Journal of Management and Business Education

JMBE

www.journaljmbe.com ISSN: 2605-1044 Published by Academia Europea de Dirección y Economía de la Empresa.
This is an open access article under the CC BY-NC license.

Artificial Intelligence (AI) as a tool for predicting the financial culture of a country

La Inteligencia Artificial (IA) como herramienta de predicción de la cultura financiera de un país

David Borreguero Arias*
https://orcid.org/0009-0009-9587-6833 (ORCID iD)
Rey Juan Carlos University (Spain)

Raúl Gómez-Martínez
https://orcid.org/0000-0003-3575-7970 (ORCID iD)
Rey Juan Carlos University (Spain)

Julio Alard Josemaría
https://orcid.org/0000-0003-1882-7375 (ORCID iD)
ESIC University (Spain)

Camilo Prado-Román
https://orcid.org/0000-0002-1540-0643 (ORCID iD)
Rey Juan Carlos University (Spain)

Borreguero Arias, D.; Gómez-Martínez, R.; Alard Josemaría, J.; & Prado-Román, C. (2024). Artificial Intelligence (AI) as a tool for predicting the financial culture of a country. *Journal of Management and Business Education*, 7(3), 477-491. https://doi.org/10.35564/jmbe.2024.0027
*Corresponding author: david.borreguero@esic.edu
Language: English
Received: 21 Jul 2024 / Accepted: 14 Oct 2024

Funding. The authors received no financial support for the research, authorship, and/or publication of this article.
Ethical Statement. The authors confirm that the data collection for the research was conducted anonymously and that there was no possibility of identifying the participants.
Declaration of conflicting interests. The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.
CRediT author statement. All authors have contributed equally to all parts of the work.

ABSTRACT
Artificial Intelligence (AI) currently presents different applications that allow, through data processing, the possibility of learning, predicting and adopting solutions in different fields of knowledge including the financial field. This research essay aims to analyze the capacity of Artificial Intelligence (AI) and supervised learning to predict the level of financial culture that individuals possess. For this purpose, 11 predictors previously selected for their possible influence on financial culture, are proposed and compared with the target variable (level of financial culture). The results obtained show that each of the 11 individual-level predictors correlate with the level of financial culture that each individual claim to have. In this respect, a general high or very high perception of the target variable is shown. However, considering the accuracy of the reference, the research shows that as the number of predictors is smaller, the accuracy of the reference decreases.

Keywords. Artificial Intelligence (AI), Financial Literacy, Supervised Learning, Machine Learning, Predictive Analysis.

RESUMEN
La Inteligencia Artificial (IA) presenta actualmente diferentes aplicaciones que permiten a través del procesamiento de datos, la posibilidad de aprender, predecir y adoptar soluciones en diferentes campos de conocimiento, entre los que se encuentra el ámbito financiero. Este trabajo de investigación tiene como objetivo analizar la capacidad de la Inteligencia Artificial (IA) y el aprendizaje supervisado para predecir el nivel de cultura financiera que poseen los individuos de un país. Para ello se proponen 11 predictores previamente seleccionados por su posible influencia en la cultura financiera y se comparan con la variable objetivo (nivel de cultura financiera). Los resultados obtenidos ponen de manifiesto que cada uno de los 11 predictores a nivel individual se correlacionan con el nivel de cultura financiera que cada individuo afirma tener. En este sentido se evidencia con carácter general una percepción, alta o muy alta de la variable objetivo. No obstante, atendiendo a la precisión del modelo el trabajo pone en evidencia que a medida que el número de predictores es menor la precisión del modelo disminuye.

Palabras clave. Inteligencia artificial (IA), Cultura Financiera, Aprendizaje Supervisado, Machine Learning, Análisis Predictivo.

INTRODUCTION

The constant changes and rapid evolution of technology in the current context make it necessary to have adequate and constant training in order to make the right decisions at a personal and professional level. The financial field is not exempt from these technological changes that also affect the knowledge and decisions made in this field. For this reason, it is necessary to achieve the specific skills and abilities for making correct decisions at a financial level (Parne, 2021). In this sense, (Domínguez, 2022) states that it is advisable to have a solid financial culture that allows us to correctly manage our money and thus avoid bad financial decisions.

On the other hand, financial culture has become a main player in determining the economic prosperity of individuals. Among the crucial points of knowledge, we can place compound interest, inflation and risk and its diversification. Aspects that, in this type of society where consumption is one of its hallmarks, involve knowing how to implement different purchasing strategies, comparing prices between different products, as well as gathering relevant information about this entire process (Domínguez, 2022).

However, the latest financial literacy report prepared by PISA (2022) establishes a worrying lack of financial culture at a global level. According to this report, Spain, with a score of (473), would be slightly above the average of the countries that participated in it (472), but below the average of the European Union (474) and far from the leading countries such as Japan (536), Korea (527) or Estonia (510). The aforementioned report highlights, among other things, the existence of an educational gap in the economic-financial field given the limited knowledge presented by European society as a whole (European Commission, 2023). This lack of knowledge can lead to a series of negative consequences for individuals such as lack of financial planning, inability to generate enough savings in emergency situations, lack of knowledge of the risks when investing, etc.

Nowadays advances made in technology, allow tools such as Artificial Intelligence (AI) to contribute to predicting and improving this financial culture. This is because, thanks to automatic algorithms or Machine Learning, Artificial Intelligence (AI) can provide an internal perception of financial behaviors, in such a way that it contributes to changing the patterns that citizens have preconceived for a better understanding and comprehension of the finance world.

Artificial Intelligence (AI) is faster, more flexibly and accurate than traditional econometric techniques (Mullainathan & Spiess, 2017). This is because Machine Learning algorithms identify patterns and correlations between different financial variables by being able to study individuals' spending perspective, their savings habits, their investments, and in this way understand and predict their financial behavior. In other words, it could help make informed financial decisions such as, for example, which shares to buy, when to sell, as well as set alerts about possible risks or market fluctuations (Alonso & Carbó, 2022). On the other hand, Artificial Intelligence (AI) can advise, personalize recommendations, teach unique strategies to improve our financial situation or suggest actions to reduce debt. In addition, through the use of mobile applications or interactive tutorials, it allows us to expand our financial culture, detecting possible fraud and risks in financial fields.

It should also be mentioned that the data provided by Artificial Intelligence (AI) would allow us to understand why a certain financial decision is made and not another, what factors will influence such decisions and how they can be modified to obtain better results. Therefore, the financial information provided could be interpreted more easily by a much broader sector of the population.

For all the reasons stated above, the use of Artificial Intelligence (AI) and predictive analysis represent a step forward in predicting and improving financial culture by providing useful information and, a priori, greater precision and optimization of the results obtained.

THEORICAL FRAMEWORK

Before dwelling into the benefits of Artificial Intelligence (AI) and predictive analytics, we must understand the meaning of both concepts. The concept of the term Artificial Intelligence (AI) dates back to the 1940s. However, it was not until 1956 when the term was coined by computer scientist and mathematician John McCarthy during the Dartmouth Conference. For McCarthy et al. (1955) conceive Artificial Intelligence (AI) as the science and engineering of making intelligent machines, especially intelligent computer programs. More recently, the Financial Stability Board (2017) defines Artificial Intelligence (AI) as the set of theories and algorithms that allow computers to develop tasks that require capabilities of human intelligence and, sometimes, improve them.

On the other hand, the concept of predictive analysis includes the use of algorithms and statistical techniques to carry out quantitative predictions and future trends related to the behavior of individuals in response to specific stimuli or situations. This prediction is made by analyzing a large volume of historical data and information in real time (Espino, 2017), which allows identifying behavioral patterns more quickly and accurately. Therefore, it could be understood that the concepts are complementary, in the sense that talking about predictive analysis becomes more relevant if we refer to time, computational learning or Machine Learning. As a branch of Artificial Intelligence (AI), computational learning is based on the study of a model defined based on data. To do this, they use algorithms or statistical techniques that help them detect significant patterns in the data used (Centeno, 2020).

For example, if a machine is to be programmed to filter spam emails, one possible solution would be to have the machine memorize those emails that the user has previously marked as spam. In this way, when receiving an email, the machine will search the set of emails previously marked as spam and if it finds a match with any of them, it will delete it. If not, it will move it to the user's inbox. However, learning by memorization is incomplete since the machine lacks the capacity to label emails not seen by the user. To overcome this new problem, introducing intuitive learning would be a possibility, that is to say, the machine must be able to move from individual examples provided by the user to a broader generalization. In order to do so, users must scan previous emails considered spam and select those words that they consider likely to appear in these emails. Thus, when a new email arrives, the machine will be able to predict its rating based on the set of words provided by the user and proceed accordingly (Shalev - Shwartz & Ben, 2014). However, intuitive learning sometimes generates a chain of events that reinforce the association of an action with a cause, incorrectly (Skinner, 1948).

If we extrapolate the previous example to the purpose of this article, we could have Artificial Intelligence (AI) memorize historical data on financial behaviors of individuals in a country, such as the investment or savings and spending patterns of individuals in the past. In this way, as Artificial Intelligence (AI) received and memorized new financial data, it would look for similarities with previous behaviors and, if it found matches, it could predict future trends (Cachón Rodríguez, et al, 2019; Gómez Martínez et al, 2024).

However, as we have seen previously, this learning-by-memorization approach is limited, since Artificial Intelligence (AI) is not capable by itself of labelling or interpreting new financial behaviors that it has not seen before. For this reason, it is proposed to introduce intuitive learning. That is, Artificial Intelligence (AI) must be able to generalize from individual examples provided by individuals. For example, individuals could provide data that they consider important related to different financial behaviors and point out factors that they consider especially relevant, such as financial education, mood, trust in the banking system, or the influence of global economic events. Thus, Artificial Intelligence (AI) would be able to predict the financial culture of individuals in a country based on the patterns identified by each individual individually. However, this learning may also have limitations. For example, if Artificial Intelligence (AI) incorrectly associates an increase in investment with a given economic event, it could wrongly predict future financial behavior based on that incorrect association.

Unlike humans, machines lack the common sense to discard these incorrect conclusions, so it is essential to provide them with appropriate learning algorithms to protect these programs from reaching such conclusions. The adequacy of these learning algorithms will depend on the amount of data we have at our disposal, that is, the greater the amount of data, the more appropriate the algorithm used will be (Jordan & Mitchell, 2015).

For all the reasons stated above, the field of computational learning or Machine Learning has branched into several subfields that occupy different types of learning tasks. However, for the purposes of this article, we are going to focus on two of these specifically: supervised and unsupervised learning (Díaz, 2021).

The first one consists of finding the relationship between an input variable and an output variable, that is to say, it is based on telling the algorithm that we are going to use the result we want to obtain for a certain value. To do this, it will be necessary to train the algorithm through many examples so that, whenever the optimal conditions are met, it is able to generate a “reasonable” result even for those test examples that it has not seen before (Rojas, 2020; Sandoval, 2018). In other words, the algorithm is able to generalize its knowledge through observation (Del Barrio, 2022). From a financial point of view, these algorithms are trained using a set of labeled data that contains information on different financial variables and observed results. These learning models are used to predict future trends and results as pointed out by Gimeno and Marqués (2022).

We would like to point out that the model used in this research work is based on supervised learning. This technique, known as Random Forest, uses commonly used computational learning algorithms or Machine Learning to create logical construction diagrams that help us solve the problem at hand (Caruana & Niculescu - Mizil, 2006; Hastie et al., 2009). For Parra (2019), it is an explanatory technique that uses a sequential, iterative and descending division process, and that, based on a dependent variable, forms homogeneous groups specifically defined by combinations of independent variables in which all the cases collected in the sample are included.

As for unsupervised learning, it is based solely on input variables, but without the existence of output variables. Therefore, there is no need to explain to the system what results we want to obtain. The difficulty with this type of algorithm is that they do not have any response examples with which to determine whether this algorithm is acting correctly (Bishop, 2007; Naeem et al., 2023). However, one of the advantages of this type of learning is that the data for training are less expensive to obtain. In the financial field, this type of learning focuses on identifying different patterns and hidden structures in financial data without the need for labels (Irigoin & Morales, 2024). That is why this algorithm can be useful for classifying clients into different groups based on their financial characteristics, offering greater personalization in the service. As mentioned above, the different learning models presented in this work will provide us with a series of evolutionary algorithms that will help us obtain ideal dynamic solutions in a constantly changing society, and often automatically. Both Artificial Intelligence (AI) and Machine Learning will be able to predict the level of financial culture of individuals, make informed short- and long-term financial decisions, as well as reduce the risks that could be associated with them.

RESEARCH METHODOLOGY

The present study focuses on investigating the predictors that influence the level of financial literacy of participants. A survey is used that collects data on 11 predictors previously selected for their theoretical relevance and possible influence on financial literacy.

Prospect Theory (Kahneman & Tversky, 1979) offers us a detailed view of how individuals make decisions in uncertain environments using heuristic shortcuts and biases that may deviate from the basic principles of probability. For this reason, financial literacy is intrinsically linked to these concepts as it describes the knowledge, behaviors, and attitudes that individuals have towards money and finance beyond traditional mathematical formulas (Housel, 2020). This financial literacy is formed over time and is influenced by various predictors, such as education, personal experience, socioeconomic environment, emotions, and demographic factors such as age, gender, and marital status of individuals.

From a demographic perspective, we can see how age, gender, education and marital status play a fundamental role in the financial culture of individuals. The different ages of individuals in the population reveal certain financial experiences and knowledge, which directly influences how they perceive and manage risk. This is why young people tend to be more likely to take financial risks due to a longer time horizon, while people in more advanced stages of their life tend to be more conservative (Hospidio et al., 2021). Likewise, gender differences in financial decision-making can also be influenced by financial culture (Trejos et al., 2021). Another predictor that has a significant impact on financial culture is the level of education of individuals. Adequate education allows individuals to make more informed and safer financial decisions. Furthermore, better educated individuals tend to develop better planning and money management skills. This means that they are able to more easily prepare budgets, plan their finances for the future, and handle any financial unforeseen events that may arise (Comisión Nacional del Mercado de Valores & Ministerio de Asuntos Económicos y Transformación Digital, 2021). Similarly, marital status can also influence financial literacy through emotional impact. According to Damián and Sánchez (2024), people in stable relationships may feel more supported and secure, which can positively influence their financial behavior. However, a study by Aguiar and Zagalaz (2022) showed that married women in Spain have a lower level of financial skills compared to married men. This same study reveals that there are no significant differences between single men and women.

On the other hand, emotions represent a powerful force capable of influencing our daily financial decisions. Certain situations, such as sports results, the weather or the state of mind, make it possible for our economic and financial decisions to vary considerably.

Sports results are another predictor that directly influences the financial culture of individuals, as they affect their mood and, therefore, their financial decisions. For this reason, sports victories have a significant impact on individuals' optimism and willingness to take risks, while defeats can have the opposite effect. Thus, if an investor has just seen his team win, he would be more inclined to make risky investments. Numerous authors analyze the effect of mood changes and their influence on markets in different sports: in football (Ashton et al., 2010; Beremunt et al., 2006; Dermirhan, 2013; Gómez & Prado, 2014;), in the American NFL (Chang et al., 2012), in rugby (Boyle & Walter, 2003) or in cricket (Mishra & Smyth, 2010).

Also, climate changes can affect individuals' moods, which in turn can influence their financial decisions. Thus, on sunny days individuals' moods improve, leading them to make optimal and risky decisions, while rainy days can have a more cautious and conservative effect. Along these lines, Hirshleifer and Shumway (2003) claim that sunny mornings are the ones that really help financial markets. Thus, the annual return achieved in sessions with clear skies in New York was 24.8%, while on rainy days it was 8.7% on average.

Similarly, mood has a direct impact on individuals' financial decisions. That is to say individuals with a positive mood will be pushed to take greater risks in their financial decisions, while individuals whose mood is negative may opt for more conservative decisions. In this regard, Harding and He (2011) conducted an experiment to determine whether investors' moods affected investment decisions. The results of this experiment show how investors induced into a positive mood are increasingly less risk-averse than investors induced into a negative mood. This phenomenon aligns with Prospect Theory (Kahneman & Tversky, 1979a) which suggests that emotions can lead to deviations from economic rationality.

The target variable, the level of financial literacy, is measured on an ordinal scale ranging from 1 to 4, where 1 represents a low level and 4 a high level of financial literacy.

Data collection is carried out through a survey distributed via social media to the university community. Participants answer questions related to the 11 predictors and the target variable, the level of financial literacy. The confidentiality and anonymity of the participants is guaranteed.

The collected data are analyzed using a Machine Learning approach. A Random Forest model is used to explore the relationship between the predictors and the level of financial literacy. This model is particularly suitable for handling multiple predictors and nonlinearities in the data. In addition, a 10-fold cross-validation is performed to assess the predictive capacity of the model and reduce the risk of overfitting.

To assess the relative importance of the predictors in predicting the level of financial literacy, a feature importance analysis is carried out. This analysis allows the most influential predictors to be identified and their impact on the target variable to be better understood. Furthermore, a predictor elimination approach is implemented, where less important predictors are successively eliminated and how the model accuracy varies is evaluated.

Taking this into account, the hypothesis of this study is:

H0: The personal characteristics of individuals are capable of predicting the level of financial literacy.

The statistics to be analyzed are:

- TP Rate (True Positive Rate): It is the proportion of positive cases that were correctly identified by the model as positive. The higher this value is, the better is the model´s ability to correctly identify positive cases.
- FP Rate (False Positive Rate): It is the proportion of negative cases that were incorrectly identified as positive by the model. A low value is desirable, as it indicates that the model makes fewer errors when classifying negative cases as positive.
- Precision: This is the proportion of positive cases correctly identified by the model among all cases identified as positive by the model. The higher this value is, the lower the number of false positive is.
- Recall: This is the proportion of positive cases correctly identified by the model among all positive cases in the dataset. The higher this value is, the lower the number of false negatives is.
- ROC Area (Area under the ROC Curve)**: This is a measure of the discriminatory capacity of the model. The closer this value is to 1, the better is the model´s ability to distinguish between positive and negative classes.
- PRC Area (Area under the Precision – Recall Curve)**: This is another measure of the model´s ability to correctly classify positive instances. Like the area under the ROC curve, a value closer to 1 indicates better model performance.

The metrics used to assess model accuracy are Recall, Rock Area, and PRC Area. The interpretation of this metric can vary depending on the context and the specific problem, but here are some general guidelines:

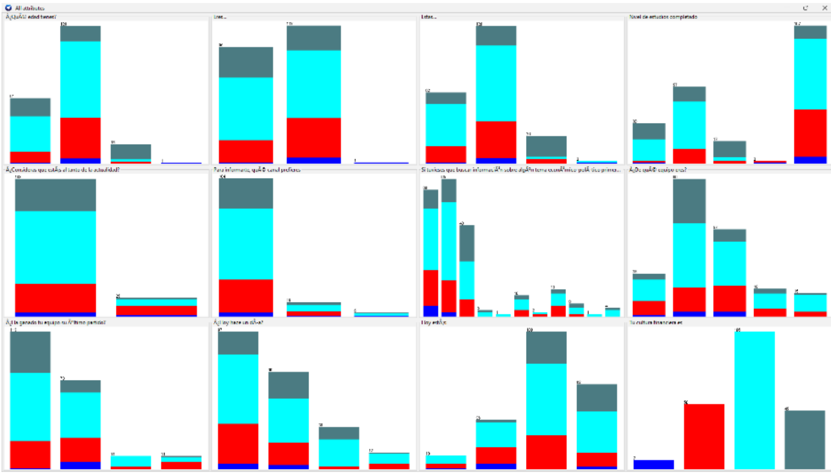
- 0: If the metric is zero, it means that the model has no ability to distinguish between positive and negative classes. Essentially, the model is predicting at random.
- Between 0 and 0.5: This range indicates poor model performance. It means that the accuracy is lower than the true positive rate, which is worse than a random approach.
- Between 0.5 and 0.7: In this range, the model has limited predictive ability but can offer some value. However, the accuracy and true positive rate are still considered to be sub – ideal.
- Between 0.7 and 0.9: This range indicates good model performance. The model is able to provide good accuracy as the true positive rate increases.
- Between 0.9 and 1: An area under the PRC curve above 0.9 is considered excellent. It indicates that the model has high accuracy even at high true positive rates, which is highly desirable in many applications.

We will validate H0 if the recall, ROC area and PRC area metrics are greater than 0.5, although we will classify as efficient models those that show metrics above 0.7.

SURVEY RESULTS

The values obtain in the 208 surveys collected throughout the month of November 2023 are shown in the following figures/tables.

Figure 1. Results of the financial culture survey



Analyzing each of the predictors delimited for the sample and its relationship with the perception of the level of financial culture indicated individually by the respondents, we can draw the following conclusions:

Those under 24 (62%) and those between 25 to 44 (29%) represent (91%) of the sample. These facts cannot surprise us since the survey was carried out through the social networks of the university community where the majority of individuals who pursue university studies are between those age gaps. It is worth to mention that 66% of respondents under 24 claim to have a high or very high financial culture. This trend being similar in the rest of the ranges. However, according to the data provided by the Eurobarometer, although 30% of Spaniards believe they have high financial knowledge, only 13% demonstrate this (European Commission, 2023).

By gender, the results obtained show that 80% of the men surveyed claim to have high or very high financial knowledge, compared to 67% of women, which represents a difference of 13 percentage points (Hospido et al., 2021). On the other hand, those individuals who claim to be married declare that they have a very high perception of their financial knowledge (75%), compared to 14% and 16% of individuals who claim to be single or in a relationship. Similarly, individuals with a higher educational level have a higher perception of their financial knowledge. That is, as individuals become more educated, they have a better perception of their financial skills. For example, (93%) of the individuals surveyed who have completed a postgraduate degree have a high or very high perception of their financial knowledge, compared to 0% with no high school degree.

On the other hand, 88% of the individuals surveyed stated that they are up to date with current events. These individuals' perception of their financial skills is high or very high (76%) compared to those who claim not to be up to date with current events (44%). The preferred means for those surveyed to stay up to date is the Internet, which contrasts with the loss of importance that families and teachers have had when it comes to teaching finances. However, according to the survey data, those individuals who stay informed thanks to written media (newspapers) show a better perception of their financial knowledge (80%) than those who stay informed by digital media (74%) or the radio (63%). In relation to this predictor, the two main sources of information within the written media are El País and El Mundo, representing 52% of the sample. The respondents who consult these written media present a high or very high financial perception.

Furthermore, predictors related to the favourite team or whether or not your team had won its last match were analyzed. It is noticeable that the Real Madrid supporters or FC Barcelona supporters (80%) have a better perception of their financial knowledge than the Atlético de Madrid fans or other teams' supporters (64%, 73% respectively). This same trend is followed by the results of those whose team had won or lost (80%) compared to drawn matches or people who were not football followers. (45%, 65% respectively).

Finally, the predictors related to the weather and to the state of mind show that those who answered on a rainy day (90%) and were in a good mood have a better financial perception than the rest of the individuals in the sample.

Table 1 presents the results of an analysis of a Random Forest classification model to predict the level of financial literacy using different sets of predictors.

The last column of Table 1 indicates which predictors were included in each data set. For example, "All predictors (1-11)" means that all predictors available in the study were used, while the other rows show the results when certain specific predictors were removed. Therefore, these results show how the model performance varies when removing different predictors from the data set. For example, it seems that removing the predictor "mood" slightly improves the accuracy and the area under the ROC curve, while removing "current perception" results in a significant decrease in several model performance metrics.

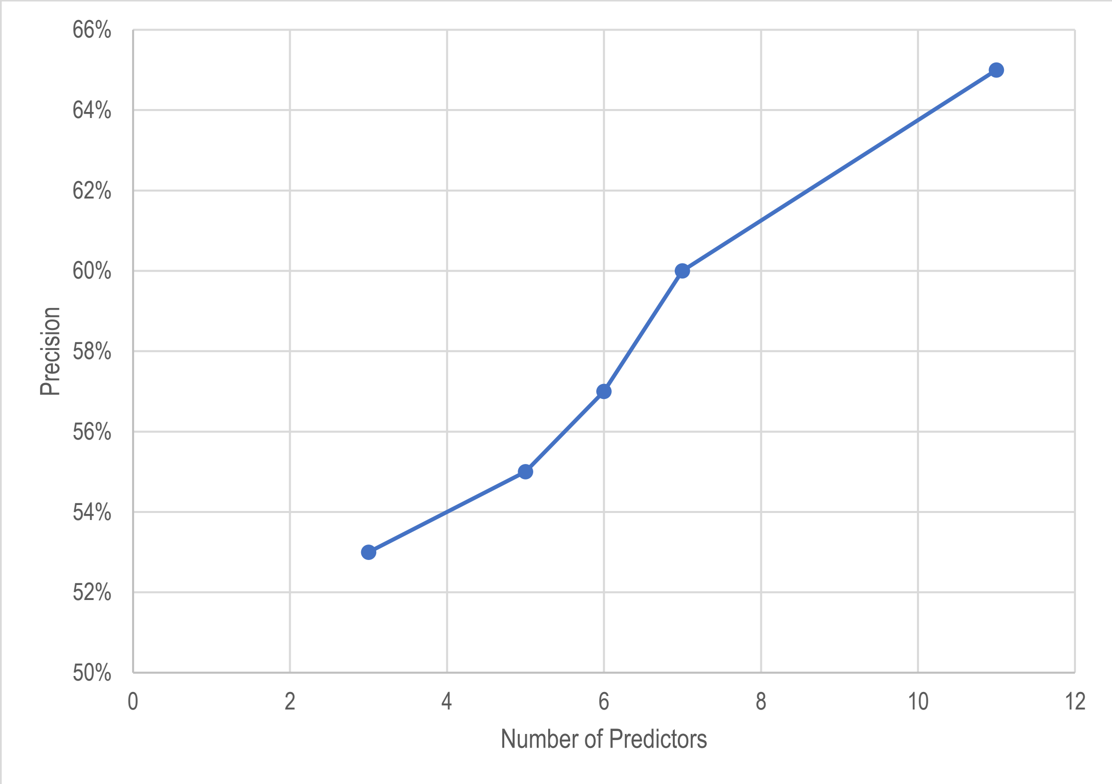
Table 1. Random forest cross – validation results

TP Rate	FP Rate	Precision	Recall	ROC Area	PRC Area	Predictors
0,659	0,241	0,667	0,66	0,78	0,68	All predictors (1-11)
0,601	0,276	0,607	0,60	0,75	0,64	No mood (1-7)
0,567	0,311	0,566	0,57	0,73	0,60	No gender (1; 3-7)
0,553	0,325	0,525	0,55	0,69	0,55	No marital status (1; 4-7)
0,534	0,451	0,432	0,53	0,52	0,39	No current events information (1; 4; 6-7)

The colour scale indicates which statistics are greater than 0.5 (in yellow) and greater than 0.7 (in green), with the rest of the cases being red, which do not validate the hypothesis H0 of this study. It is observed that all the trained models have predictive capacity, except for the PRC Area of the last model trained with only 4 predictors. These results do not allow us to validate the study hypothesis.

We also observe that the precision of the models degrades as we reduce the predictors included in the training of the model, with a success rate of positive reals ranging from 66% when we have all the predictors to a rate of 53% when only 4 variables are predicted (Figure 2).

Figure 2. Evolution of precision



DISCUSSION, CONCLUSIONS AND IMPLICATIONS

Financial literacy is based on a set of economic and financial knowledge that everyone should master in order to solve everyday problems. Concepts such as inflation, interest rates and risk diversification appear more and more frequently in news programmes, current affairs programmes and talk shows, so their knowledge and understanding is essential for a society that is increasingly complex from an economic point of view. However, the latest reviewed reports related to the level of financial literacy both in the world in general and in Spain in particular reveal worrying data. Focusing on Spain, we can see that although the perception of respondents about their level of financial literacy is high, less than half demonstrate that they possess such knowledge (European Commission, 2023; PISA, 2022).

This is where the need arises to find a tool that allows us to predict the level of financial literacy of individuals as effectively and accurately as possible. In the current context, where digitalization is increasingly present in our lives, Artificial Intelligence (AI) has become a key tool when it comes to predicting, analyzing and interpreting information. The exponential growth of data to which individuals and organizations have access, as well as advances in Machine Learning, make this technology a competitive advantage when it comes to predicting patterns and making informed financial decisions.

Therefore, once the focus of this article was contextualized, a research work was carried out that tries to demonstrate the capacity that Artificial Intelligence (AI) has to predict the level of financial culture of the individuals who participated in the sample. To do this, information was collected on 11 predictors previously selected for their possible influence on financial culture and they were compared with the target variable (level of financial culture) measured on an ordinal scale ranging from 1 to 4. This comparison was made using a Random Forest model. In addition, to evaluate the predictive capacity of the model and reduce the risk of overfitting, a 10-partition cross-validation was carried out.

The results obtained in the present study show that, when each of the 11 predictors is analyzed individually and related to the level of financial culture that each individual in the sample claims to have, there is a general perception of the target variable that is high or very high. This contrasts with the reports mentioned throughout the study. However, looking at the accuracy of the model, we can see how the lower the number of predictors, the lower the accuracy of the model.

This opens up new avenues of research, such as the need to test the initial hypothesis, the formulation of more precise predictors based on the results obtained, the consideration of a new study methodology or the use of a larger sample. The review of any of these factors can positively influence the ability to validate the hypothesis.

In short, Artificial Intelligence (AI) will be able to predict, through an algorithm, a variable that will generally be binary, with parameters of total flexibility and without any pre-established relationship between these variables to generate the corresponding results. And this could represent a significant advance with respect to traditional econometric techniques.

REFERENCES

Aguiar, I., y Zagalaz, J. R. (2021). *Women and Financial Literacy in Spain. Does Marital Status Matter?* Journal of Women & Aging, 34(6), 785–799. https://doi.org/10.1080/08952841.2021.1991194

Alonso, A., y Carbó, J.M. (2022). *Inteligencia Artificial y Finanzas: Una alianza Estratégica (Artificial Intelligence and Finance: A Strategic Alliance).* Banco de España. Occasional Paper No. 2222. https://doi.org/10.2139/ssrn.4252710

Ashton, J. K., Gerrard, B., y Hudson, R. (2010). *¿Do National Soccer Results Really Impact on The Stock Market?* Applied Economics, 43(26), 3709–3717. https://doi.org/10.1080/00036841003689762

Berument, H., Ceylan, N. B. y Gozpinar, E. (2006). *Performance Of Soccer on The Stock Market: Evidence from Turkey.* The Social Science Journal, 43(4), 695–699. https://doi.org/10.1016/j.soscij.2006.08.021

Bishop, C. (2007). *Pattern Recognition and Machine Learning.* New York, NY: Springer.

Boyle, G. y Walter, B. (2003). *Reflected Glory and Failure: International Sporting Success and The Stock Market.* Applied Financial Economics, 13, 225–235. https://doi.org/10.1080/09603100210148230

Cachón Rodríguez, G., Gomez Martinez, R., Martinez-Navalon, J.-G., & Prado-Roman, C. (2019). Artificial intelligence to predict loyalty to university. *Journal of Management and Business Education*, 2(1), 17–27. https://doi.org/10.35564/jmbe.2019.0003

Caruana, R., y Niculescu-Mizil, A. (2006). *An Empirical Comparison of Supervised Learning Algorithms.* Association for Computing Machinery, New York, NY, USA, 161–168. https://doi.org/10.1145/1143844.1143865

Centeno, A. (2020). *Big Data. Técnicas de Machine Learning para la Creación de Modelos Predictivos para Empresas.* [Trabajo Fin de Carrera, Universidad Pontificia de Comillas]. Repositorio Comillas. http://hdl.handle.net/11531/45878

Chang, S., Chen, S., Chou, R. K. y Lin, Y. (2012). *Local Sports Sentiment and Returns of Locally Headquartered Stocks: A Firm-Level Analysis.* Journal of Empirical Finance,19(3), 309–318. https://doi.org/10.1016/j.jempfin.2011.12.005

Comisión Nacional del Mercado de Valores y Ministerio de Asuntos Económicos y Transformación Digital. (2021). *Plan de Educación Financiera 2022 – 2025.* Banco de España.

Consejo de Estabilidad Financiera (2017). *Artificial Intelligence and Machine Learning in Financial Services.* P011117.pdf (fsb.org)

Damián, Z. Y., y Sánchez, J. A. (2024). *Educación, Cultura e Inclusión Financiera: Una Revisión Bibliográfica.* Actas del VIII Congreso de Investigación, Desarrollo e Innovación de la Universidad Internacional de Ciencia y Tecnología. https://doi.org/10.47300/actasidi-unicyt-2023-29

Del Barrio, D. (2022). *Aplicación del Aprendizaje Automático en Modelos de Materia Activa.* [Proyecto Fin de Carrera, E.T.S.I. Industriales, Escuela Técnica Superior de Ingenieros Industriales]. Archivo digital UPM. https://oa.upm.es/70193

Demirhan, D. (2013). *Stock Market Reaction to National Sporting Success: Case of Istanbul Stock Exchange.* Pamukkale Journal of Sport Sciences, 4(3), 107–121.

Díaz, J. (2021). *Aprendizaje Automático y Aprendizaje Profundo.* Ingeniare. Revista Chilena de Ingeniería, 29(2), 180-181. https://dx.doi.org/10.4067/S0718-33052021000200180

Domínguez, J.M. (2022). *La Cultura Financiera en la Sociedad Española: Conocimientos, Competencias y Hábitos Financieros.* Panorama Social, n. º 35. https://dialnet.unirioja.es/servlet/articulo?codigo=8683126

European Commission (2023). *Monitoring the Level of Financial Literacy in the EU.* Flash Eurobarometer 525. https://europa.eu/eurobarometer/surveys/detail/2953

Espino, C. (2017*). Análisis Predictivo: Técnicas y Modelos Utilizados y Aplicaciones del Mismo – Herramientas Open Source que Permiten su Uso*. [Trabajo Fin de Grado, Universitat Oberta de Catalunya]. Repositori Institucional O2. http://hdl.handle.net/10609/59565

Gimeno, R., y Marqués, J.M. (2022). *Tradición e Inteligencia Artificial: Oportunidades y Retos del Machine Learning para los Servicios Financieros.* ICE, Revista De Economía, (926). https://doi.org/10.32796/ice.2022.926.7403

Gómez, R. y Prado, C. (2014). *Sentimiento del Inversor, Selecciones Nacionales de Fútbol y su Influencia Sobre Sus Índices Nacionales. Revista Europea de Dirección y Economía de la Empresa*, 23(3), 99-114. https://doi.org/10.1016/j.redee.2014.02.001

Gómez Martínez, R., Medrano-García, M. L., & Aznar-Sánchez, T. (2024). Artificial intelligence to predict university master's program recommendations. *Journal of Management and Business Education*, 7(1), 25–36. https://doi.org/10.35564/jmbe.2024.0002

Harding, N. y He, W. (2011). *Investor Mood and The Determinants of Stock Prices: An Experimental Analysis.* Accounting and Finance, Forthcoming. http://dx.doi.org/10.2139/ssrn.1786344

Hastie, T., Tibshirani, R., y Friedman, J. H. (2009). *The Elements of Statistical Learning: Data Mining, Inference, and Prediction.* New York, NY: Springer.

Hirshleifer, D. y Shumway, T. (2003). *Good day Sunshine: Stock Returns and The Weather.* Journal of Finance, 58, 1009–1032. https://doi.org/10.1111/1540-6261.00556

Hospido, L., Machelett, M., Pidkuyko, M. y Villanueva, E. (2021). *Encuesta de Competencias Financieras (ECF).* Banco de España. https://doi.org/10.53479/34752

Housel, M. (2020). *The Psychology of Money. Timeless Lessons on Wealth, Greed, and Happiness.* Harriman House.

Irigoin, U., y Morales, C. (2024). *El Machine Learning en las Finanzas.* Mount Scopus Journal. https://hcommons.org/deposits/item/hc:68005

Jordan, J.M., y Mitchell, T.M. (2015). *Machine Learning: Trends, Perspectives, and Prospects.* Science 349, 255-260. https://doi.org/10.1126/science.aaa8415

Kahneman, D. y Tversky, A. (1979). *Prospect Theory: An Analysis of Decisions Under Risk.* Econometrica, 47(2), 263–291. https://doi.org/10.2307/1914185

McCarthy, J., Minsky, M., Rochester, N., y Shannon, C.E. (1955). *A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence*. AI Magazine, 27(4), 12 - 14. https://doi.org/10.1609/aimag.v27i4.1904

Mishra, V., y Smyth, R. (2010). *An Examination of The Impact of India's Performance in One-Day Cricket Internationals on The Indian Stock Market.* Pacific-Basin Finance Journal, 18(3), 319–334. https://doi.org/10.1016/j.pacfin.2010.02.005

Mullainathan, S., y Spiess, J. (2017). *Machine Learning: An Applied Econometric Approach.* Journal of Economic Perspectives, 31 (2), 87 – 106. https://doi.org/10.1257/jep.31.2.87

Naeem, S., Ali, A., Anam, S., y Munawar, M. (2023). *An Unsupervised Machine Learning Algorithms: Comprehensive Review.* International Journal of Computing and Digital Systems. http://dx.doi.org/10.12785/ijcds/130172

Rojas, E. M. (2020). *Machine Learning: Análisis de Lenguajes de Programación y Herramientas para Desarrollo.* Revista Ibérica de Sistemas e Tecnologias de Informação, Nº (E28), 586-599.

Sandoval, L. J. (2018). *Algoritmos de Aprendizaje Automático para Análisis y Predicción de Datos.* Revista Tecnológica; no. 11.

Trejos, D. F., Osorio, S. L., Corrales, L. V., y Duque, P. (2021). *Toma de Decisiones Financieras: Perspectivas de Investigación.* Revista de Ingenierías Interfaces, vol. 4, no. 1, pp. 1 – 22. https://dialnet.unirioja.es/servlet/articulo?codigo=8661426

Parne, P. (2021). *Artificial Intelligence & Machine Learning Role in Financial Services.* Advances In Machine Learning. https://doi.org/10.5121/csit.2021.111504

Parra, F. (2019). *Estadística y Machine Learning con R.* Editorial Académica Española. https://bookdown.org/content/2274/bibliografia.html

PISA (2022). *Competencia Financiera. Informe Español.* Instituto Nacional de Evaluación Educativa. https://www.libreria.educacion.gob.es/libro/pisa-2022-competencia-financiera-informe-espanol_184455/

Shalev-Shwartz, S., y Ben-David, S. (2014*). Understanding Machine Learning: From Theory to Algorithms.* Cambridge: Cambridge University Press. https://doi.org/10.1017/CBO9781107298019

Skinner, B.F. (1948). *Superstition in the pigeon.* Journal of Experimental Psychology, 38 (2), 168 – 172. https://doi.org/10.1037/h0055873

ANNEX

Annex Questionnaire

The survey has been distributed through various online forms accessible via Google Forms. The questionnaire consists of the following questions:

- Level of Financial Literacy (Target):
  1. Your financial culture is (1-4)
- Predictors of Personal Characteristics:
  2. How old are you?
     - Under 24 years.
     - From 25 to 44 years
     - From 45 to 65 years
     - Over 65 years
  3. What is your gender?
     - Male
     - Female
     - Other
  4. What is your current marital status?
     - Single

- Married
- Divorced
- In a relationship
- Other

5. Level of education completed
    - Primary
    - Secondary
    - High School – Vocational Training (Intermediate Level)
    - Undergraduate
    - Postgraduate
    - Doctorate
6. Do you consider yourself – up to date with current events?
    - Yes
    - No
7. Which channel do you prefer for information?
    - Digital Media (Internet)
    - Print Media (Newspaper)
    - Radio or TV
8. If you had to look up information on an economic – political topic, you would first consult:
    - El País
    - El Mundo
    - 20 Minutos
    - El Español
    - ABC
    - El Confidencial
    - La Razón
    - Ok Diario
    - El Periódico
    - La Vanguardia
    - El Correo
    - La Voz de Galicia
    - Other
9. Which team do you support?
    - Real Madrid
    - FC Barcelona
    - Atlético de Madrid
    - Other
    - I am not a fan of this sport
10. Did your team win their last match?
    - Yes
    - No
    - Draw
    - I do not follow any team.
11. What is the weather like today?
    - Sunny and bright
    - Cloudy
    - Raining
    - Snowing
12. How are you feeling today? (1-4)

- Very sad
- Sad
- Happy
- Very happy