International Journal of
Financial Studies

MDPI

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Forecasting Financial Literacy Levels with Respect to Consumer Shopping Behaviour

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Abstract: Contemporary consumer society is deeply intertwined with the concepts of money and shopping, which are closely related yet often studied separately. Despite their interconnectedness, there is a notable gap in research that simultaneously addresses financial literacy as a tool for effective money management and informed shopping decisions. This study investigates the relationship between these concepts through theoretical analysis and an empirical survey conducted in the Slovak Republic. Given the similarities in business environments across V4 countries, we posit that our findings may have broader applicability. Survey results were analysed using selected statistical methods, including the chi-square test of independence, to test hypotheses related to financial literacy. Where dependencies were identified, contingency coefficients were used to quantify their strength. Additionally, predictive models of financial literacy levels of two types were developed. Firstly, models were created for both predictive and explanatory purposes using the CHAID classification tree and logistic regression demonstrating high performance, clarity, and interpretability. Secondly, several prediction models using advanced machine learning techniques were created for highly precise predictions of financial literacy levels.

Keywords: financial literacy; shopping behaviour; classification tree; logistic regression; machine learning techniques

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Academic Editors: Neringa Vilkaitė-Vaitonė and Partha Gangopadhyay

Received: 13 December 2024
Revised: 31 January 2025
Accepted: 7 February 2025
Published: 14 February 2025

Citation: Kicova, E., Svabova, L., Ponisciakova, O., & Rosnerova, Z. (2025). Forecasting Financial Literacy Levels with Respect to Consumer Shopping Behaviour. *International Journal of Financial Studies*, *13*(1), 26. https://doi.org/10.3390/ijfs13010026

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1. Introduction

The topics of financial literacy and consumer shopping behaviour are highly relevant in today's society. Financial literacy encompasses both knowledge and the ability to make sound financial decisions at the right time. It not only involves understanding fundamental financial concepts but also applying this knowledge to manage finances responsibly. Financial literacy plays a crucial role in shaping an individual's purchasing behaviour, budgeting, saving, debt management, and investment decisions. Research indicates that individuals with higher financial literacy are more likely to make informed financial choices, improving financial well-being (Lusardi & Mitchell, 2014). Financially literate consumers tend to engage in deliberate, need-based purchasing while avoiding impulsive and debt-fueled spending, which can lead to long-term financial distress (Klapper et al., 2015). In contrast, those with lower financial literacy are more susceptible to short-term financial incentives, often resulting in suboptimal financial decisions and higher debt levels (OECD, 2020).

Additionally, studies suggest that financial literacy enhances self-control and mental budgeting, contributing to more disciplined financial management and long-term financial security (Xiao & Porto, 2017). This skillset significantly influences not only individual

behaviour but also the functioning of society as a whole. Financial literacy contributes to improving the standard of living, reducing unemployment, ensuring currency stability, and shaping the overall economic culture of a society (Sconti, 2024; Kadoya et al., 2021).

Consumer shopping behaviour is in a strong relationship with financial literacy. This relationship holds significant implications for consumer welfare and the ability to manage personal finances. Financially literate consumers are better equipped to plan their income and expenses, adjusting expenditures to align with their financial means. Moreover, financial literacy fosters sustainable purchasing decisions supporting short-term and long-term consumer goals (Disney & Gathergood, 2013; Huhmann & McQuitty, 2009; Bernheim et al., 2001). Conversely, consumer shopping behaviour may also influence levels of financial literacy, highlighting the bidirectional relationship between these two areas.

Therefore, this study aims to examine the current level of financial literacy, its differences among population groups, its relationship with financial behaviour, and finally, the influence of financial literacy on purchasing patterns. By the analysis in this study, we aimed to identify the financial knowledge gaps that would lead to poor purchasing decisions, but mainly, we wanted to reveal the consumer characteristics most associated with low financial literacy. The main contribution of this paper lies in its predictive approaches to financial literacy levels, integrating both classical statistical methods and advanced machine learning models. This dual perspective not only offers highly accurate predictions but also provides insights into the interpretability and practical applicability of these models.

Given its wide implications, we consider the analysis of the current state of financial literacy levels highly relevant and still necessary, especially because of the rapid growth of financial systems and rapid changes in consumer financial products and consumer behaviour. The results of our study and similar current studies can be used for the development of tailored financial education programs and policies. As listed in the following parts of the article, several studies found that such educational programs positively impact the financial behaviour of their beneficiaries. A deeper insight offered by this study can guide the development of tailored financial education programs, helping policymakers and financial educators implement effective, targeted interventions for at-risk groups. Last but not least, understanding financial literacy and customer purchasing behaviour holds substantial value for enterprises, especially in today's consumer-driven economy.

The paper is organised as follows: The next section reviews relevant literature, focusing on the interrelationship between financial literacy and shopping behaviour, as well as predictive modelling techniques. The methodology section outlines the variables selected for analysis, the data collection process through a questionnaire survey, and the statistical and machine learning methods employed. In the results section, we present the findings of hypothesis testing and the performance comparison of predictive models. The discussion section highlights the implications of these findings for theory and practice. Finally, the conclusion summarises the key contributions, outlines limitations, and suggests directions for future research.

2. Literature Review

Financial literacy is a highly topical issue, and for this reason, a wide range of definitions of financial literacy can be found in the literature. These definitions agree that it is a set of skills, knowledge, and value attitudes leading to financial security for oneself and their family. A person can be considered financially literate if, on the one hand, they can navigate money issues and, at the same time, responsibly manage their family budget (Ocel et al., 2023; Pearson & Korankye, 2023). This involves an understanding of basic economic and financial concepts and the ability to identify financial risks. It can also be described as a combination of an individual's ability, motivation, and confidence to use

their knowledge to make effective decisions regarding the present and the future. From our perspective, financial literacy influences the purchasing behaviour of the population (Sharma et al., 2023).

The level of financial literacy across EU countries according to the EU Barometer (Eurobarometer, 2023) is shown in Figure 1. The scores were obtained in a survey containing 12 questions on basic concepts such as income, credit, loans, investments, savings, and interest rates. The total number of respondents was 26,139. The percentage of high financial literacy scores ranges from 11% in Portugal and Latvia to 27% in Denmark, Slovenia, and Sweden, with the Netherlands scoring the highest at 28%. When comparing countries with low scores, Finland is the worst performer, with up to 27% of respondents from this country answering less than five questions correctly. When comparing Slovakia with the Visegrad Four countries, it can be concluded that, based on these results, the level of financial literacy in Slovakia is the highest, followed by the Czech Republic, Hungary, and Poland.

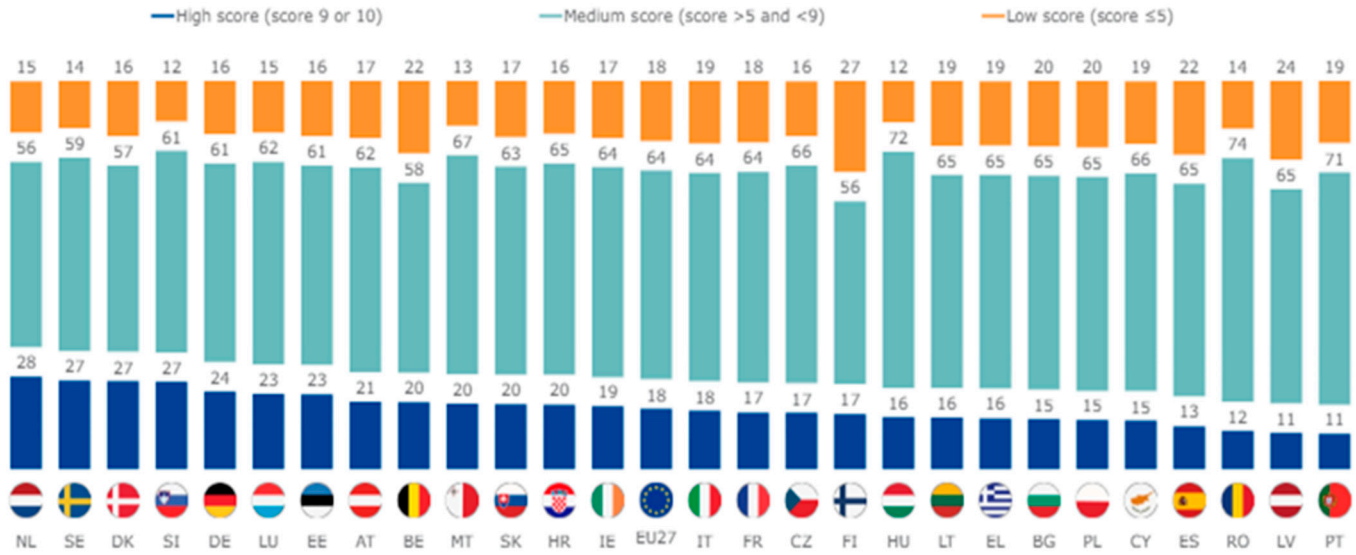


Figure 1. Percentage representation of financial literacy in European Union countries, Source: Eurobarometer (2023).

The concept of purchasing behaviour, like financial literacy, has been addressed by many authors. Munoz-Cespedes et al. (2021) point out that it is important to emphasize that greater attention must be given to financial literacy from both private and public sectors so that it can be used to drive more sustainable behaviour by individual consumers.

Financial literacy is highly correlated with long-term positive economic outcomes. (Galizzi et al., 2023). However, in today's world, it is also an essential part of every individual's life. It is the ability to work with money, understand basic financial indicators, and also to plan for the financial future (Gignac et al., 2023). It is usually interpreted in the literature as knowledge needed to make good decisions about personal investments, debts, and other matters related to personal finance (Bottazzi & Lusardi, 2021; Pearson & Korankye, 2023). Several authors have addressed gender as an important factor in assessing the level of financial literacy (Jones et al., 2024; Boggio et al., 2014; Guðjonsson et al., 2022). According to their findings, we can conclude that men generally have a higher level of financial literacy than women. The reason might be that finance is more understood as a male domain. In their study, Guðjonsson et al. (2022) emphasize that women are more cautious about finances, have less financial knowledge than men, and show greater mistrust when dealing with financial issues.

Sufficient financial literacy is part of healthy self-confidence and higher financial satisfaction (Nemeth et al., 2022; Pearson & Korankye, 2023). It contributes to economic and psychological well-being (Gignac et al., 2023). Several studies confirm that financial literacy directly affects financial anxiety, independent of the effects of verbal intelligence, formal education, and age (Gignac et al., 2023; Bottazzi & Lusardi, 2021). From a behavioural economics perspective, important determinants of financial literacy are overconfidence, self-control, myopia, and risk aversion (Sekita et al., 2022). Nowadays, everyone must be able to use their financial literacy knowledge. It is necessary to make good decisions and handle money efficiently. According to Krishna et al. (2010), financial literacy is crucial for people trying to avoid debt. Financial problems are often connected to the fact that the individual does not know how to manage their finances. Financial problems arise from inappropriate management, including inappropriate use of loans and insufficient financial planning, often associated with lower income. Due to a lack of financial planning, problems like impulsive buying of unnecessary items can arise.

In his study, Remund (2010) outlined the following key indicators affecting financial literacy: 1. Budgeting; 2. Understanding loans; 3. Saving; and 4. Investing. Another of the already standard definitions of financial literacy is the awareness, knowledge, skills, attitudes, and behaviours that enable one to make the right decisions in order to achieve personal financial well-being (Kadoya et al., 2021). The economic awareness of the population contributes to the reduction of unemployment, the stability of the national currency, and the formation of a new economic culture among the population, but this requires, above all, an average level of financial literacy (Gignac et al., 2023). Financial awareness helps to understand key concepts and, consequently, use them in making decisions about income, expenditure, and savings, choosing appropriate financial instruments, and budgeting or accumulating funds for future goals (Kuzma et al., 2022). According to the authors Yulianto (2023) and Mancone et al. (2024), an individual's financial literacy is influenced by their income.

To conclude the analysis of the different definitions of financial literacy, it can be stated that all of them agree that this ability is essential nowadays. Financial literacy is usually associated with concepts such as credit, interest, interest rates, APR, saving, investing, or concepts from the insurance industry (Gianakos et al., 2023; Ming & Jais, 2021).

Another aspect of studying financial literacy is its determinants. In their study, Zaimovic et al. (2023) identified many predictors of financial literacy, such as education, gender, age, knowledge, etc. Several studies indicate significant variation in financial literacy levels across demographic segments, including age, education, income, and even geographic location. For instance, younger adults often demonstrate lower financial literacy than older adults with work experience (H. Chen & Volpe, 1998). Likewise, individuals with higher education or income levels typically exhibit better financial literacy, although this trend can vary based on cultural and socioeconomic factors (Atkinson & Messy, 2012). The disparity in financial literacy levels has drawn the attention of policymakers and educational institutions, who seek to develop targeted financial education programs to address these gaps (Hastings et al., 2013). When investigating the factors that influence financial literacy, authors often deal with the education factor, which has been shown to significantly impact the level of financial literacy (Lusardi et al., 2019; Christelis et al., 2010). However, there are also opponents of such an opinion. As Narula (2022) claims, the minimal impact of financial literacy training on better financial results is known. Bialowolski et al. (2022) add that financial literacy is not a panacea for consumers' financial problems, as those facing a high risk of financial distress seem unaffected by financial literacy. Interventions beyond financial literacy might be needed to address financial distress effectively.

Many studies focused on financial literacy point to its benefits. Murendo and Mutsonziwa (2016) revealed in their research that financial literacy positively influences savings behaviour for both rural and urban individuals. Furthermore, financial literacy positively influences informal and formal savings. According to the authors, policy interventions that foster financial literacy are needed to improve individuals' saving behaviours. According to Zhang and Chatterjee (2023), financial literacy plays a protective role and alleviates financial stress and anxiety. According to F. Z. Chen et al. (2023), another benefit is the relationship between sufficient financial literacy and the way of spending money. The authors claim that financial knowledge positively affects consumer credit card ownership and desirable financial behaviours of credit card usage and is negatively related to undesirable credit card behaviours. Andreou and Anyfantaki (2020) add that there is a statistically positive relationship between the levels of financial knowledge and the frequency of i-banking use. More importantly, financially illiterate consumers appear to report far more often than their financially literate peers the lack of trust in i-banking, as well as a lack of self-confidence in financial and digital skills, as the main reasons for not using this service. However, the benefits of sufficient financial literacy are conditioned by certain factors.

An example can be the result of a study by Phalke (2023), where the author highlights the importance of marketing campaigns on the impact of an individual's financial literacy. According to the author, an individual is largely influenced by advertising campaigns that interfere with their financial literacy and, last but not least, influence their purchasing behaviour.

Purchasing behaviour also includes, besides the purchasing itself, external influencing factors (Sharma et al., 2023). There is also a need to understand the types of lifestyles of consumers, who are strongly influenced by companies' sales and communication activities and are prone to impulse buying behaviour (Ocel et al., 2023). Consumer behaviour is subject to various research from different perspectives. One of them is a study by Lim et al. (2023), which finds that consumer behaviour research in JCB has grown substantially in terms of collaboration (co-authorships), global reach (countries), productivity (publications), and impact (citations). The research topics of consumer behaviour were also analysed by Ma et al. (2024), who claim that major research themes in consumer behaviour research in the last two decades have shifted from the focus on fundamentals of consumer behaviour, consumers' decision-making process, and the development of more robust measures and analytical methods, to the focus on service quality and consumer satisfaction, online consumer behaviour and virtual communities, and sustainable consumption, as well as the experiential aspects of consumer behaviour.

Knowledge of customer behaviour plays an important role in formulating strategies for business marketing approaches. The aim is to know the customers, their needs, and their motives and thus guide the relevant marketing activities. The modern world and its technological conveniences encourage individuals to use other online, second-hand, or green shopping forms (Abeysekera et al., 2022; Mazhar et al., 2022). Subjective norms and preferences are important in shopping. This is because shopping behaviour is a specific type of behaviour emerging in the consumption process and changing under the influence of various factors. With a change in age, income, or social status, customers' preferences change, as do their shopping habits regarding preferences, motives, distance to the store, or frequency of purchases (Calvo-Porral et al., 2023). Differences between consumers' attitudes and behaviours enable a shift towards sustainable consumption (Szaban, 2023).

Focusing on the connections between financial literacy and the purchasing behaviour of consumers, the research has brought the following results. Individuals with higher financial literacy tend to engage in more informed and deliberate shopping practices (Garg & Singh, 2018). For example, low financial literacy often causes undervaluation of the

long-term impact of purchases on personal finances, which may lead consumers to debt (Lusardi & Tufano, 2009). Furthermore, financially literate consumers are better equipped to understand the true cost of credit, helping them avoid high-interest debt associated with impulsive or unplanned purchases (Disney & Gathergood, 2013). Consequently, financially literate consumers tend to make more sustainable shopping choices that align with their long-term financial goals, showing a preference to avoid overconsumption (Huhmann & McQuitty, 2009).

Financial literacy also influences broader financial planning behaviour, which in turn affects shopping habits. Research indicates that individuals with greater financial knowledge are more likely to engage in behaviours associated with financial planning, such as investing in assets (van Rooij et al., 2011).

Various interventions aimed at improving financial literacy have demonstrated a positive impact on consumer behaviour. Financial education programs have shown the potential to enhance consumer knowledge and reshape spending habits. A study by Bernheim et al. (2001) suggests that financial education in high schools leads to improved saving and spending behaviour later in life. Similarly, financial literacy programs help employees make better-informed financial decisions, reducing impulsive buying and encouraging financial planning (Lusardi et al., 2017).

As can be seen, numerous studies explore the impact of financial literacy on various financial behaviours, such as budgeting, saving, debt management, or investment decisions. However, many studies analyse financial literacy separately from consumer shopping behaviour. Some studies focus on financial education's role in improving savings and investment choices, while others explore consumer shopping habits from a behavioural perspective, often without linking these decisions explicitly to financial literacy levels. Therefore, our study aims to fill this gap by examining financial literacy as a predictor of consumer shopping patterns. Moreover, prior studies often rely on traditional statistical models to assess financial literacy determinants. By applying machine learning models alongside traditional statistical methods, our study aims to identify significant factors influencing financial literacy using a predictive approach.

3. Materials and Methods

For the purpose of this study, we conducted a questionnaire survey. Based on theoretical knowledge and previously conducted research, we established hypotheses, which were rigorously analysed using selected statistical methods. Moreover, we also created financial literacy models serving two purposes. Here, it is essential to distinguish the primary purpose of the prediction models: whether they are intended for explanatory or for predictive purposes. If the primary objective is to explore and describe the relationships between the outcome variable and explanatory variables, traditional statistical techniques such as logistic regression, decision trees of various types (CART, CHAID, C5.0, etc.), discriminant analysis, or nearest neighbour technique are usable. Using these models, interpretations of the relationships provide actionable insights. In this study, we used the CHAID decision tree technique and logistic regression to create the models with a pretty high prediction accuracy, which also serves to describe the significant relationships between the financial literacy level and the characteristics of respondents.

However, aiming at the prediction task, i.e., forecasting the values of the outcome variable without the need for interpreting the process of how the model processed the input data and created the forecast, various sophisticated machine learning techniques should be used. Therefore, in this study, we created several prediction models using advanced machine learning techniques such as neural networks, Bayesian networks, support vector machines, extreme gradient boosting (XGBoost) techniques, and random forests. Given

the input respondent's characteristics values, these models should generate highly precise predictions of the financial literacy levels.

In this section, we describe the data collection process and the data itself, the statistical methods used to analyse relationships, and the techniques used for creating the prediction models.

3.1. Questionnaire Survey and Data Used for Analysis

The questionnaire contained a total of 27 questions. The first questions were used to obtain basic information about the respondents, such as their gender, age, region of current residence, marital status, education, occupation, and average monthly income. Then, the next questions were designed to measure financial literacy level. These questions focused on financial reserves, savings, investments, credit, and insurance. The next part of the questionnaire focused on the expenditure of the respondents. Here, we wanted to find out the trends in the respondents' spending of money on certain items, factors influencing their buying behaviour, and their attitude towards advertisements while shopping. The last questions were aimed at comparing shopping online and in brick-and-mortar stores.

To collect data through a questionnaire survey, we first needed to determine the minimum survey sample size. The minimum sample size of respondents needed to achieve the specified confidence level of the results was determined using the following relationship (Abebe et al., 2022; Thompson, 2022):

$$n = \frac{\frac{z_{\alpha}^2 \cdot p \cdot (1-p)}{e^2}}{1 + \frac{z_{\alpha}^2 \cdot p \cdot (1-p)}{e^2 \cdot N}} \quad (1)$$

where

α—significance level, where $\alpha = 1$—the required confidence level; in this study we use $\alpha = 0.05$, so the confidence level is 95%.

z_{α}—the critical value of the normalised normal distribution at the specified confidence level; in this study, we use $z_{\alpha} = 1.96$.

p—the proportion of the prevalence of the trait of interest, where if we have done a pre-survey and found the proportion of the prevalence of the trait of interest from the pre-survey, we use this sampling proportion, and if we have not done a pre-survey or there is a problem in determining the prevalence of the trait of interest p, we use $p = 0.5$ where the sample size is the largest. In this study, we use the value $p = 0.5$.

e—allowable error rate (margin); in this study, we use $e = 0.05$.

N—the size of the base population; in this study, we use the size of the base population. As the survey focuses on the analysis of the financial literacy of the Slovak population, the total size of the adult population (18 years of age and older) as of 31 December 2023, is a total of 4,340,226 inhabitants.

We determined the minimum sample size using the above Formula (1). Potential respondents were citizens of the Slovak Republic over 18 years old. Our goal was to focus on respondents with sufficient theoretical knowledge and practical experience in the analysed area. For this reason, we analysed the entire group of respondents older than 18 years. At the end of 2023, the number of inhabitants meeting this condition was registered at the level of 4,340,226. Based on the calculation, the minimum survey sample size was 385 respondents.

The questionnaire survey was conducted through the Survio website and distributed through social networking sites like Facebook and Instagram. We also used QR codes as a quick and efficient method of recruiting respondents without having profiles on social networking sites. This form of data collection offered us several advantages, including a

broader reach to respondents, low mailing costs, fast data processing, and the anonymity of the survey. On the other hand, it also had its drawbacks. We essentially excluded respondents from the sample who did not have access to the Internet or sufficient technical skills to complete the online survey.

The survey was conducted between January and March 2024. A total of 391 respondents participated, of which 43.7% were male and 56.3% were female. In terms of age, the 18–26 age group was the most represented in the survey, which can be explained by the fact that we conducted the survey through social networks.

In contrast, the least represented group was respondents aged 77 and over (nine respondents). Regarding education, the largest group was high school-educated respondents with a high school diploma (36.3% of responses). The second-largest group (23.3% of respondents) was those with a level II university degree. The least represented groups were respondents with a third level of higher education (3.3% of respondents) and those with a primary education (4.6%).

We have created six categories for the average monthly salary: the lowest salary up to €700 and the highest above €3000. The largest group in this respect was respondents with a monthly income of €1001–1500 (29.9% of respondents). The second-largest group was respondents with an income below €700 (25.1%). The smallest group was respondents with an income of more than €3000 (5.6% of respondents). The overall characteristics of the sample of respondents are shown in Table 1.

Table 1. Characteristics of respondents and distribution of the sample.

Variable	Values	Frequency	Percent
gender	men	171	43.7
	women	220	56.3
age in years	18–26	150	38.4
	27–35	95	24.3
	36–44	103	26.3
	45–53	24	6.1
	54–64	14	3.6
	65+	9	2.3
education	primary	18	4.6
	high school (without graduation)	43	11.0
	high school (with a high school diploma)	142	36.3
	university degree I	84	21.5
	university degree II	91	23.3
	university degree III	13	3.3
income in €	less than 700	98	25.1
	701–1000	53	13.6
	1001–1500	117	29.9
	1501–2000	75	19.2
	2001–3000	26	6.6
	more than 3000	22	5.6

3.2. Questionnaire Survey Hypotheses

Based on the literature review, we established the following hypotheses regarding financial literacy.

Hypothesis 1 (H1). *There is a relationship between gender and financial literacy level. Men have a higher level of financial literacy than women.*

Hypothesis 2 (H2). *There is a relationship between education level and financial literacy level. Higher-educated residents have higher levels of financial literacy.*

Hypothesis 3 (H3). *There is a relationship between the experience of using bank loans and the level of financial literacy. Using bank credit increases the level of financial literacy in the population.*

Hypothesis 4 (H4). *There is a relationship between the level of financial literacy and the influence of advertising on purchasing behaviour. A lower level of financial literacy is associated with being influenced by advertising in purchasing behaviour.*

Hypothesis 5 (H5). *There is a relationship between using a bank loan to buy, build, or remodel a property and the level of financial literacy. Experience with a bank loan for housing increases the level of financial literacy.*

Hypothesis 6 (H6). *There is a relationship between income and level of financial literacy. People in the highest income groups have higher financial literacy.*

3.3. Methodology of Analysis—Hypothesis Testing

To test the stated hypotheses, we created a dichotomous dependent variable of financial literacy. We divided the level of financial literacy into two levels, namely, higher literacy and lower literacy. We determined the values of this variable based on the number of correct answers to the questions in the questionnaire related to the financial literacy screening. We selected those questions for which only one answer was correct among the multiple answers offered (seven questions in total). The following questions were used for this purpose:

- What is investing?
- What are the most important parameters in an investment?
- What is a mortgage loan?
- What is consumer credit?
- Which interest rate is represented by the abbreviation p.a.?
- What is life insurance?
- Who is the person, or legal person, who has concluded an insurance contract with an insurance company?

When creating a binary scaled variable characterizing financial literacy level, we adopted a threshold of five correct answers out of seven (approximately 71%) to classify respondents as financially literate. This approach aligns with methodologies in existing research, where achieving around 70% to 75% correct responses is often used to denote a high level of financial knowledge. For instance, a study by Atkinson and Messy (2012) on measuring financial literacy noted that a cut-off representing 75% of the available points is a level at which respondents may be considered to have a high level of knowledge about the subjects tested. Additionally, the concept of setting a cut-score or passing point at 70% is common in various assessments to categorize examinees, as discussed in assessment literature (Kass, 1980). Conversely, if a respondent answered a maximum of four questions correctly, we consider their financial literacy lower. By setting our threshold at five out of seven correct answers, we ensure that respondents demonstrate proficiency across financial topics, providing a comparable measure of financial literacy level.

This procedure divided our sample into 216 (55.2%) respondents with lower financial literacy and 175 (44.8%) with higher financial literacy.

To test the stated hypotheses, we use the chi-square test of independence. This test should be used to examine the relationship between two categorical variables. This test involves constructing a contingency table to summarise the frequency of different

combinations of the categories. The null hypothesis for this test states that the two variables are independent, while the alternative hypothesis indicates an association between them.

The expected frequencies for each cell in the contingency table are compared with the observed frequencies to perform the chi-square test.

The *p*-value derived from the chi-square distribution is used to determine the test result and its significance. If the *p*-value is less than the chosen significance level, the null hypothesis is rejected, indicating a statistically significant association between the variables.

If the test revealed an association between the variables, we use Cramer's V coefficient to quantify the strength of this association. This coefficient represents the most used measure of association between two nominal variables, derived from the chi-square statistic. Its values should be between 0 and 1, where 0 indicates no association and 1 indicates a perfect association. If the two variables under study are dichotomous, the Phi coefficient can also be used. In this case, its value is identical to Cramer's V coefficient, but Phi can also take negative values, which can be interpreted cautiously. Subsequently, we used the so-called sign schema to examine the observed relationships between the degree of financial literacy and a particular respondent's trait in more detail. It is used in cases where we want to determine which specific categories of individual variables are related. This scheme is suitable only if we have revealed a statistically significant relationship between the factors under study using the chi-square test. Both these procedures are based on the same principle: quantifying the residual between the theoretical and empirical frequencies. In doing so, the chi-square test uses the squares of these residuals to calculate the value of the test criterion and the sign scheme uses the residuals themselves to find the largest positive and negative differences between combinations of categories of the two qualitative variables.

The name of the sign scheme is derived from the fact that the sign type of the residual describes the direction of the deviation. The signs of the differences are indicated in the calculation by marks that suggest the direction of the observed dependence. When the empirical frequency is not significantly different from the expected frequency, this residual is denoted by the 'o' mark. A positive residual, i.e., a higher empirical frequency than the theoretical, is indicated by '+'. A negative residual, i.e., a lower empirical frequency than the expected theoretical, is indicated by '−'. One to three signs are used to highlight the difference's magnitude, which also indicates the level of statistical significance. One mark is used for the statistical significance of the residual at the 95% level, two for the 99% level, and three for the 99.9% level.

The sign scheme serves the same or similar objective, such as correspondence analysis. However, its advantage over this method is its ease of applicability, even in the case of dichotomous variables. Correspondence analysis in some software, such as SPSS Statistics, cannot be conducted if one or both variables are dichotomous.

For all hypothesis tests in this study, we used a significance level of 0.05. Statistical hypothesis testing and other analyses are performed using IBM SPSS Statistics version 26 and 30 and IBM SPSS Modeler software version 18.3.

3.4. Methodology of Analysis—Classification Models for Predictive and Explanatory Purposes

Firstly, our objective is to develop classification models to predict individuals' levels of financial literacy. By analysing various predictor variables, we aim to categorise financial literacy into distinct levels accurately. Moreover, the aim is to use this model not only for predictive purposes but also for identifying key factors influencing financial knowledge and skills, i.e., describing the relationships between the explanatory individual's characteristics and their financial literacy levels.

For this purpose, we used several modelling techniques, such as discriminant analysis, decision trees (specifically, the algorithms CART and CHAID), nearest neighbour, and logistic regression. All these machine learning techniques serve to solving a classification task (Kovacova et al., 2024; Valaskova et al., 2023), which is exactly our task of predicting the level of financial literacy. Besides that, all these models are interpretable and, thus, should be used to describe the relationships of the input variables and outcome variables. We used the input variables listed in Tables 1 and 2 as the input variables.

Table 2. Distribution of variables used in the classification models.

Variable	Values	Frequency	Percent
bank loans experience	no	190	48.6
	yes	201	51.4
advertisment influence	no	222	56.8
	yes	169	43.2
advertisment medium	Internet	103	26.3
	social networks	148	37.9
	TV	66	16.9
	newspapers	14	3.6
	radio	11	2.8
	I don't feel influenced	49	12.5
financial reserve	no reserve	91	23.3
	1–3 months	116	29.7
	4–6 months	91	23.3
	6–12 months	37	9.5
	more than 12 months	26	6.7
	I don't know	30	7.7

To create classification models with higher performance, we balanced the subsamples of respondents with a lower and higher financial literacy to obtain approximately equal numbers of individuals in both groups. For this purpose, we used the oversampling technique, where the smaller group has a higher weight in modelling to equal the size of the bigger group, where the exact weight is set as a ratio of both groups. As a result, we get the groups of respondents with lower and higher financial literacy with 216 (50.5%) and 212 (49.5%) respondents, respectively. Among the modelling techniques mentioned above, the best performance was achieved by the logistic regression. Moreover, we used the CHAID classification tree because of its interpretability. Therefore, we characterise these two methods in brief.

Logistic regression is a statistical method that models the relationship between a binary or multinomial dependent variable and one or more independent variables. It leverages the logistic function to transform the linear combination of the predictors into a probability value between 0 and 1. Let the outcome variable Y be binary, where Y = 1 with probability p and Y = 0 with probability $1 - p$. Let $X_1, X_2, \ldots, X_m$ be m predictor variables. The logistic regression model expresses the log odds of the outcome Y being one as a linear combination of the predictor variables:

$$log\frac{p}{1-p} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_m X_m \quad (2)$$

Here, $\beta_0, \beta_1, \ldots \beta_m$ are the parameters to be estimated, where their estimations are denoted by $b_0, b_1, \ldots, b_m$. The logistic function then converts the linear combination of predictors into a probability:

$$p = 1/(1 + exp(-\beta_0 - \beta_1 X_1 - \beta_2 X_2 - \cdots - \beta_m X_m)) \quad (3)$$

Parameter estimation in logistic regression is typically done using the maximum likelihood method. The likelihood function is defined as:

$$L(\beta_0,\ \beta_1,\ \beta_2, \ldots,\ \beta_m) = \prod {p_i}^{y_i} \cdot (1 - p_i)^{1-y_i} \quad (4)$$

where the product is over all observations i, y_i is the observed outcome (0 or 1) for the i-th observation, and p_i is the predicted probability of $Y = 1$ for the i-th observation.

The maximum likelihood estimates are obtained using iterative techniques by maximising the log-likelihood function (Gabrikova et al., 2023; Svabova & Kramarova, 2021).

$$\ln L(\beta_0,\ \beta_1,\ \beta_2,\ \ldots,\ \beta_m) = \sum (y_i \ln p_i + (1 - y_i) \ln(1 - pi)) \quad (5)$$

CHAID (Chi-squared Automatic Interaction Detection) is a decision tree algorithm for classification tasks involving categorical target variables (Milanovic & Stamenkovic, 2016). The algorithm initiates with the entire dataset in the root node. Using the chi-squared statistic, it automatically selects the most relevant predictor variable based on its separation effectiveness. The dataset is then divided into two or more subsets, with the algorithm automatically determining the variable's splitting criterion. Unlike other decision tree algorithms, CHAID permits the division of a node into more than two subsets (Ritschard, 2013).

The validity of each split is evaluated using the chi-square test of independence between the target and predictor variables. This test assesses the statistical significance of differences in the target variable across categories of the predictor variable. If the chi-square test indicates significance, the split is accepted, and the algorithm continues; otherwise, the node becomes a terminal (leaf) node and is not split further. This process is repeated until specified stopping criteria are met (Huhmann & McQuitty, 2009). In our application, the criteria included a maximum tree depth of 5, a minimum of 3% of cases in a parent node, 2.5% in a child node, a minimum change in expected call frequencies for the chi-square test of 0.001, and a maximum of 100 iterations for convergence.

To prevent overfitting, the tree can be pruned by removing branches with the least importance, thereby enhancing the model's generalisation capabilities.

3.5. Methodology of Analysis—Classification Models for Predicting Purposes

A second type of prediction model created was the models serving for highly precise predictions of financial literacy levels. For this purpose, various machine-learning techniques are usable. We used six of them: Bayesian Network, Linear Support Vector Machines (LSVM), Extreme Linear Gradient Boosting (XGBoost Linear) technique, Extreme Gradient Boosting Tree (XGBoost Tree) technique, Random Forest, and Neural Network. These advanced machine learning models are able to capture the complex, non-linear relationships among the predictors, and their predictions are, therefore, highly precise. However, it is crucial to mention that their black-box nature often limits their utility for interpretation and understanding the underlying mechanisms.

Bayesian Networks are probabilistic graphical models that depict the dependencies between variables using a directed acyclic graph. They are useful for modelling uncertainty and identifying causal relationships, as they use prior knowledge and adjust predictions

based on new data using Bayesian inference. The model represents joint probability distributions, which, to some extent, allows for interpreting the relationships among features. However, the interpretation clarity should be lost quickly for a larger set of predictors. Moreover, they can be computationally intensive for large datasets and, therefore, require careful selection of predictors.

Linear Support Vector Machines (LSVM) are designed to find the best linear separation of the outcome variable classes in a whole space of predictors, maximising the margin between data points from different classes. LSVM work by solving a convex optimisation problem, ensuring global optimality of the solution. The technique also employs kernel functions to handle cases where data are not linearly separable, though the focus here is on its linear variant. This technique is usable for high-dimensional large datasets because of its computational efficiency. However, it can struggle when dealing with noisy data or overlapping class distributions, as its decision boundaries are rigid.

XGBoost Linear, a specialised implementation of the Extreme Gradient Boosting algorithm, combines the strengths of linear models with gradient boosting techniques. The model is particularly valuable in cases where the data exhibit linear relationships, as it improves the prediction performance of the linear model. The predictive power of linear models is boosted by iteratively minimising the loss function, thereby addressing the limitations of simpler linear regression techniques. To prevent overfitting, the model incorporates regularisation parameters like L1 and L2. The disadvantage is their lower power compared to tree-based approaches for highly non-linear patterns.

XGBoost Tree, another Extreme Gradient Boosting framework variant, builds ensembles of decision trees by iteratively optimising "weak learners" through gradient boosting. It is designed to handle complex, non-linear relationships in the data by creating a sequence of decision trees, where each subsequent tree corrects the errors of its predecessor. To control overfitting, regularisation parameters are also used. This technique is highly usable for large datasets. For achieving more precise splitting, it incorporates advanced features like handling missing values and weighted quantile sketching. The model's ability to capture intricate patterns and interactions among features makes it highly effective for predictive tasks in financial literacy. However, it is necessary to mention that the resulting model is highly complex and thus uninterpretable.

Random Forest is an ensemble method that combines predictions from multiple decision trees to improve accuracy and generalizability. Each tree in the forest is trained on a random subset of the data using bootstrap aggregation (bagging), which reduces variance and prevents overfitting. During training, only a random subset of features is considered for each split, further enhancing the model's robustness to irrelevant or noisy variables. Random Forest is interpretable regarding feature importance metrics, allowing for this basic understanding of financial literacy drivers. However, the model may struggle with very large datasets due to the computational and memory requirements.

The Neural Network model is inspired by the architecture of the human brain. It processes data through layers of interconnected nodes (neurons). Each neuron applies a non-linear activation function to the weighted sum of its inputs, enabling the network to capture complex patterns, non-linear relationships, and interactions of the explanatory input variables. Neural Networks are highly flexible and can approximate almost any function, making them a powerful and widely used technique. However, they require large amounts of data to train the model effectively. Overfitting can also be a challenge.

3.6. Evaluation of Models' Prediction Performance

The performance of the models is evaluated by the confusion matrix, and evaluation measures are calculated from it. A confusion matrix is a 2×2 table showing the numbers

of correctly and incorrectly predicted cases placed into the groups of those with lower and higher financial literacy. Individual predictions are noted as follows. TP represents the number of true positive cases, FP is the number of false positive cases, TN is the number of true negative cases, and FN is the number of false negative cases. Here, a positive case is a person with lower financial literacy, as we considered this category more important to recognise. The evaluation measures used for quantifying the model's performance are the following (Clichici & Moagar-Poladian, 2022; Gabrikova et al., 2023):

- $Acc = \frac{TP+TN}{TP+FP+TN+FN}$ is an overall accuracy of the model;
- $Sen = \frac{TP}{TP+FN}$ is sensitivity, representing a row % of true positive predictions;
- $Spec = \frac{TN}{FP+TN}$ is specificity, representing a row % of true negative predictions;
- $P = \frac{TP}{TP+FP}$ is precision, representing a column % of true positive predictions;
- $F = \frac{2TP}{2TP+FP+FN}$ is F-measure, calculated as a harmonic mean of accuracy and sensitivity.

In addition to these evaluation metrics, if available for a particular technique, we present the predictors' importance metric. Its values are presented graphically with the variables in the order of their importance, where the sum of all the importance is one.

4. Results

In this section, we analyse the survey results from several perspectives. Firstly, we evaluate the outcomes of the questionnaire survey, then we present the results of testing the established hypotheses, and finally, we highlight the possibilities of predicting financial literacy using "classical" interpretable models (logistic regression and CHAID tree) as well as models created by advanced machine learning techniques.

4.1. Results of the Questionaire Survey

Regarding the financial behaviour of respondents regarding provisioning, the dominant group (30% of respondents) have a provision of 1 to 3 months' income. The second largest group was those without provision (approximately 25% of respondents). The least represented group (1% of respondents) was those who indicated "Other" as an alternative. Up to 43% of respondents considered real estate investment the most appropriate form. This is followed by equities (33% of respondents), bonds (10%), and money market funds (8%). Cryptocurrencies (4%) and Forex (2%) were the least used forms. It is interesting to note that 68% of respondents correctly answered the knowledge question in the questionnaire, what is investing, but only 58% of respondents knew the most important parameters of investing.

51% of respondents have experience with bank loans, and these loans are usually used to finance housing (85% of respondents), the purchase of a motor vehicle (10% of respondents), and holidays (15% of respondents). Surprising were the findings that loans are also used to obtain capital for investment (4% of respondents). Various authors have highlighted this phenomenon, which has been identified as a problem of high financial literacy (Kass, 1980; Milanovic & Stamenkovic, 2016; Abeysekera et al., 2022). Our respondents also use loan money to buy gifts (1% of respondents). In doing so, we can mention that 84% of the respondents understand the concept of a mortgage loan, and 88% understand the concept of a consumer loan. Therefore, we were surprised that up to 60% of respondents understood the abbreviations p.a. and APR.

In the area of insurance, we can state that 66% of respondents understand the concept of life insurance. However, terms such as policyholder and insured person are unknown to about 56% of the respondents. Among the types of insurance, respondents mainly use life insurance, PPL, and household insurance. The least used are investment, risk, and travel insurance.

In questions focused on purchasing behaviour, we analysed spending habits on selected items (household expenses, food, clothing and footwear, transport, health, post and telecommunications, hobbies, education, etc.). When shopping, we analysed the 12 categories that most influence the respondents' consumption of funds. Almost 70% of respondents are most influenced by their own experience and the price of products. However, recommendations and discounts are also of great importance. According to respondents, social media, TV, influencers, and celebrities are the least important. In the questionnaire, we also focused on the influence of advertising as an important determinant of the purchasing behaviour of the respondents. As many as 49% of respondents indicated that, from their perspective, they are not influenced by advertising. Following on from the previous question, an interesting finding was that among respondents who admitted to being influenced by advertising, the most frequently reported being influenced by advertising on social media (38%) and on the Internet (26%), and the least frequently by advertising in newspapers (4%) and radio (3%).

The way respondents shop for different types of goods is shown in Figure 2. In all categories surveyed, shopping in brick-and-mortar stores is preferred. The online form of shopping is particularly interesting for organic food, bike and car parts, and books.

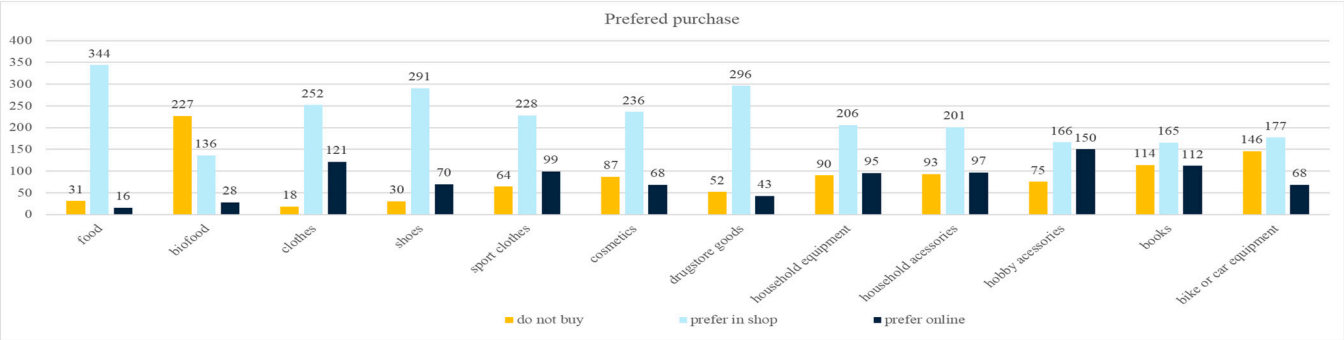


Figure 2. Preferred mode of purchase, Source: own elaboration.

In what respondents see the advantages of online shopping and shopping in brick-and-mortar stores, we found out at the end of the questionnaire survey. For online shopping, these were typically discounted prices (46.3%), continuous opening hours (43.7%), breadth of range (43%), and time savings (43.2%). The advantage of brick-and-mortar stores for most respondents (54.7%) is immediate product access. They also see an advantage in the easier way to make a complaint (37.9%), ease of shopping (33.5%), additional advice (30.9%), and speed of shopping (28.6%). They consider ease of payment (24%), loyalty programmes (15.3%), convenience of delivery (10.5%), and the ability to try the product (10.5%) to be less important.

In the survey, we found that respondents' highest expenses were directed to food purchases, household running, and transport. These three expenditure groups coincide with the net private expenditure of households, published annually by the Statistical Office of the Slovak Republic on its website. According to the respondents, the lowest expenses were on post and telecommunications, household accessories, and education. These results are presented in Table 3.

Table 3. Expenditure of respondents.

Order	Highest Spending Respondents	Lowest Spending Respondents
1.	Food	Post and telecommunications
2.	Expenditure related to the running of the household (housing, water, electricity, gas)	Household accessories
3.	Transport	Education
4.	Clothing and drugstore	Hobby
5.	Health	Clothing

The following figure shows the shopping preferences of the respondents. This figure is constructed as a web graph (network diagram) and visually represents the relationships between different product categories in online shopping preferences. In this graph, each node corresponds to a specific product category, such as organic food, groceries, or drugstore products. The edges (connections between nodes) represent co-purchasing relationships, indicating that respondents frequently buy the two connected categories together. The thickness of an edge reflects the strength of the relationship, meaning that thicker edges indicate more frequent co-purchasing behaviour. This visual structure allows for an intuitive understanding of shopping behaviour, highlighting the most common purchasing patterns among respondents. Figure 3 depicts only those edges with at least 10 occurrences for better clarity.

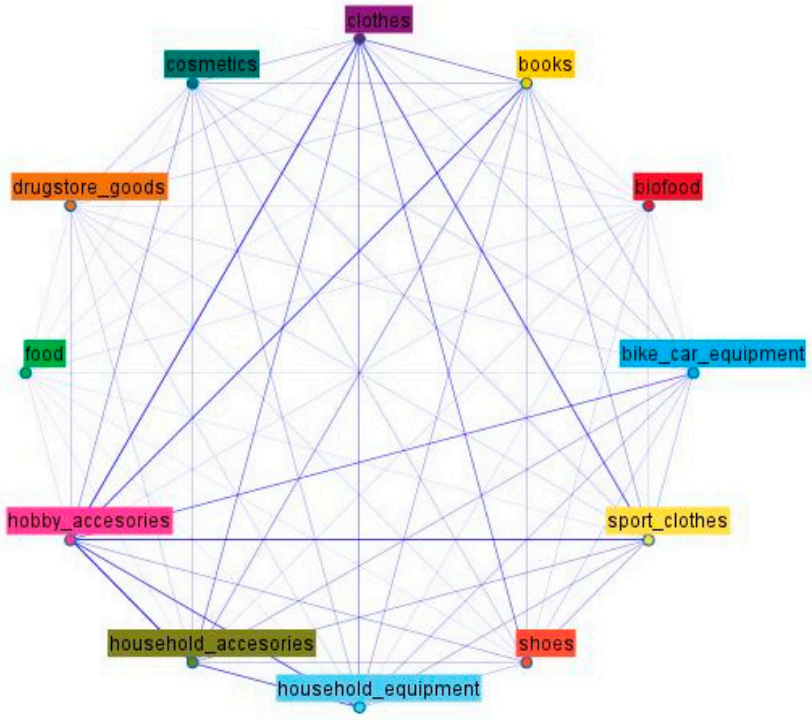


Figure 3. Preference of goods when shopping online. Source: own elaboration.

Our respondents prefer to shop online, especially for products such as organic food, groceries, and drugstores. Figure 3 also shows that this relationship is most pronounced. Based on these relationships, it can be concluded that customers usually shop for organic food, groceries, and drugstores simultaneously. The relationship between food, drugstores, and car or bicycle accessories is also frequent. Other relationships are less significant.

4.2. Results of Hypothesis Testing

In determining and testing the individual hypotheses, we focused primarily on the area of financial literacy. This part of the analysis aimed to determine the relationship between the population's characteristics, behaviour, and financial literacy level. In the following, we will present the results of testing the hypotheses established.

Testing Hypothesis H1: There is a relationship between gender and financial literacy level. Men have a higher level of financial literacy than women.

This hypothesis is tested using a pair of dichotomous categorical variables: gender and financial literacy of the respondents. The contingency table (see Table 4) shows the frequency distribution of respondents by their combination of gender and financial literacy level. Each row and column also contains the cumulative number of respondents in the specific category.

Table 4. Contingency table of empirical counts for gender and financial literacy.

Gender	Lower Financial Literacy	Higher Financial Literacy	Total
Men	81	90	171
Women	135	85	220
Total	216	175	391

To test the first stated hypothesis using the chi-squared test, we formulated the following statistical hypotheses:

Hypothesis H0. *There is no relationship between gender and level of financial literacy.*

Hypothesis H1. *There is a statistically significant relationship between gender and level of financial literacy.*

The test is performed at the 0.05 significance level. The test statistic value is 7.62, and the *p*-value of the chi-square test is 0.006. Considering this result, we can conclude that there is a relationship between gender and financial literacy level.

Considering the previous result, we take a closer look at the level of financial literacy for both genders using a sign scheme. Table 5 reports the results of quantifying the residuals assessed using the sign scheme. This scheme offers a practical and interpretable presentation of the results. The signs are calculated based on a comparison of the empirical and theoretical number of respondents in each combination of financial literacy level and gender. The positive sign means that there is a higher number of respondents with the particular combination than was expected if financial literacy and gender have been independent, whereas the negative sign indicates that fewer people have such a combination of categories than was expected in the case of their independence.

Table 5. Sign scheme for gender and financial literacy.

Gender	Financial Literacy	
	Lower	Higher
men	--	++
women	++	--

From the results of this analysis, it is evident that higher levels of financial literacy are more likely to be achieved by males, and lower levels are more likely to be experienced by females. This result is significant at the 0.01 level of significance.

The strength of the relationship between gender and financial literacy level can be quantified using Cramer's V coefficient of 0.140 (p-value = 0.006). In this case, since both variables are dichotomous, we can also report the value of the Phi coefficient. Its value is −0.140 (p-value = 0.006). Thus, there is a moderate association between gender and financial literacy.

Testing Hypothesis H2: There is a relationship between education and financial literacy. Higher-educated residents have higher levels of financial literacy.

Table 6 is a contingency table of the empirical education and financial literacy level frequencies. These values were determined from the data on respondents' answers and represent the numbers of respondents in a combination of each level of education and financial literacy level, together with the row and column cumulative numbers.

Table 6. Contingency table of empirical frequencies for education level and financial literacy.

Education	Lower Financial Literacy	Higher Financial Literacy	Total
primary	14	4	18
secondary	34	9	43
higher secondary	95	47	142
university 1st degree	39	45	84
university 2nd degree	28	63	91
university 3rd degree	6	7	13
Total	216	175	391

Given that the conditions for the use of the chi-squared test are met in this case, we formulated the following hypotheses:

Hypothesis H0 (H0). *There is no relationship between education and level of financial literacy.*

Hypothesis H1 (H1). *There is a statistically significant relationship between education and the level of financial literacy.*

In this case, the chi-squared test statistic is 46.495, and the p-value of the test is significantly less than the established significance level. Given this result, we reject the null hypothesis in this case and accept the alternative hypothesis. Through this test, we found a significant relationship between education and the financial literacy level of the population.

Given the observed dependence between education and financial literacy, it is reasonable to quantify the strength of this dependence, for example, by using Cramer's V. Its value of 0.345 (p-value < 0.001) can be described as a mild to moderate dependence.

To examine the relationship between education and financial literacy in more detail, it is useful to use a sign scheme. Table 6 shows the significance of the adjusted residuals according to the sign scheme to reveal the relationship between education and financial literacy levels. The highest significance (0.001) is for the combination of university education of the second degree, which is significantly more likely to lead to higher financial literacy, and, conversely, significantly fewer residents with this level of education attain lower financial literacy. At the same time, both levels of secondary education are significantly more likely to have lower levels of financial literacy (0.001).

Table 7 presents the relationship between financial literacy levels for each level of respondents' education. It highlights the increased or decreased numbers of people with both levels of financial literacy in each level of education (compared with the expected number in case of independence between the financial literacy level and level of education).

Table 7. Sign scheme for the level of education and financial literacy.

Education	Lower Financial Literacy	Higher Financial Literacy
primary	+	-
secondary	+++	---
higher secondary	+++	---
university 1st degree	o	o
university 2nd degree	---	+++
university 3rd degree	o	o

Testing Hypothesis H3: There is a relationship between the experience of using bank loans and the level of financial literacy.

Table 8 reports the frequencies of respondents according to their experience with bank loans and their financial literacy level, together with the rows' and columns' cumulative numbers. These numbers are calculated from the respondents' answers.

Table 8. Contingency table of empirical frequencies for experience with bank loans and financial literacy.

Bank Loan	Lower Financial Literacy	Higher Financial Literacy	Total
yes	107	94	201
from	109	81	190
Total	216	175	391

In this case, the statistical tests to test the stated hypothesis using the chi-square test are formulated as follows:

Hypothesis H0 (H0). *There is no relationship between experience using bank loans and level of financial literacy.*

Hypothesis H1 (H1). *There is a statistically significant relationship between experience using bank loans and level of financial literacy.*

The chi-squared test statistic value is 0.675, and the p-value of the test is 0.411. Thus, in this case, we do not have enough evidence to reject the null hypothesis, and we have to conclude that we could not find a relationship between the experience of using bank loans and the level of financial literacy.

Testing hypothesis H4: There is a relationship between the level of financial literacy and the influence of advertising on purchasing behaviour. A lower level of financial literacy is associated with being influenced by advertising in purchasing behaviour.

Table 9 is a contingency table of the empirical frequencies, showing the number of combinations of financial literacy level and the influence by advertising on purchase behaviour.

Table 9. Contingency table of empirical frequencies for the impact of financial literacy on being influenced by advertising in purchasing behaviour.

Influence by Advertising	Lower Financial Literacy	Higher Financial Literacy	Total
yes	86	83	169
no	130	92	222
Total	216	175	391

To test the stated hypothesis H4, we formulated the following statistical hypotheses:

Hypothesis H0 (H0). *There is no relationship between the level of financial literacy and the influence of advertising on purchase behaviour.*

Hypothesis H1 (H1). *There is a statistically significant relationship between the level of financial literacy and the influence by advertising on purchasing behaviour.*

The chi-squared test statistic is 2.284, and the p-value of the test is 0.131. Based on this result, we have to conclude that we did not find enough evidence to reject the null hypothesis of independence between financial literacy and being influenced by advertising on purchase behaviour.

Testing Hypothesis H5: There is a relationship between the financial literacy level and the use of bank credit to buy, build, or renovate a home.

Contingency Table 10 shows the actual frequencies of respondents in each combination of using bank loans for real estate purposes and financial literacy level. In this case, we have selected only those respondents who indicated in the questionnaire that they had experience with bank credit. A follow-up question in the questionnaire asked in more detail what they had used this credit for.

Table 10. Contingency table of empirical frequencies for using bank credit for housing purposes and financial literacy.

Bank Loans for Real Estate	Lower Financial Literacy	Higher Financial Literacy	Total
yes	86	90	176
from	21	4	25
Total	107	94	201

As in all other tests, the conditions for using the chi-square test are met. Therefore, we set up the statistical tests as follows:

Hypothesis H0 (H0). *There is no relationship between using bank credit for housing purposes and the level of financial literacy.*

Hypothesis H1 (H1). *There is a statistically significant relationship between the use of bank credit for housing purposes and the level of financial literacy.*

In this case, the test result is represented by a chi-squared statistic value of 10.856 and a test p-value less than the chosen significance level (p-value < 0.001). Therefore, we can reject the null hypothesis and formulate the conclusion by testing this hypothesis, namely that there is a significant relationship between the level of financial literacy and the use of bank credit for purchasing, constructing, or renovating housing.

Table 11 shows the sign scheme for these two variables. The results are identical across the two levels of financial literacy but with opposite trends. A higher number of financially literate people are more likely to use bank loans for housing, whereas a significantly lower number of those who would not use bank loans for housing have lower levels of financial literacy. This is compared with the situation of independence between using bank loans for real estate and financial literacy level.

Table 11. Sign scheme for usage of bank loans for real estate and financial literacy.

Bank Loans for Real Estate	Lower Financial Literacy	Higher Financial Literacy
yes	---	+++
from	+++	---

Given the observed relationship between financial literacy and the use of bank credit for the purpose of purchasing, building, or renovating housing, it is appropriate to quantify the strength of this relationship, for example, using the Cramer's V coefficient, which in this case was 0.232 (p-value < 0.001). This result indicates a moderately strong relationship between the variables analysed. Since both variables are dichotomous in this case, we can also use the value of the coefficient Phi, which is the same as the coefficient of Cramer V but has a negative sign, to quantify their relationship. Its value is, therefore, −0.232 (p-value < 0.001) and indicates an "inverse" relationship between the use of credit to finance real estate and financial literacy. Thus, a higher level of financial literacy is associated with using credit for property financing purposes. This is an identical result to the sign-scheme result above.

Testing Hypothesis H6: There is a significant relationship between income and level of financial literacy.

Table 12 shows the empirical frequencies of individual income levels in combination with the financial literacy level calculated from the respondents' answers.

Table 12. Contingency table of empirical frequencies for income and financial literacy.

Income	Lower Financial Literacy	Higher Financial Literacy	Total
less than 700 €	61	37	98
701 €–900 €	34	19	53
901 €–1400 €	75	42	117
1401 €–2000 €	31	44	75
2001 €–2800 €	10	16	26
more than €2800	5	17	22
Total	216	175	391

As in the previous cases, we set the following form of statistical hypotheses:

Hypothesis H0 (H0). *There is no relationship between income and level of financial literacy.*

Hypothesis H1 (H1). *There is a statistically significant relationship between income and level of financial literacy.*

Testing resulted in a chi-square test statistic value of 25.596 and a p-value for the test < 0.001. In this case, we again found sufficient evidence to reject the null hypothesis of independence of the two variables under study and can confirm that there is a significant relationship between income and the level of financial literacy.

Since we have confirmed the dependence between financial literacy and income, examining their relationship in more detail using a sign scheme is justified. The results are shown in Table 13. The positive signs indicate the combinations of financial literacy level and income that are more likely to occur, whereas the negative signs indicate the combinations of categories with lower occurrence than should be expected in case the financial literacy and income level have been independent.

Table 13. Sign scheme for income and financial literacy.

Income	Lower Financial Literacy	Higher Financial Literacy
less than 700 €	o	o
701 €–900 €	o	o
901 €–1400 €	+	-
1401 €–2000 €	--	++
2001 €–2800 €	o	o
more than €2800	--	++

We found a significant relationship for the combination of the €901–€1400 income category, with such individuals significantly more likely to fall into the lower financial literacy category (p-value < 0.05). Conversely, higher income groups are significantly more likely to fall into the sufficiently financially literate category (the €1401–€2000 income group and the more than €2,800 income group (p-value < 0.01)).

Given the observed dependence between income level and financial literacy, it is interesting to quantify the strength of the dependence using Cramer's coefficient, which in this case had a value of 0.256 (p-value < 0.001), which can be described as a moderately strong dependence between the variables under study.

Summary of hypotheses testing

Table 14 summarises the results of the above-mentioned hypotheses testing. The hypotheses are stated in a shortened form as a relationship of the financial literacy level (in the table denoted by FLL). The association wasn't further examined if the relationship between the financial literacy level and the characteristic was not revealed. Therefore, we do not mention the value of association coefficients and the sign scheme results.

Table 14. Summary of hypotheses testing.

Hypothesis Focus	Result	Strength of the Relationship (Coefficient of Association)	Sign Scheme Main Results
H1: relationship between gender and FLL	confirmed	moderate association (Cramer V = −0.14)	Higher FLLs achieved by males; lower levels by females
H2: relationship between education level and FLL	confirmed	moderate association (Cramer V = 0.345)	2nd degree of university education leads to higher FLL; both levels of secondary education have lower FLL
H3: relationship between the experience of using bank loans and the FLL	unconfirmed		
H4: relationship between the FLL and the influence of advertising on purchasing behaviour	unconfirmed		
H5: relationship between using a bank loan to buy, build, or remodel a property and the FLL	confirmed	moderate association (Phi = −0.232; Cramer V = 0.232)	A higher FLL is associated with using credit for property financing purposes.
H6: relationship between income and FLL.	confirmed	moderate association (Cramer V = 0.256)	Category with income of €901–€1400 falls into lower FLL; higher income groups fall into higher FLL

4.3. Predictive Models for Financial Literacy Levels—Interpretable Models for Explanatory and Predictive Purposes

In this section, we present the classification models for modelling financial literacy using several input variables as characteristics of the respondents or their experience with financial products. We present the results of the model created by the CHAID technique and the logistic regression. Both these were chosen as high-performance models because of their readability and interpretability. Figure 4 presents the importance of predictors in the CHAID decision tree. The most important predictor in this model is the level of education (importance 0.65). The other places belong to income (0.11), gender (0.10), medium of their influence by advertisement (0.07), and age (0.07).

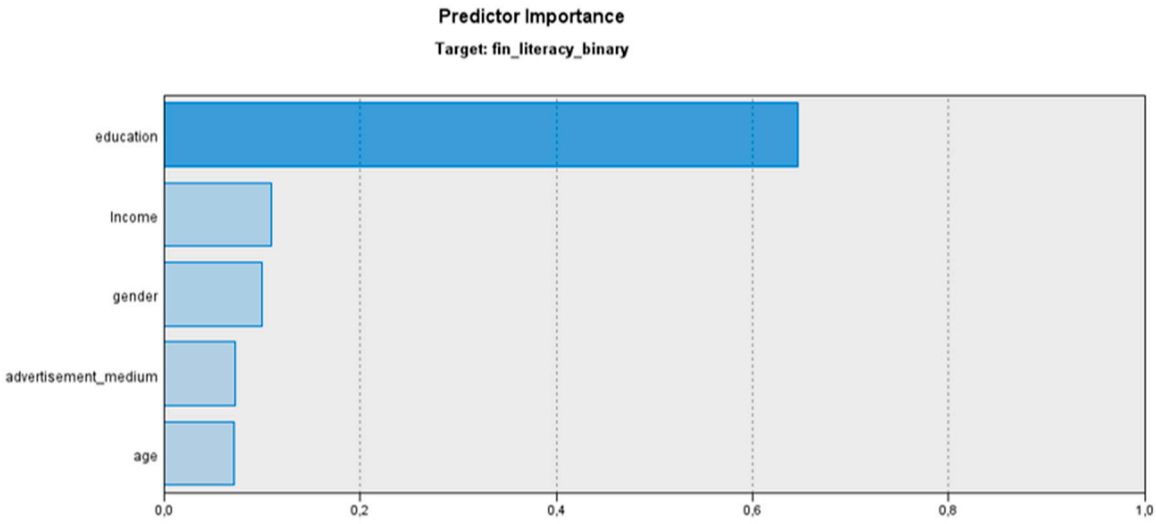


Figure 4. Importance of predictors in the CHAID model.

Figure 5 presents the CHAID decision tree. In the first division, people are divided into three groups according to their level of education. The first group comprises people with primary, secondary, and higher secondary education. This group is further divided into two by the medium of advertisement which people are influenced by. In the first group, people are influenced by the Internet, social networks, TV or newspapers. Furthermore, they are divided according to their age group, where people between the age of 45 and 53 years tend to have higher level of financial literacy, whereas the resting age groups are further divided by their level of education, but both these groups are predicted to have lower levels of financial literacy. Therefore, we can say that primary or secondary education is connected to a lower level of financial literacy, except for the 45–53 age group.

The second main branch of the tree belongs, in fact, to the group of people with a university education of first degree. These are further divided by their gender, where men with this education have a higher level of financial literacy, whereas women with the same level of education have lower.

Finally, the third main branch belongs to those with second and third levels of university education and is further divided by gender. However, both genders with this level of education are predicted to have higher levels of financial literacy. Therefore, we can say that people with second and third degrees of university education tend to have higher levels of financial literacy.

The second model of logistic regression is in Table 15. The model was created by the forward stepwise method. The estimated coefficients are in the column noted by B, and the values in column Exp (B) can be interpreted as the probabilities of achieving a higher level of financial literacy under given values of explanatory variables. The coefficients are for

the higher level of financial literacy, where the lower level was a reference category. The first category was automatically chosen as a reference for each categorical variable.

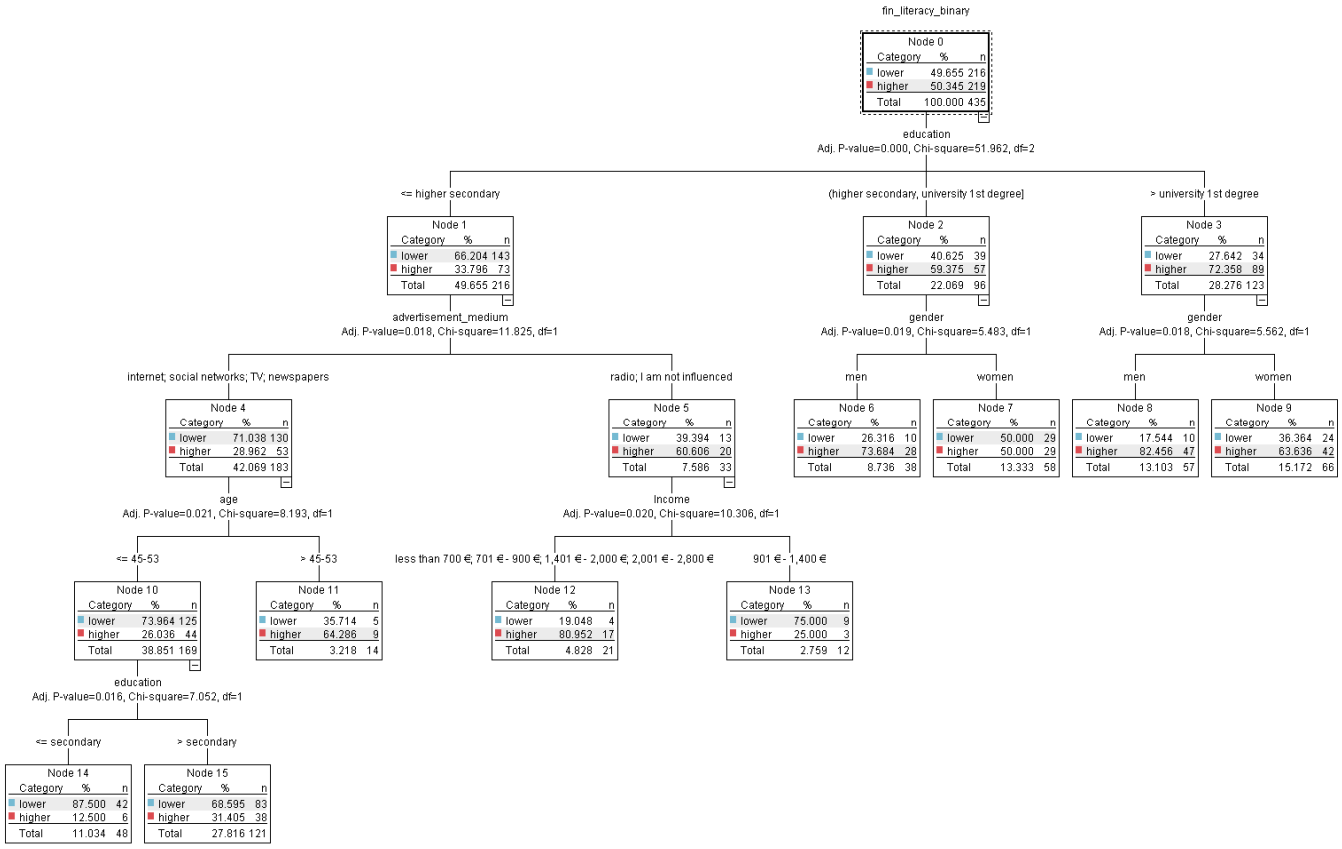


Figure 5. CHAID decision tree for the level of financial literacy.

Table 15. Logistic regression model for higher financial literacy.

	B	S.E.	Wald	Sig.	Exp(B)
Income			15.22	0.01	
income 701 €–900 €	0.01	0.38	0.001	0.98	1.01
income 901 €–1400 €	−0.65	0.32	4.17	0.04	0.52
income 1401 €–2000 €	0.22	0.39	0.33	0.57	1.25
income 2001 €–2800 €	0.21	0.53	0.17	0.69	1.24
income more than €2800	1.18	0.61	3.73	0.05	3.24
advertisement influence no	−0.54	0.25	4.83	0.03	0.58
advertising medium			13.96	0.02	
advertisement medium social networks	−0.21	0.28	0.58	0.45	0.81
advertisement medium TV	−0.69	0.35	3.84	0.05	0.50
advertisement medium newspapers	−1.16	0.73	2.49	0.11	0.31
advertisement medium radio	0.62	0.67	0.85	0.36	1.86
advertisement medium not influenced	0.73	0.40	3.45	0.06	2.08
education			40.80	<0.001	
secondary education	0.04	0.72	0.004	0.96	1.04
education higher secondary	1.28	0.64	4.03	0.05	3.59
education university 1st degree	1.83	0.64	8.14	0.004	6.23
education university 2nd degree	2.64	0.68	14.96	<0.001	13.99
education university 3rd degree	1.57	0.84	3.47	0.06	4.82
gender women	−0.67	0.24	7.48	0.01	0.51
Constant	−0.69	0.62	1.21	0.27	0.50

For income, all the groups except those between 901 € and 1400 € have a higher probability of having a higher level of financial literacy than the lowest income group. For instance, the group with the highest income of more than 2800 € has a 3.24 times higher probability of having a higher level of financial literacy than the group with the lowest income of less than 700 €. Similar interpretations should be formulated for all income groups. The influence of income is statistically significant. However, among the specific income levels, only the third and last are in their financial literacy significantly different from the first reference category of the lowest income level.

For the level of education, we can conclude that all the levels of education have multiple times higher probability of having a higher level of financial literacy than the reference category of people with primary education. However, secondary education'sinfluence on financial literacy is statistically insignificant at the 0.05 significance level.

Finally, women have a 0.51 times lower probability of having higher financial literacy than men. Moreover, the influence of gender is statistically significant at the 0.05 significance level. The importance of predictors is depicted in Figure 6. In agreement with the first model, the most important variable was education (importance 0.49), followed by income (0.19), gender (0.13), medium of their influence by advertisement (0.12), and being influenced by an advertisement (0.07).

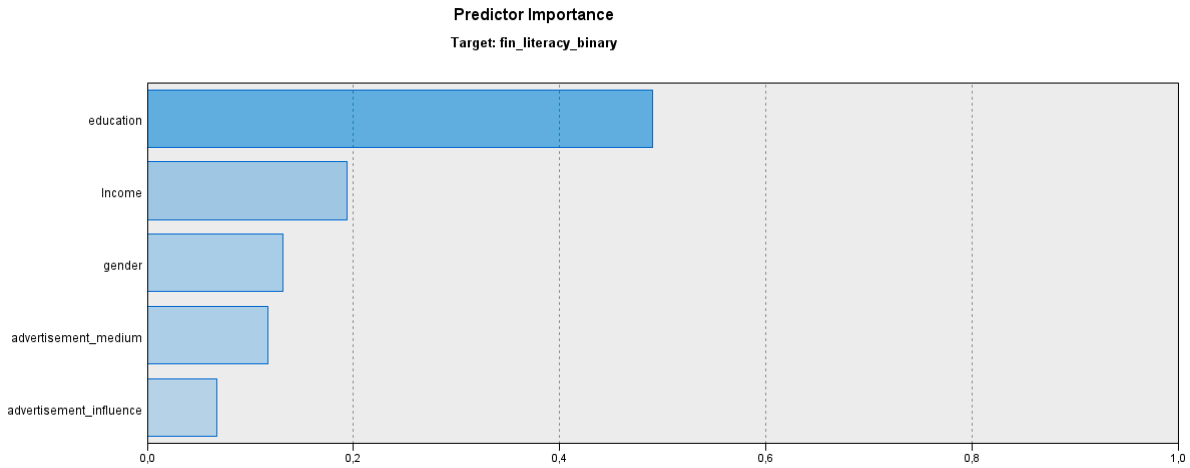


Figure 6. Importance of predictors in the logistic model.

Both models were evaluated by the confusion matrix and the overall classification accuracy. The results of the models' evaluation are in Table 16.

Table 16. Evaluation of models for financial literacy.

CHAID Model			**Logistic Regression Model**		
Financial Literacy	**Predicted**		**Financial Literacy**	**Predicted**	
actual	lower	higher	actual	lower	higher
lower	176	40	lower	157	59
higher	52	161	higher	26	187
accuracy	78.6		accuracy	80.2	
sensitivity	81.5		sensitivity	72.7	
specificity	75.6		specificity	87.8	
precision	77.2		precision	85.8	
F-measure	79.3		F-measure	78.7	

In this table, lower financial literacy is considered a target value of the outcome variable. Therefore, the sensitivity means the percentage of people correctly predicted as

having lower financial literacy. On the other hand, specificity means the percentage of people correctly predicted as having a higher level of financial literacy.

4.4. Predictive Models for Financial Literacy Levels—Advanced Models for Predictions

For predicting the financial literacy levels with a high accuracy, the above-mentioned machine learning models should be effectively used. The main advantage of these methods is their ability to capture the complex and non-linear relationships among the predictors, resulting in their pretty high prediction performance. On the other hand, the main disadvantage of these sophisticated techniques is their weak interpretability of results. These techniques are considered black boxes, and the user does not know the prediction calculation procedure. Therefore, if used for prediction purposes, these techniques are highly recommended. In these models, we used the same set of predictors as in the previous two models.

We used the following techniques: Bayesian Network, Linear Support Vector Machine (LSVM), XGBoost Linear, XGBoost Tree, Random Forest, and Neural Network, with an automatic selection of the best models based on their prediction performance. All these techniques are suitable for solving the classification problem of predicting financial literacy levels.

As mentioned above, it is hard to present the model itself for these techniques because the relationships between the outcome variable and the predictors used in the model are not readable. Therefore, we can only present the predictors' importance (not available for all models in the SPSS Modeler software version 18.3) and the evaluation measures calculated from the confusion matrix. These results are presented in Table 17. The three most important predictors are presented in the order of their importance with the level of importance in the parentheses (if available).

Table 17. Advanced predictive models for financial literacy.

Bayesian Network			**LSVM**			**XGBoost Linear**		
Financial Literacy	**Predicted**		**Financial Literacy**	**Predicted**		**Financial Literacy**	**Predicted**	
actual	lower	higher	actual	lower	higher	actual	lower	higher
lower	174	42	lower	208	8	lower	164	52
higher	54	167	higher	5	204	higher	68	153
predictors	-		predictors	education (0.31) income (0.17) advertisment influence (0.16)		predictors	-	
accuracy	78.0		accuracy	96.9		accuracy	72.5	
sensitivity	80.6		sensitivity	96.3		sensitivity	75.9	
specificity	75.6		specificity	97.6		specificity	69.2	
precision	76.3		precision	97.7		precision	70.7	
F-measure	78.4		F-measure	97.0		F-measure	73.2	
XGBoost Tree			Random Forest			Neural Network		
financial literacy	predicted		financial literacy	predicted		financial literacy	predicted	
actual	lower	higher	actual	lower	higher	actual	lower	higher
lower	188	28	lower	213	3	lower	152	64
higher	36	185	higher	7	214	higher	68	141
predictors	income: level 2 advertisment medium: Internet reserve: none		predictors	education (0.18) reserve (0.18) income (0.11)		predictors	education (0.16) age (0.13) income (0.13)	
accuracy	85.4		accuracy	97.7		accuracy	68.9	
sensitivity	87.0		sensitivity	98.6		sensitivity	70.4	
specificity	83.7		specificity	96.8		specificity	67.5	
precision	83.9		precision	96.8		precision	69.1	
F-measure	85.5		F-measure	97.7		F-measure	69.7	

As can be seen, some models achieved a high prediction performance that exceeds the two previously presented simple models. The highest overall accuracy was achieved by the Random Forest model, followed by the LSVM Model. Moreover, both these models have a high value of sensitivity to cases with a lower level of financial literacy. Therefore, if used in practice, we can consider their predictions of financial literacy level very precise. However, both these models are completely useless for interpretation purposes, at least because the software used for their creation presents almost no details about the created models.

All other models achieved similar values of evaluation measures as the first two models of the CHAID tree and Logistic Regression. One surprise is the Neural Network model, which did not achieve as high values of evaluation measures as some other models. If the predictors' importance was available, it is visible that the most important predictors are the same or very similar to those in the first two models.

5. Discussion

This section of the paper aims to highlight important facts and findings related to the survey analysis conducted. Based on the theoretical foundations, we established several hypotheses that were subsequently analysed using selected statistical methods. These statistical analyses utilise several respondents' socioeconomic characteristics, opinions, and experiences. The same characteristics were also used to create predictive models for the financial literacy levels. We employed two types of predictive models as follows. Firstly, we created interpretable "simple" statistical models for predictions as well as for descriptions and, secondly, advanced models for predictions. The key parameters included education, income, gender, advertisement influencing medium, and the age of respondents.

Based on the survey responses, we can conclude that the financial literacy is at an expected level. The previous section provides a relatively detailed description of the respondents' knowledge and experiences in the area of financial literacy, as well as findings related to their shopping behaviour.

The formulated hypotheses and their verification yielded interesting results, both expected and unexpected. Particularly valuable is the use of a sign scheme, which provides deeper insight into the relationship between specific levels of financial literacy and the categories of the variable being analysed concerning it. From hypothesis testing, we can conclude that men are more financially literate than women. Additionally, education has a significant impact on the level of financial literacy, with higher financial literacy being much more likely among university-educated individuals.

Interestingly, we found that secondary education tends to lower financial literacy levels. The use of bank loans generally does not affect financial literacy, except in the case of loans for housing purposes. However, we believe it is crucial to continue analysing this area, particularly in cases where respondents borrow money for investments. Several authors highlight this issue and refer to such situations as "too high financial literacy" (Kadoya et al., 2021; Kuzma et al., 2022).

Although our hypothesis about the dependence between financial literacy and advertising influencing consumer purchasing behaviour was not confirmed, the hypothesis between income and financial literacy already shows a moderately strong dependence. This is an important finding from our point of view and in the field of purchasing behaviour.

Forecasting, or prediction, is a significant prerequisite for further development in any analysed area. From our perspective, forecasting financial literacy levels holds an essential position from a societal standpoint. "Classical" statistical methods, such as the CHAID decision tree and logistic regression, offer highly precise predictions and also provide opportunities for describing the obtained results. Besides these, we created several models

by employing more sophisticated machine learning methods, whose primary advantage lies in their high prediction accuracy of financial literacy levels.

By comparing these two approaches to predicting financial literacy levels, we can conclude that simpler statistical methods exhibit a relatively high level of prediction performance. Furthermore, their main benefit lies in their simplicity, clarity, and straightforward interpretability. For advanced machine learning models, we must acknowledge that their accuracy is sometimes significantly higher. These models have a low error rate, making their predictions highly reliable. For some models, it is possible to interpret the key determinants of financial literacy based on predictor importance. However, it must be admitted that interpreting the relationships between variables in these models is complex, if not nearly impossible. Be that as it may, if used for prediction, these models are highly recommendable.

Moreover, from almost all the model outputs, it is possible to clearly describe the sequence of importance of the explanatory factors of the financial literacy levels, such as education, income, gender, advertising, and age. These variables confirmed their importance in individuals' financial literacy levels. However, from our point of view, they simultaneously influence purchasing behaviour. In the questionnaire survey, respondents mentioned the field of education as the most common problem of low financial literacy, whether from the point of view of duplicative education, uninteresting or boring education, the inappropriate personality of the teacher, or the teacher's lack of interest in teaching or students.

Moreover, our analyses point to the area of secondary education. This is where we see the potential for improvement in the education system. Financial literacy at the secondary school level does not exist as a separate subject. Instead, it is only a part of related subjects. This attitude toward financial education usually results in differences in financial literacy among individual levels and types of schools. Several authors point out that students are often not interested in learning. They also emphasise that duplicate education on the same topic usually does not increase this interest. (Ming & Jais, 2021; Ritschard, 2013) However, we dare to say that financial literacy and financial education are considered essential in everyone's life, and a lack of financial literacy can lead to bad economic decisions (Machine Learning Mastery, 2014).

We also consider the requirements for financial literacy teachers to be crucial. Only a few studies examine the beliefs and attitudes of financial literacy teachers. This was also visible in the respondents' answers, where they indicated the teacher's personality as a frequent reason for obstacles in their financial literacy. According to existing surveys, most undergraduate students consider developing their financial literacy important. However, these surveys typically focus on higher education (Kawamura et al., 2021; Clichici & Moagar-Poladian, 2022; Nemeth et al., 2022).

Our survey also confirms that higher education significantly impacts financial literacy. From our point of view, only a sufficiently motivated, financially literate teacher can positively motivate students and influence their financial literacy level. We suggest that financial literacy education should also use an entertaining format. Games in this area can provide a credible and entertaining way of learning, which can help to increase students' interest in the subject. These games are already capable of simulating various financial situations in practical life.

As such, education has an impact on income levels. According to our analysis, income directly affects financial literacy. The higher the income, the higher the financial literacy. We consider this finding to be important. As income increases, expenses usually also increase. In the survey, we found that the respondents' biggest expenses were purchasing food, running the household, and transport. These three expenditure groups are also consistent

with the net private household expenditure published by the Office for National Statistics in 2023. According to this survey, the lowest expenditure is on post and telecommunications, household accessories, and education. This is a very interesting finding from our point of view and would be worthy of further analysis.

Our research contributes to the state of knowledge by examining financial literacy as both a tool for money management and a determinant of informed purchasing decisions. While existing literature separately analyses financial literacy's impact on savings, investment, and borrowing, fewer studies integrate its role in shaping consumer shopping behaviour. Additionally, employing a dual analytical approach by combining traditional statistical methods with advanced machine learning models offers both explanatory and predictive approaches for financial literacy levels. The models were created using real evidence from the Slovak Republic, contributing to understanding financial literacy in Central Europe, a region often underrepresented in global studies.

Although studying financial literacy is very important, and we consider our research unique in the sense that it connects the level of financial literacy with the purchasing behaviour of the population, it must be admitted that it has several limitations. One of them is the under-representativeness of older age groups within our sample, which is a common challenge in Internet-based surveys, where technology proficiency often correlates with participation rates. This demographic imbalance may introduce a bias, potentially affecting the generalizability of our findings to the entire population. To address this weakness, it is possible to use reweighting of the age groups to responses from underrepresented age groups to align the sample more closely with population demographics. This approach would help ensure that the perspectives of all demographic groups, including older individuals, are more accurately reflected in the results, contributing to more robust and generalizable findings. Besides that, the study relies on self-reported data provided by the respondents themselves about their shopping habits, which may introduce subjective biases to the study results.

Another limitation of this study is that while statistical hypothesis testing has allowed us to identify significant associations between financial literacy and consumer behaviour, these methods, in fact, do not establish causal relationships. Hypothesis testing identifies patterns and correlations within the data, but it does not determine whether higher levels of financial literacy directly cause specific consumer behaviours. Factors such as unmeasured external influences or underlying variables may also contribute to these observed associations. Future research using experimental or longitudinal designs could help to clarify causal pathways, offering a deeper understanding of how financial literacy may shape consumer behaviour over time.

As presented in the paper, various statistical or machine-learning techniques should also be used to predict financial literacy level. We used two statistical methods and six advanced machine-learning techniques to compare the precision and importance of predictors within the models. However, it is essential to distinguish the primary purpose of the prediction models: whether they are intended for descriptive purposes or prediction tasks. Advanced machine learning models are able to capture complex, non-linear relationships among predictors, resulting in high precision and sensitivity of their predictions. However, their black-box nature often limits their utility for interpretation and understanding the underlying mechanisms. In contrast, traditional statistical methods like logistic regression, discriminant analysis, decision trees, etc., provide interpretable outputs, making them useful for our descriptive objectives, which provides an advantage for actionable insights.

However, despite the weaknesses mentioned above, the study makes significant practical, theoretical, and academic contributions. It expands existing knowledge of financial literacy by introducing a predictive approach that not only assesses but also forecasts finan-

cial literacy levels using developed machine learning models. The results provide insights for policymakers and financial educators to create targeted educational programmes that can address key weaknesses identified in individual demographic groups. Moreover, it should assist marketers in understanding financially literate consumers, allowing them to tailor responsible marketing strategies that promote sustainable and informed purchasing decisions. Last but not least, the study offers a methodological framework for integrating statistical and machine learning techniques, which can be a reference for future researchers examining financial literacy.

6. Conclusions

This study investigated the relationship between financial literacy and consumer purchasing behaviour within the Slovak Republic, aiming to reveal and quantify the impact of variouss demographic and financial factors on financial literacy level. Our research sought to determine if variables such as gender, education level, income, and exposure to advertising influence financial literacy and, in turn, consumer behaviour. Using logistic regression and CHAID classification models, we identified significant predictors of financial literacy and examined how these factors interact with consumer choices and financial behaviours. We also created several models using machine learning techniques to compare the prediction performance and the importance of the predictors in the models for financial literacy level.

The analysis confirmed several key findings. Men generally demonstrated higher levels of financial literacy than women, and financial literacy was notably higher among respondents with advanced educational qualifications. Income also emerged as a significant factor, with higher-income individuals exhibiting stronger financial knowledge and a greater capacity to make informed financial decisions. Additionally, while financial literacy did not appear to affect the influence of advertising on purchasing behaviour, it was positively associated with responsible borrowing practices, such as taking out loans specifically for real estate purposes. These findings suggest that financial literacy is essential in fostering more deliberate, goal-oriented consumer behaviours.

The implications of this research extend to both social and managerial domains. Socially, the study highlights the need for targeted financial literacy education across demographic segments, especially for women and lower-income groups, to address financial knowledge disparities. Enhanced financial literacy among these groups could lead to more sustainable purchasing decisions, reduced financial stress, and improved long-term economic stability for individuals and families. From a managerial perspective, companies can use insights from this study to understand consumer financial behaviours better and develop more responsible marketing strategies. Enterprises might consider offering financial literacy tools and resources to foster trust and encourage informed consumer decision-making, especially when promoting products involving credit or long-term financial commitments.

In conclusion, this study underscores the value of financial literacy as a determinant of responsible consumer behaviour and highlights the importance of tailored financial education. Future research might explore longitudinal approaches to assess how financial literacy evolves and continues to shape consumer behaviour over time, providing a more comprehensive understanding of its impact.

Author Contributions: Conceptualisation, E.K. and L.S.; methodology, E.K. and L.S.; software, L.S.; validation, O.P., Z.R. and E.K.; formal analysis, E.K. and O.P.; investigation, O.P.; resources, E.K. and O.P.; data curation, L.S.; writing—original draft preparation, E.K. and L.S.; writing—review and editing, E.K., L.S., O.P. and Z.R.; visualisation, E.K., O.P. and Z.R.; supervision, E.K.; project administration, E.K.; funding acquisition, L.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Slovak Grant Agency for Science (VEGA) under Grant No. 1/0509/24.

Institutional Review Board Statement: The study was conducted according to the ethical standards of the organisation and approved by the Faculty of Operation and Economics of Transport and Communications, University of Zilina (date of approval 12 December 2023).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study. All subjects agreed to participate in the questionnaire survey and to the use and publication of its results.

Data Availability Statement: Data are available from the authors upon reasonable request.

Acknowledgments: This article has benefited from constructive feedback on earlier drafts by the editors, the chief editor, and the anonymous reviewers.

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

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