but worse in precision and F1. Among the four algorithms, LightGBM achieves the highest precision but the lowest recall and ROC-AUC. The probit model achieves balanced performance, with competitive results in precision, recall, F1, and ROC-AUC compared to the machine learning models, although it lags behind slightly in accuracy. However, the probit model performs exceptionally well in Şırnak, with the highest evaluation metrics. As explained in Section 4.2, this outcome aligns with the fact that traditional empirical models are designed for small samples, whereas machine learning is best with large datasets. For the Şırnak sample, XGBoost and CatBoost have the same accuracy, but XGBoost is better at precision, recall, F1, and ROC-AUC. Thus, XGBoost is superior to CatBoost, and LightGBM is better than random forest in accuracy, recall, F1, and ROC-AUC but worse in precision. Random forest has the lowest performance in all metrics except precision. As a result, XGBoost is the best model for both samples as a machine learning algorithm. Thus, we prefer the XGBoost algorithm for interpretability sequences in

Table 2
Evaluation results.

Algorithms	Accuracy	Precision	Recall	F1	ROC-AUC
CatBoost	0.9091	0.8113	0.8431	0.8269	0.8876
	(0.9277)	(0.9)	(0.8182)	(0.8571)	(0.8927)
XGBoost	0.9192	0.8302	0.8627	0.8462	0.9008
	(0.9277)	(0.8636)	(0.8636)	(0.8636)	(0.9072)
Random forest	0.8939	0.8409	0.7255	0.7789	0.8389
	(0.8675)	(0.8667)	(0.5909)	(0.7027)	(0.7791)
LightGBM	0.8889	0.8889	0.7018	0.7843	0.8331
	(0.9036)	(0.85)	(0.7727)	(0.8095)	(0.8618)
Probit	0.884	0.813	0.794	0.803	0.858
	(0.966)	(0.922)	(0.955)	(0.939)	(0.963)

Notes: The values in parentheses indicate the evaluation results in Şırnak Province, whereas the other values are for Istanbul Province.

TreeSHAP.

The XGBoost SHAP summary plot in Şırnak displayed in Fig. 1 illustrates the estimated results of the XGBoost algorithm. In Fig. 1, the SHAP values are represented on the horizontal axis (x-axis), whereas the determinants of PPS participation features are represented on the vertical axis (y-axis). As the model output variable (PPS participation) takes a value of one for participation and zero otherwise; positive SHAP values correspond to participation, whereas negative SHAP values correspond to nonparticipation. In Fig. 1, the color blue (red) signifies low (high) values of participation features. Based on this information, Fig. 1 can be interpreted as follows. A decline in the income level leads to a reduction in the SHAP value. This suggests a positive correlation between private participation and income levels. Similarly, higher values of EDUC, PPSLIT, PPALIT, GENDER (females), PERCEPTION, PRESENT HEDONISTIC, AGREEABLENESS, CONSCIENTIOUSNESS, LOCUS (an external locus of control), ERET, and AGE are associated with high SHAP values, indicating that these features contribute to the prediction of pension participation. However, higher values of OPENNESS, COMPULSIVE, NEUROTICISM, EXTRAVERSION, PRESENT FATALISTIC, LOCUS (an internal locus of control), FINLIT, ERET, and GENDER (males) correspond to negative SHAP values, implying that an increase in the value of these variables raises the likelihood of nonparticipation.

Fig. 2 illustrates the XGBoost SHAP summary plot for Istanbul Province. In contrast to the results for the Şırnak sample, these results show that PPS participation in Istanbul Province is influenced most by variables such as PPSLIT, PERCEPTION, and LOCUS, rather than sociodemographic variables. Fig. 2 reveals that PPSLIT plays the most crucial role in determining participation in private pensions, whereas FUTURE is the least influential. PPSLIT is a significant variable, which has a positive effect on participation rates. Similarly, PERCEPTION generally has a positive influence on PPS participation, as evidenced by the predominantly positive SHAP values. In contrast, LOCUS has high values distributed in negative SHAP values, suggesting a negative relationship between an external locus of control and PPS participation. EDUC, AGREEABLENESS, PPALIT, GENDER (females), NEUROTICISM, INC, CONSCIENTIOUSNESS, COMPULSIVE, and PRESENT HEDONISTIC have a positive impact on the model output, meaning that people whose level of them is high are more likely to participate in PPS. However, high values of FINLIT, PRESENT FATALISTIC, AGE, OPENNESS, PROCRASTINATION, ERET, and GENDER (males) tend to negatively affect PPS participation.

Unlike the results for the Istanbul and Şırnak samples, LOCUS,

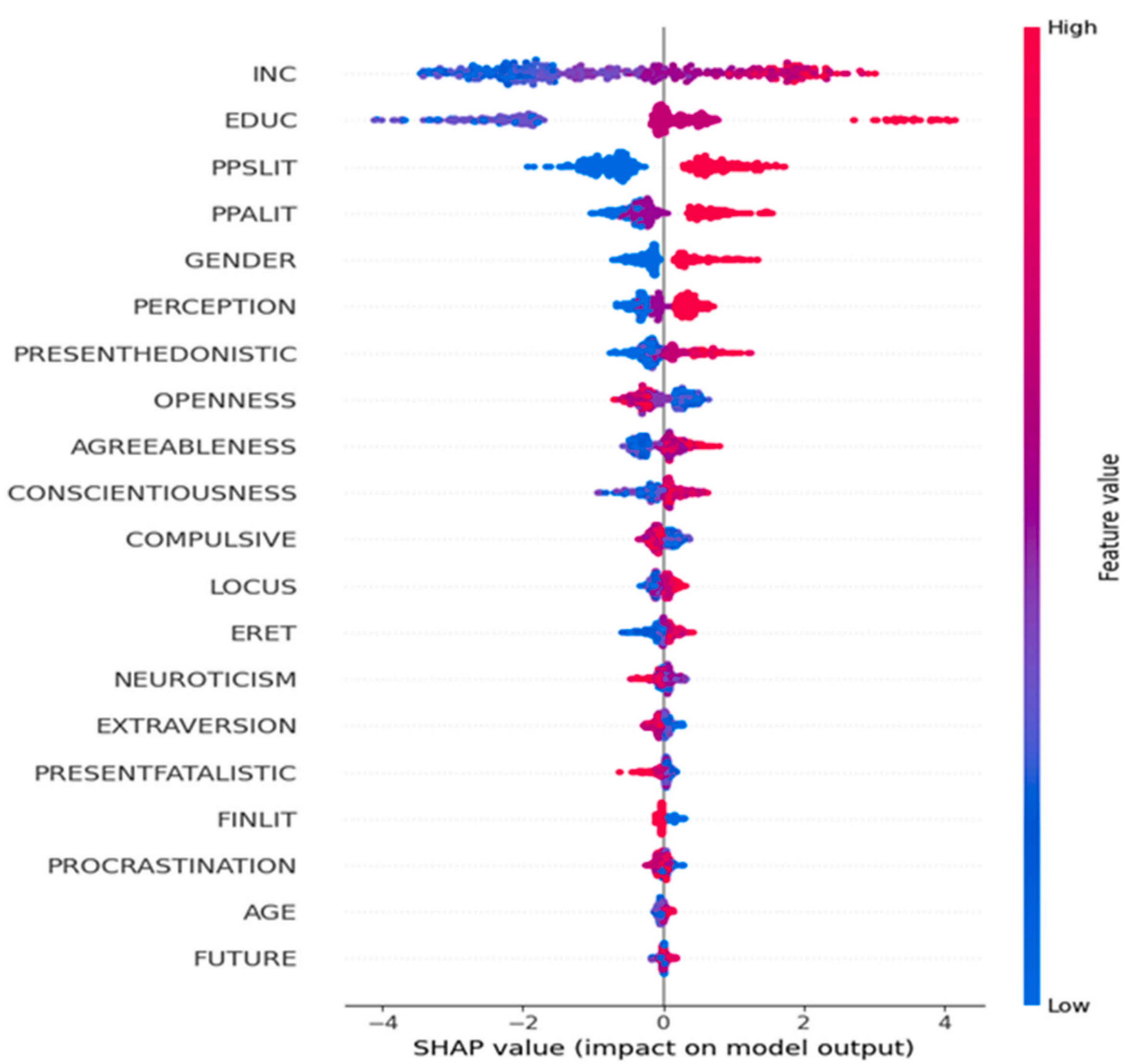

Fig. 1. XGBoost SHAP summary plot for Şırnak Province.

Notes: The vertical order signifies the relative significance of the variable. The red color denotes a high value, and the blue color signifies a low value of the variable. The horizontal axis represents the influence of the variable's value on the output. The density exhibited by the dots indicates their intensity.

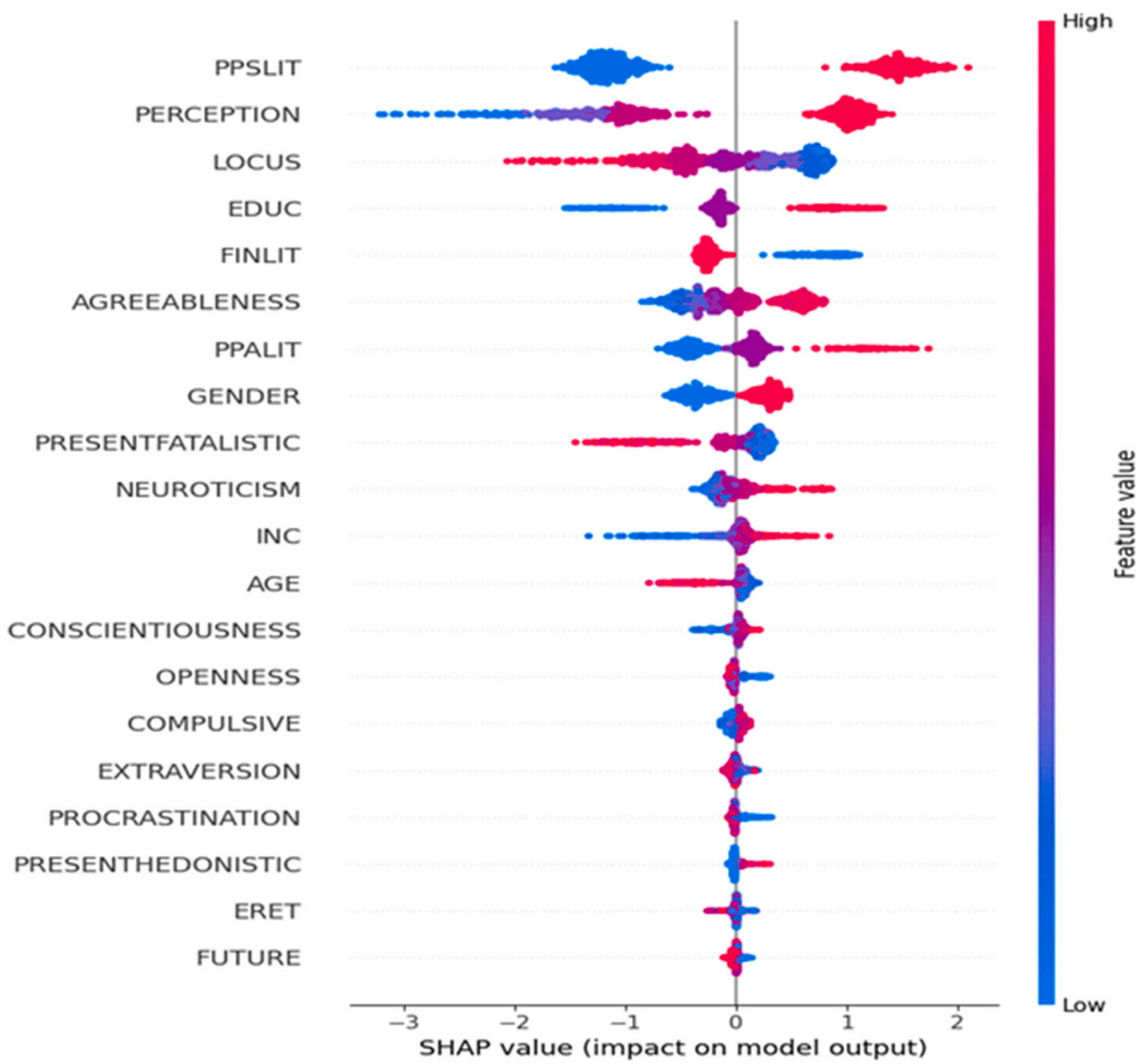

Fig. 2. XGBoost SHAP summary plot for Istanbul Province.
Notes: The vertical order signifies the relative significance of the variable. The red color denotes a high value, and the blue color signifies a low value of the variable. The horizontal axis represents the influence of the variable's value on the output. The density exhibited by the dots indicates their intensity.

NEUROTICISM, AGE, COMPULSIVE, and ERET affect PPS participation in different ways. To examine the reason for this difference, we use the interaction between typical feature analysis, shown in Fig. 3a–j. These results indicate that individuals in the Şırnak sample who have both an external locus of control and high present-hedonistic behavior have a higher tendency to participate in PPS. The results demonstrate that the status consumption mechanism of compulsive buying is dominant for individuals with an external locus of control by interacting with present-hedonistic behavior, and thus they tend to participate in PPS. In addition, in the Istanbul sample, individuals with both an internal locus of control and basic pension literacy participate more in PPS. In the Şırnak sample, individuals with high neuroticism have a low probability of participating in PPS, whereas individuals with medium and low neuroticism have a higher tendency to participate in PPS. In addition, individuals with high advanced pension literacy and medium values of neuroticism have the highest probability of participating in PPS, whereas individuals with high neuroticism and advanced pension literacy have the lowest probability of participating in PPS. These results show that the negative effect of neuroticism on PPS participation stems from people's risk aversion factor. In the Istanbul sample, PPS participation increases as neuroticism increases. This finding suggests that neuroticism positively affects PPS participation through compulsive buying. In addition, high basic pension literacy increases the tendency of individuals with medium neuroticism to participate in PPS. In the Şırnak sample, individuals of up to 33 years old do not tend to participate in PPS. Individuals in this age range have concentrated high openness. Therefore, they have a low tendency to participate in PPS because of openness. In the Istanbul sample, individuals generally tend to participate in PPS until the age of 47. Individuals with advanced pension literacy in the low and medium age groups have a higher tendency to participate in PPS, whereas individuals with advanced pension literacy in the high age group tend not to participate in PPS.

The reason for the different effects of compulsive buying is that the Şırnak and Istanbul samples are affected by a lack of self-respect and a status consumption mechanism, respectively. In the Şırnak sample, individuals with high compulsive buying and present-hedonistic values have a higher probability of participating in PPS than those with high compulsive buying and low present-hedonistic values. In addition, in the Istanbul sample, individuals with high compulsive buying and agreeableness tend to participate more in PPS. The effect of the adequacy of the PPS on the participation of individuals differs between the Istanbul and Şırnak samples because of their basic or advanced pension literacy,

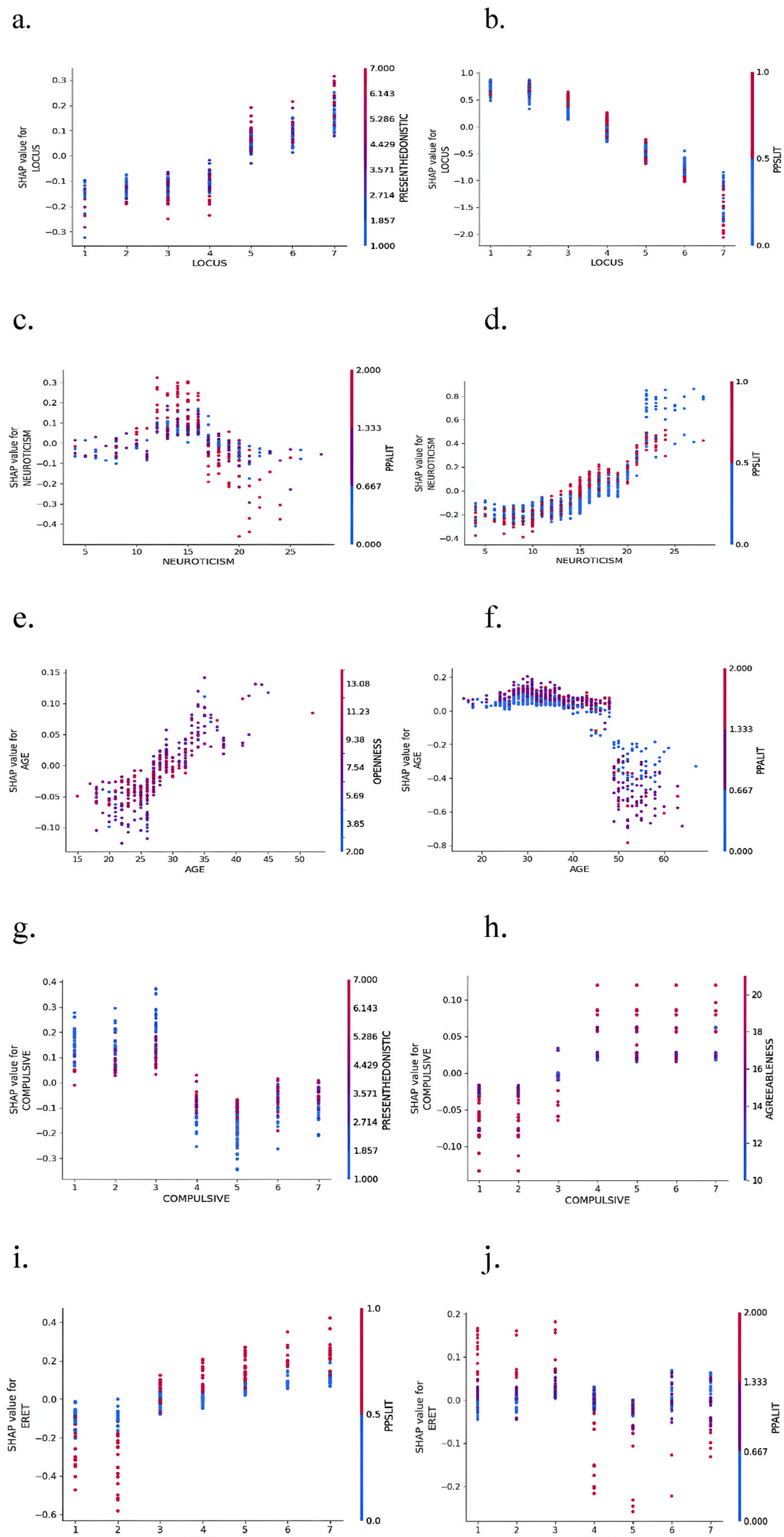

Fig. 3. Effect of interaction between typical features using XGBoost.
Notes: Fig. 3a, c, 3e, 3g, and 3i represent the results for the Şırnak sample and Fig. 3b, d, 3f, 3h, and 3j for the Istanbul sample.

respectively. In the Şırnak sample, people who find the PPS inadequate mostly have basic or no pension literacy, so they tend not to participate in PPS, whereas in Istanbul, those who find the PPS inadequate tend to participate in it because they have moderate or advanced pension literacy.

The probit estimation results in Table 3 confirm the findings of the XGBoost SHAP analysis. In a manner similar to that of the XGBoost SHAP analysis results, the table reveals notable differences between Istanbul and Şırnak in the factors that influence private pension participation. Specifically, in Istanbul, EXTRAVERSION negatively affects the likelihood of PPS participation, whereas AGREEABLENESS positively influences it. Additionally, CONSCIENTIOUSNESS and NEUROTICISM have significant positive effects on PPS participation. In contrast, OPENNESS, PROCRASTINATION, and FUTURE have a negative impact. FINLIT is associated with a significant reduction in the probability of PPS participation. For Şırnak, AGREEABLENESS and CONSCIENTIOUSNESS have significant positive effects. However, OPENNESS has a negative impact, and FINLIT significantly reduces the probability of PPS participation. In both samples, PERCEPTION positively influences PPS participation, EDUCATION increases the likelihood of participate, and GENDER plays a significant role in participation (and females are more likely to participate). Additionally, PRESENT HEDONISTIC positively influences PPS participation, whereas PRESENT FATALISTIC has a negative impact. PPSLIT and PPALIT are both strongly positive, indicating that higher levels of basic and advanced pension literacy significantly increase PPS participation. Finally, INCOME has a significantly positive impact on PPS participation in both samples, but AGE negatively affects participation in Istanbul. Interestingly, LOCUS has contrasting effects: it negatively impacts PPS participation in Istanbul but positively impacts it in Şırnak.

Table 4 lists the differences between the Şırnak and Istanbul samples in terms of dominant behavioral and personality characteristics. In the Istanbul sample, agreeableness, conscientiousness, extraversion, and openness are dominant personality traits, whereas in Şırnak sample, these personality traits are not dominant although they have high rates. Nevertheless, neuroticism has low and similar values in both samples. With respect to behavioral factors, in the Istanbul sample procrastination is dominant, but in Şırnak sample, the external locus of control is also a dominant behavioral factor, along with procrastination. Finally, the rate of compulsive buying, future, pessimism, present hedonistic, and present fatalistic behavioral factors is higher in the Şırnak sample than in the Istanbul sample.

Our empirical findings are consistent with those in the literature, including Piotrowska (2019), Dragos et al. (2020), Balasuriya and Yang (2019), Van Rooij et al. (2011), Diaz et al. (2021), Allik et al. (2009), Oishi et al. (2015), and Burger (2014). Additionally, we conclude that the effect of the adequacy of the PPS and age on PPS participation is determined by the differences in pension literacy levels between the two samples. Finally, the empirical findings confirm that dominant behavioral factors vary by regional geography.

The Tree SHAP findings offer support for various methodologies that elucidate the correlation between PPS participation, personality traits, behavioral factors, pension financial literacy, and sociodemographic variables. Openness and agreeableness emerge as the preeminent personality traits with a significant impact on participation in the Şırnak and Istanbul samples, respectively, suggesting that individuals with higher openness and agreeableness are more inclined to engage in PPS. Basic pension literacy holds more sway than advanced pension literacy, indicating that basic knowledge of pension systems plays a pivotal role. Present hedonistic and locus of control are the most important behavioral factors in the Şırnak and Istanbul samples, respectively. Present-hedonistic tendencies are associated with an increased likelihood of participation, potentially because of compulsive buying behaviors. However, present-fatalistic tendencies have a negative influence on PPS participation, which might indicate a connection with procrastination. Among sociodemographic groups, females and those who are middle-aged have a greater propensity to participate in PPS in both samples. High basic financial literacy negatively affects PPS participation in both samples, possibly because financially literate individuals perceive PPS as an investment opportunity, rather than a tool for retirement savings. The trait of agreeableness is a positive influence, aligning with the theory of planned behavior. This implies that people who are not strongly inclined to competitiveness, self-centeredness, and mistrust are more inclined to participate. Extraversion is a personality trait with a negative impact on participation. This indicates that extraverts, who are more sociable and prone to hedonistic consumption, have a lower likelihood of engaging in

Table 3
Probit estimation results.

Variable	Istanbul		Şırnak	
	Coefficient	Marginal effect	Coefficient	Marginal effect
EXTRAVERSION	−0.0576***	−0.0065***	−0.0410	−0.0015
AGREEABLENESS	0.2263***	0.0256***	0.5423***	0.0193***
CONSCIENTIOUSNESS	0.0509**	0.0057**	0.2614***	0.0093***
NEUROTICISM	0.0757***	0.0086***	−0.0101	−0.0004
OPENNESS	−0.0812***	−0.0092***	−0.2996**	−0.0107***
PROCRASTINATION	−0.1302***	−0.0147***	0.0943	0.0034
FUTURE	−0.0918*	−0.0104*	−0.3500	−0.0125*
PRESENT HEDONISTIC	0.1420***	0.0160***	0.8744***	0.0311***
PRESENT FATALISTIC	−0.1856***	−0.0210***	−0.5633***	−0.0201***
LOCUS	−0.5901***	−0.0667***	0.6941***	0.0247***
PESSIMISM	0.0149	0.0017	0.0706	0.0025
COMPULSIVE	0.0052	0.0006	0.1582	0.0056
ERET	−0.0444	−0.0050	0.3695***	0.0132***
PERCEPTION	1.9343***	0.2187***	1.0337***	0.0368***
FINLIT	−1.6967***	−0.1918***	−3.4468***	−0.1227***
PPSLIT	3.5713***	0.4037***	5.2221***	0.1859***
PPALIT	1.2235***	0.1383***	1.8673***	0.0665***
INC	0.0001***	0.0000***	0.0006***	0.0000***
GENDER	1.2739***	0.1440***	2.6671***	0.0949***
EDUC	1.7375***	0.1964***	7.6857***	0.2736***
AGE	−0.0354***	−0.0040***	−0.0300	−0.0011
CONSTANT	−15.6544***		−57.2705***	
Pseudo R^2	0.6631		0.8869	
Log likelihood	−203.432		−27.3661	
N	990	990	415	415

Note: ***, **, and * significant at 1%, 5%, and 10%, respectively.

Table 4
The dominant personality traits and behavioral factors in Şırnak and Istanbul samples.

Variable	Şırnak		Istanbul	
	The number of individuals with a score of 5 or more	The percentage of individuals with a score of 5 or more (N = 415)	The number of individuals with a score of 5 or more	The percentage of individuals with a score of 5 or more (N = 990)
AGREEABLENESS	166	40	682	68.89
COMPULSIVE	189	45.54	359	36.26
CONSCIENTIOUSNESS	163	39.28	532	53.74
EXTRAVERSION	157	37.83	569	57.47
FUTURE	285	68.67	834	84.24
LOCUS	231	55.66	394	39.8
NEUROTICISM	63	15.18	140	14.14
OPENNESS	136	32.77	548	55.35
PESSIMISM	153	36.87	246	24.85
PRESENT FATALISTIC	176	42.41	349	35.25
PRESENT HEDONISTIC	138	33.25	149	15.05
PROCRASTINATION	249	60	534	53.94

PPS. The trait of conscientiousness has a positive impact, which corresponds to the theory of planned behavior. This finding suggests that people who have a strong sense of responsibility and self-control are more likely to participate in PPS. The perception of protection is a pivotal factor in PPS participation. People who view PPS as a means of financial security are more likely to participate. Differences in personality are found across regional geography. Table 3 lists the differences between the Şırnak and Istanbul samples in terms of dominant behavioral and personality characteristics. The difference in dominant or intense personality traits in the Şırnak and Istanbul samples shows that geographic differences influence personality traits and behavioral factors. In addition, the differences in the most influential personality traits and behavioral factors in participating in PPS in the Şırnak and Istanbul samples also support this argument. Finally, among the machine learning algorithms, XGBoost is more robust and reliable for interpreting variable importance than random forest.

6. Conclusion

This study investigates the determinants of participation in PPS under various sociodemographic, personality traits, behavioral factors, and pension and basic financial literacy constraints while also considering the nuanced influence of regional geography. Moreover, it provides valuable theoretical and empirical insights into the factors that influence individual decisions to participate in PPS, comparing Şırnak and Istanbul samples. The paper makes several theoretical contributions to the literature. First, we combine geographic, behavioral, and psychological dimensions to explore PPS participation. Notably, our findings highlight that geographic variations in a country significantly impact financial behaviors. Second, the inclusion of psychological variables enhances our understanding of individual decision-making about pension participation. Third, basic pension literacy has a stronger influence than advanced literacy in shaping PPS participation decisions. Fourth, we emphasize the critical role of a perception of protection—individuals' trust in financial systems—in encouraging PPS involvement. Lastly, we demonstrate the potential of machine learning techniques for modeling PPS factors, particularly with larger samples.

Our findings have several significant implications for economic policy makers. Openness, agreeableness, and conscientiousness are personality traits that are positively related to PPS participation, whereas extraversion negatively affects PPS participation. Present hedonistic and locus of control are dominant behavioral factors in the Şırnak and Istanbul samples, respectively. Present-hedonistic tendencies are associated with an increased likelihood of participation, potentially due to compulsive buying behaviors. Basic pension literacy is more influential than advanced pension literacy. Regional geography influences personality traits and behavioral factors, which in turn affect PPS participation. We find differences between the Şırnak and Istanbul samples in terms of the dominant or intense personality traits and behavioral factors, which reflects Türkiye's geographic diversity. We also find differences between the Şırnak and Istanbul samples in the most influential personality traits and behavioral factors in participating in PPS, which suggests that regional factors play a role in shaping individual preferences and behaviors regarding PPS participation. Moreover, we show that locus of control, neuroticism, age, compulsive buying, and an inadequate public pension system have different impacts on PPS participation in the two samples. Individual income and gender are identified as the most critical sociodemographic factor that influences PPS participation in Şırnak and Istanbul, respectively. Among the sociodemographic groups, females and people who are middle-aged have a higher likelihood of participating in PPS. This suggests that targeted policies and marketing efforts to increase participation rates should focus on these demographic groups. High basic financial literacy has a negative impact on PPS participation, possibly because those who are financially literate are aware of alternative financial tools for accumulating savings. This finding implies the need for tailored financial education efforts to clarify the role of PPS in retirement planning. Protection perception emerges as a crucial factor in PPS participation. This highlights the importance of government incentives and marketing campaigns that emphasize the protective aspects of PPS. Finally, XGBoost is a more robust and reliable algorithm for interpreting variable importance than the others. The probit model, which is a traditional empirical method, performs exceptionally well, achieving the highest evaluation metrics in the Şırnak sample, which is smaller than that of Istanbul. However, for Istanbul, the XGBoost algorithm has the best performance among the many evaluation metrics.

When designing strategies to promote PPS participation policy makers should consider these findings. To increase PPS participation, policy makers should consider the diverse effects of personality traits and behavioral factors across geographic regions and design region-specific interventions that appeal to the dominant characteristics of each region. They should also target females and people who are middle-aged as the sociodemographic groups most likely to participate in PPS and provide them with adequate information and incentives to enroll in the PPS. Moreover, they should raise the level of pension literacy, especially among those with high basic financial literacy but low awareness of the benefits of PPS. This could be achieved through tailored financial education programs that explain the role of PPS in retirement planning and the advantages of PPS over alternative investment tools. Policy makers should strengthen the perception among potential participants of protection by the PPS, by emphasizing the government incentives and guarantees offered to PPS members. This could be achieved through effective marketing campaigns that highlight the protective aspects of PPS and the risks of relying solely on the PPS. Finally, they should create incentives for acting in a more present-oriented way or design rules that prevent narrow-minded behavior.

These incentives should yield benefits for participants in PPS in the long term and should encompass a wide range of personality traits and behavioral factors. Additionally, efforts should be made to create a sense of protection and control around PPS, targeting the middle-aged and women as potential participants.

This study has several limitations. First, the period when the survey data were collected—from September 2022 to March 2023—coincided with heightened global tensions due to the Russia-Ukraine war, which might affect the results. The lack of explanation about the impact of this turbulent period, at both a global scale and specifically in Türkiye, is a shortcoming of the model. Second, practical constraints, including financial considerations and time restrictions, necessitated our focus on only two provinces. Lastly, the use of cross-sectional data precludes analysis of temporal changes, as longitudinal data are not available for these regions.

Several avenues for future research exist for building on this study. First, expanding the geographic scope to include additional regions in Türkiye or other countries would yield valuable insights. Second, conducting longitudinal studies to track changes in participation in the PPS over time is essential. Additionally, further exploration of psychological factors and their interaction with sociodemographic characteristics could enhance our understanding. Advanced machine learning models that might improve the accuracy and interpretability of results warrant investigation. Lastly, assessing the effectiveness of policy interventions aimed at increasing PPS participation by underrepresented groups, conducting comparative studies among countries with different pension systems, and examining the impact of macroeconomic changes on PPS participation are all crucial areas for further investigation.

CRediT authorship contribution statement

Can Verberi: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, and, Supervision, and, Project administration. **Muhittin Kaplan:** Writing – review & editing, Supervision, Project administration, and, Investigation.

Declaration of generative AI in scientific writing

None.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.bir.2024.12.010.

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