Operational Research in Engineering Sciences: Theory and Applications
First online
ISSN: 2620-1607
eISSN: 2620-1747
DOI: https://doi.org/10.31181/oresta010422181b

DOES DEMOGRAPHICS INFLUENCE THE RISK BEHAVIOUR OF URBAN INVESTORS? A MACHINE LEARNING MODEL BASED APPROACH

Amrita Bhattacharya [1], Avijan Dutta [1], Samarjit Kar [2]*

[1] Department of Management Studies, National Institute of Technology, West Bengal, India
[2] Department of Mathematics, National Institute of Technology, West Bengal, India

Received: 21 October 2021
Accepted: 11 January 2022
First online: 01 April 2022

Original Scientific Paper

Abstract. *The purpose of this paper is to examine the influence of demographic attributes on investment decision-making. We consider six demographic attributes such as gender, age, education, profession, income and number of dependents for analysing their influence on the investment decision making of the urban investors of the Asansol-Durgapur industrial belt, West Bengal, India and intend to forecast the risk tolerance behaviour. Around 2000 respondents took part in our study. The primary data were analysed using logistic regression and subsequently, we used the linear discriminant analysis method for validation purposes. We notice that gender and profession are the two demographic factors that have the most significant impact on the financial risk tolerance (FRT) of the retail investors, whereas income and number of dependents have negligible impact.*

Keywords: *Retail urban investors; Financial Risk Tolerance (FRT); Investor Behaviour; Demographic Factors; Logistic Regression; Linear Discriminant Analysis*

1. Introduction

One of the evident characteristics of the financial market is volatility which necessitates the importance of assessment of risk vis-à-vis any investment decision to formulate a portfolio for an investor (Gupta et al., 2019a; Biswas et al., 2019; Karmakar et al., 2018). As a result, it is quite imperative to study the pattern of stock price movements, returns, dividends, the performance of the constituting organizations and the influence of the macroeconomic variables, for example, bond rates, interest rates, policy decisions, and global market scenario. A plethora of research has been conducted to describe and predict stock market changes.

* Corresponding author.
amrita.bhattacharya@dnshm.ac.in (A. Bhattacharya), dutta.avijan@nitdgp.ac.in (A. Dutta) Samarjit.kar@maths.nitdgp.ac.in (S. Kar),

However, conventional models work on the efficient market hypothesis (EMH) which assumes that the markets are efficient and stable and investors are rational in decision-making. Investment options depend on the fundamental intention to maximize the return on investment while minimizing the risk (Toma, 2015). However, the ability to withstand a risk level varies from investor to investor according to their behavioural nature (Gupta et al., 2019b) which contradicts the assumption of EMH that all investors are similarly rational.

In this context, a strand of literature related to the behavioural influence of investors on investment decision-making has emerged in the last two decades. This section of growing literature, popularly known as 'Behavioural Finance' (BF) has been a subject matter of research for policymakers and strategists in recent times. The fundamental aim of BF related work is to find out the underlying intention and behavioural pattern and psychological aspects such as cognition, personality, and emotions of the investors during pre-investment, investment and post-investment phases and their reaction to available information (Madition, et al., 2007). BF supplements the historical data based prediction of stock price movements for deriving a robust model to mitigate the disposition bias (Takeda et al., 2013; Jonsson et al., 2017). BF has its genesis in the seminal work of Tversky and Kahneman (1974) who propounded that investors do not behave rationally always and hence, it is important to estimate the perceived risk. Over the years since the work of Tversky and Kahneman (1974), several researchers contributed significantly to developing the gamut of BF (Bayer, Bernheim & Scholz, 2009; Junkus & Berry, 2010; Weber, Weber & Nosic, 2013).

However, demographic factors like gender, race, age, social status, peer group influence, and culture play a significant role in shaping out the psychological bias for the common investors apart from their economic considerations. Therefore, only analysis of the market fluctuations subject to the influence of the company performance, and macroeconomic impact and prediction of future stock prices may not provide the true picture to analyse the investment decision-making process. For understanding the rationale behind the formation of a portfolio, these demographic factors also need to be given due considerations. The level of risk tolerance of a particular investor largely affects the timing to enter the market, selection of stock type, stock holding period, the decision to sell, composition of the portfolio and many other issues. For these reasons, the field of BF has been allured a substantial number of contributions from several researchers (for instance, Barber and Odean, 2013; Lin, 2011). In a recent paper, Alwahaibi (2019) has comprehensively pointed out the relevance of BF as below:

"Investment decisions are usually being complicated by emotional process, mental mistakes and individual personality traits…….. the objective of having an understanding and at the same time predicting the behaviour of an economy is intimately linked to understanding individual attitudes towards risk…… behavioural finance happens to be a contemporary field that tends to merge the theory of behavioural cognitive psychology with conventional economics and finance with a view to giving reasons on why individuals made financial decisions that are irrational."

With this pretext, the present study attempts to discern the impact of the demographic factors on the urban retail investors' behaviours while they make investment decisions, particularly focusing on risk factors. Since every human being is treated as a bundle of emotions that defines a unique character, behavioural finance studies are always paid off. In addition, as we consider demographic factors as influencing variables here, location plays an important role. Here, we focus on urban retail investors residing in the three major cities of West Bengal, namely Kolkata, Asansol and Durgapur. If we look at the cities of choice, it is evident that predominantly, income is assumed to be the most important factor. However, does that mean another influence of demographic factors is insignificant? In this paper, we aim to find the answer to this question. Within our search, we found that the studies on risk behaviours of urban retail investors are rare in nature. Therefore, this paper might be of importance to the research fraternity and policy-makers. The rest of the paper is organized as follows. In section 2, we present the demographic variables used in this study. Section 3 briefly describes the methodology, while in section 4 summarizes the results. Section 5 discusses some of the implications of this study. Finally, section 6 concludes this paper while highlighting some of the future scopes.

2. Related Work

The extant literature shows the relevance and significance of considering demographic factors in explaining and predicting the behaviours of the investors in formulating investment decisions and selection of portfolios and their reaction to the fluctuations in the market conditions. Way back, Chen & Volpe (1998) advocated that age, gender and experience significantly influence the risk-taking behaviours of the investors. Following this work, Schooley & Worden (1999) noted that the level of education has a positive correlation with the risk taking ability of the investors. Mutswenje (2009) observed an interrelation between the constructs of BF theory and the behaviour of the average investors. Shleifer et al. (2010) argued that demographic and socio-economic factors significantly influence the investment decision-making process. Dash (2010) contemplated on the financial planning of the investors and mentioned that age and gender differences the investors in terms of their financial goals and lead to different choices in forming their portfolio at varying risk levels. Lutfi (2011) made an attempt to examine the causal relationship among the demographic factors such as gender, age, marital status, education, income, and the number of a family with the risk taking behaviour and investment pattern of the investors and found significant interrelation. Geetha and Ramesh (2012) further contributed by considering the dependent variables like period of investment, source of information, frequency of investment and degree of analysis in the Indian context and observed that demographic factors influence investment decisions. In tune with this work, Kannadhasan (2015) further extended by considering factor such as occupation. Heena (2015) aimed to ascertain the relationship between demographic features and personality elements and risk behaviour of the investors and observed a significant impact of income. Chavali and Mohan Raj (2016) endeavoured to address the gap between an individual's perceived and actually obtained return vis-à-vis risk tolerance level and presented a notable finding that most often, individual investor overestimates their risk tolerance level under the desire of social recognition. Alquraan et al. (2016) conducted a study at Saudi Stock Market by considering behavioural finance attributes like loss averse, perception of risk and overconfidence in addition to demographic factors to examine their impact on investment decisions.

The authors noted the significant impact of behavioural finance attributes and education on the investment pattern. Lan et al. (2018) carried out a large scale study on over 9000 equity investors in China to investigate and predict the investment decision behaviour on the basis of demographic attributes and observed that demographics is closely associated with investment behaviour. Alwahaibi (2019) attempted to classify the investors on the basis of the influences of several demographic variables on risk taking abilities of the investors and investment patterns. Some other studies in this regard were made by Isidore & Christie (2018), Dangi & Kohli (2018), and Raut & Das (2015) to investigate the impact of behavioural biases; Gautam & Matta (2016) to examine the effect of attitudinal factors on the investment decision-making and Paramashivaiah, Puttaswamy & Ramya (2014) to introspect into the investment behaviour of the women investors.

More recently, Ezekiel and Oshoke (2020) studied the influence of demographic factors on investment behaviour of individual investors residing in Edo State of Nigeria *u*sing the maximum likelihood method of estimation to estimate four multinomial logit equations and showed that educational level, occupation and marital status are the main demographic determinants of individual investor's behaviour. The regression results obtained by Nosita et al (2020) indicated gender and age to be statistically insignificant but marital status, income, and education to be significantly important in determining risk tolerance of about 850 Indonesian individual investors.
In the most recent Indian context, Chaudhary et al (2021) analysed about 500 responses received from the residents of Haryana state in India using multinominal regression and found that gender, residence, and work situation positively affected the investment behaviour of respondents. In another work, Chakkaravarthy et al (2021) used regression analysis to study the financial risk profile of investors living in Chennai city of India and found that the socio demo factors like age, income, occupation have a significant influence on the risk taking capacity of the investors whereas gender does not have any significant relation with the investor's risk profile.

In this paper, we consider six demographic attributes such as gender, age, education, profession, income and number of dependents for analysing their influence on the investment decision making of the investors of urban Kolkata and the Asansol-Durgapur industrial belt, West Bengal, India and intend to forecast the risk tolerance behaviour. To the best of our knowledge there is no report in the literature which has conducted a study on the investor behaviour of this location making our work as the first attempt to understand and forecast investor behaviour of this locality. Table 1 summarises the demographic factors considered by us.

Table 1. Demographic factors and related hypotheses used in this study.

Demographic variable	Relevance	References	Hypothesis
Income (X1)	The level of income decides the affordability and a general notion is that once the basic needs are met, people tend to invest	Dohmen, Falk, Huffman, Sunde, Schupp, and Wagner (2011); Kumar & Goyal (2016)	Higher income investor has more FRT than lower (H1)
Gender (X2)	It is evident from the literature that there are emotional differences among male and	Jianakoplos & Bernasek (2006); Sapienza, Zingales & Maestripieri	Male has more FRT than female (H2)

	female investors because of the influence of gender. Females are susceptible to herding than male while later is more confident than the former.	(2009); Lin (2011); Barber & Odean (2013); Kumar & Goyal (2016)	
Age (X3)	The priorities of life and investment goals get changed with age. It is seen that young aged people are more risk taker and get influenced by peers while the middle and upper middle-aged investors are more stable and take strategic decisions at an affordable risk level	Prosad et al. (2015); Tekçe et al. (2016)	An investor with more education have higher FRT (H3)
Education (X4)	An educated investor is more analytic and informed while they are assessing different investment options and calculative in risk taking.	Deaves et al. (2010); Goo et al. (2010); Ates et al. (2016); Pašalić et al. (2020)	The younger investor has higher FRT than older (H4)
Profession (X5)	Profession often determines the level of income. A salaried person depends on a fixed income and most often prefers to invest in a structured way. It is seen from the literature that optimistic results, overconfidence and the disposition effect rise with the better profession	Grable & Lytton (1999); Prosad et al. (2015)	Salaried individuals have higher FRT than others (H5)
Number of dependents (X6)	Higher the number of dependents, higher is the burden of running the family and lower is the tendency in the investment and risk taking abilities. Moreover, the nature of the financial goals also changes with the number of dependents.	Holt & Laury (2002); Hallahan, Faff and McKenzy (2003)	An increase in the number of dependents decreases FRT(H6)

3. Research Methodology

The objective of this paper is to apply statistical methods to the data collected from the respondents living in Kolkata, Durgapur and Asansolcities in order to develop a simplified model for the prediction of their risk behaviour based on their demographic data. With the six above-mentioned demographic factors as independent variables, the dependent variable that we want to predict from this study is the risk response, i.e., how likely an investor will make an investment through risky instruments, namely mutual funds, shares, stocks, etc. Cook and Whittle (2015), defined an individual’s risk profile as the extent to which an individual prefers certain rewards compared to uncertain yet larger rewards. In general, the individual who favours a low probability outcome is a risk taker and an individual who does not favour a high probability outcome is a risk averse.

In our work, data were collected from 2000 respondents using a structured questionnaire during the period of September to December 2017 from retail investors residing in Kolkata covering diverse demographic factors. The questionnaire was prepared to keep in mind the typical questionnaires used by financial advisors of investment agencies to ensure the appropriateness of the survey. The raw data collected were then subjected to Multi-logistic regression analysis to develop a model to forecast the probability of the response based on six independent demographic variables as above. Age, income and number of dependents were measured on ratio scales whereas gender, education and profession were measured on a nominal scale. The detailed codes used to categorise the responses received against each of the independent variables are listed in Table 2.

Table 2. List of independent variables and their response codes used in the study

Variable	Coding
Income (X1) in INR	> 20,000 = 0; 20,000-50,000=1; 50000-120,000; > 120,000
Gender (X2)	Male = 1; Female = 0
Age (X3)	20 – 40 = 2; 40 - 60 = 1; Above 60 = 0
Number of dependents (X4)	0 - 5 (absolute number)
Education (X5)	Under graduate = 0; Graduate = 1; Post graduate = 2; Above = 3
Profession (X6)	Salaried = 0; Self-employed = 1

FRT of an individual investor was the only dependent variable in the analysis and was classified into two categories: risk-takers were coded as 1 and risk-averse were coded as 0. Respondents were requested to choose the responses that best described their financial investments through risky instruments (such as shares, stocks and mutual funds) in the percentage of their total savings in order to classify them into appropriate. Respondents with more than 30% of total investment in shares, stocks and mutual funds were categorised as Risk takers whereas those with less than 30% investment in shares, stocks and mutual funds were categorised as Non-risk takers.

In this paper, we use a widely used machine learning framework such as Logistics Regression for the following reasons:

i) Logistic regression does not assume a linear relationship between the dependent (risk) and independent variables (demographic factors). The dependent variable must be dichotomous (2 categories) and the independent variables need not be interval, nor normally distributed, nor linearly related, nor of equal variance within each group.

ii) The categories (groups) of the demographic factors must be mutually exclusive and exhaustive; a case can only be in one group and every case must be a member of one of the groups.

iii) Logistic regression determines the impact of multiple independent variables presented simultaneously to predict the membership of one or two dependent variable categories.

For analysis purposes, we use SPSS (version 20) and python tools in this paper.

4. Findings and Discussion

In order to examine whether the data is normally distributed and since the data under consideration was relatively large (2000 samples), we perform the Kolmogorov-Smirnov test using SPSS the results of which are presented in table 3.

Table 3. Results of Kolmogorov-Smirnov Test

Demographic factors		Income	Gender	Age	Dependents	Education	Profession
Normal Parameters	Mean	1.95	1.37	2.13	2.10	2.05	1.86
	Standard Deviation	.893	.483	.694	1.197	.874	.873
Most Extreme Differences	Absolute	.234	.407	.260	.183	.226	.255
	Positive	.234	.407	.260	.183	.226	.255
	Negative	-.159	-.275	-.241	-.166	-.175	-.162
	Kolmogorov Smirmov (Z)	10.454	18.221	11.624	8.205	10.129	11.425
Asymp. Sig. (2 tailed)		.000	.000	.000	.000	.000	.000

In general, if the significance value is less than .05 at 5% confidence level, then the data is said to be normally distributed. Table 3 shows that the significance is .000 for all demographic variables, which confirms the normality test.

Logistic regression is used to test the role of demographic factors as a differentiating factor as this can handle both continuous and categorical variables. The overall model was statistically significant at 5% level. Table 4 compares the observed and predicted category of individuals, the degree of their prediction accuracy and the success of the classification of the sample. The performance of the model was assessed by cross-tabulating the observed response categories with the predicted response categories which are shown in the classification table 4. Here, whenever the predicted probability was greater than the cutoff value of 0.5, the predicted response category was treated as 1. It can be seen in table 4 that the model correctly classified 68.20% of non risk takers and 87.70% of those who are risk taker with an overall prediction of 81.20%.

Table 4. Classification Table Predictor (SPSS)

Observed	Predicted		
	Non-Risk Taker	Risk Taker	Correct percentage (%)
Non-Risk Taker	456	213	68.2
Risk Taker	164	1167	87.7
Overall Percentage			81.2

Table 5 shows the logistic regression coefficients- Wald tests, odds ratio (Exp (B)) for each predictor used in the FRT model. Table 5 has several important elements. The significance of each predictor is explained by Wald statistics which has a chi-square distribution. Wald can be explained through the significance level. If the significance is more than .05 then the hypothesis is rejected. However, in our case, all the variables have a significance level 0, which indicates that all the hypotheses are accepted and that the logistic regression is statistically significant. This means that all the six demographic factors (Income, Gender, Age, Dependent, Education, and Profession) are significant and influences the FRT of the retail investor. The high values of Exp (B) associated with Gender and Profession (12.290 and 11.079, respectively) in table 5 indicate the strong dependence of the investors FRT on these two demographic factors. On the other hand, very small values of Exp (B) associated with income and number of dependents indicate negligible dependence of the investors' FRT on these two demographic factors.

Table 5. Logistic regression parameters of the model for FRT

	B	SE	Wald	Df	Sig.	Exp (B)
Income (X1)	-3.248	0.263	152.882	1	.000	0.039
Gender (X2)	2.509	0.293	73.569	1	.000	12.293
Age (X3)	1.996	0.195	104.757	1	.000	7.357
Dependents (X4)	-0.953	0.175	29.680	1	.000	0.386
Education (X5)	1.760	0.301	34.283	1	.000	5.810
Profession (X6)	2.405	0.214	34.283	1	.000	11.079
Constant	-5.788	0.367	248.428	1	.000	0.003

To test the goodness of fit, Hosmer - Lemeshow test was conducted as this provides useful information about the model. The significance level for chi-square was found to be .000, which indicates acceptance of the null hypothesis which states that there is not much difference between the predicted and the observed values. This result shows that the model is fit with chi-square value at 172.875 of this model at 0.01 significance level. This indicates that the logistic regression is meaningful, in accordance with the dependent variable related to each specified independent variable.

Logistic regression classifier (LRC) and linear discriminant analysis (LDA) are used on the dataset for the purpose of prediction. Some of the important associated hyperparameters for the classifier are reported in Table 6. Each of these hyperparameters is tuned using the class RandomizedSearchCV, provided in the scikit-learn library of Python.

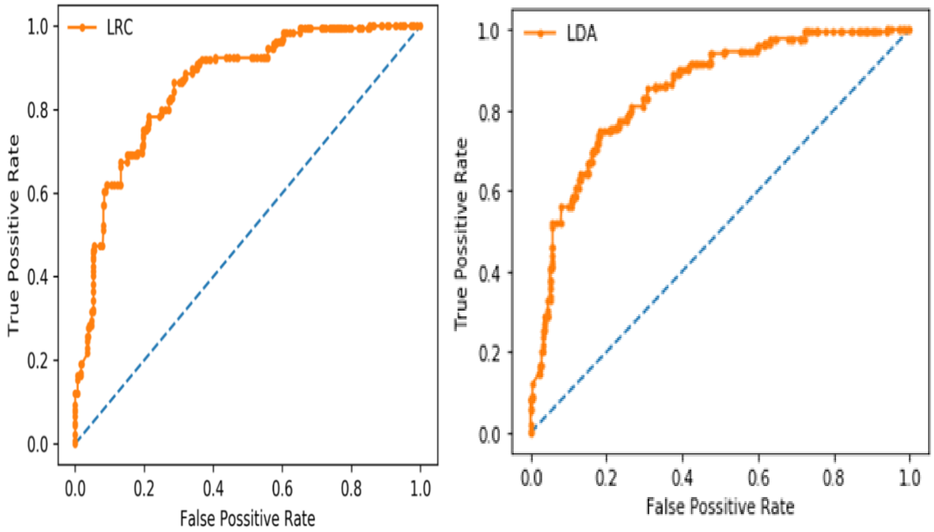
Table 6. Hyperparameters of LRC and LDA

LRC		LDA	
Hyperparameter	Value	Hyperparameter	Value
tol	0.0001	$solver$	'svd'
$solver$	saga	$store\_covariance$	True
max_iter	300	$--$	$--$
$fit\_intercept$	True	$--$	$--$

For the prediction purpose, the dataset is divided into 70:30 percentage ratio to determine the training and testing dataset. Subsequently, LRC and LDA are trained on the training dataset and their predictive capability are measured considering the testing dataset in terms of five performance metrics, accuracy, precision, recall, f1-score and receiver operating characteristic (ROC) score. The accuracy, precision, recall, f1-score and ROC score for LRC are calculated as 0.80, 0.76, 0.77, 0.77 and 0.77, respectively. Whereas, for LDA, the corresponding values of accuracy, precision, recall, f1-score and ROC score are determined as 0.79, 0.76, 0.76, 0.76 and 0.76. Accordingly, we observe that LRC outperforms LDA with respect to each of these five performance metrics. Furthermore, we provide the ROC curve and the confusion matrix for both LRC and LDA in Fig 1 and Fig 2 respectively.

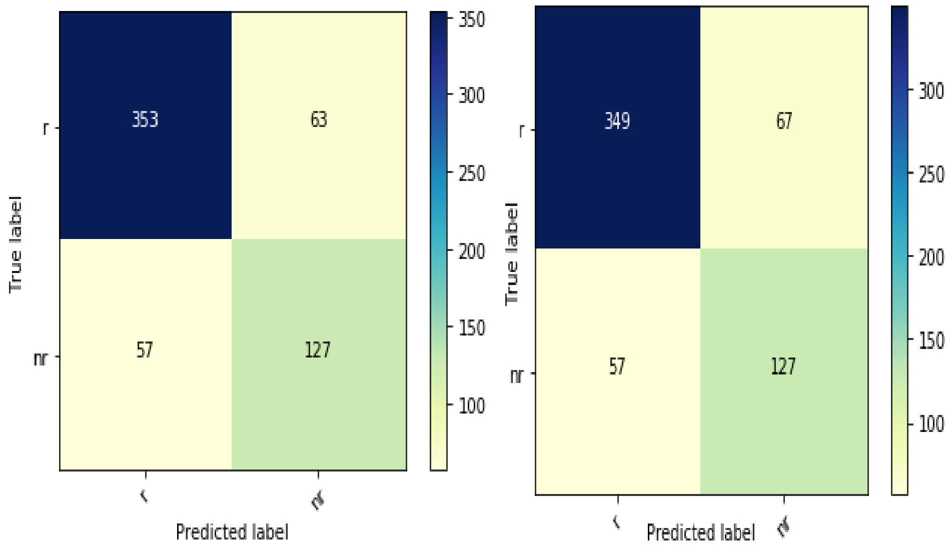
Here, it is to be mentioned that for our dataset, we have conducted experimental trials on our dataset using various classifiers and eventually observed that LDA and LDC generate better ROC scores. Hence, for the comparison purpose of our results, we have selected these two classifiers for our dataset in this study. Furthermore, it is also observed that the dataset which we have considered consists of only 2000 instances (samples) which are relatively small to train the machine learning estimators. This essentially becomes the limitation of our study.

The findings above are largely in accordance with previous literature. For example, one of the key findings of this study is that salaried men have a much higher level of FRT than un-salaried women. This finding is similar to the findings of Croson & Gneezy (2009), Grable & Lytton (1999), and Grable (2000) who also suggested that men are more risk takers than women. Another important finding of this study is that the Profession of the investor (whether self-employed or salaried) has a strong influence on the FRT which is also in good agreement with other studies (Shtudiner, 2019). Also, the finding that the level of FRT decreases with an increase in age in this study is consistent with the study of Kannadhasan (2015).



(a) (b)

Figure 1. ROC curve of (a) LRC and (b) LDA



(a) (b)

Figure 2. Confusion matrix of (a) LRC and (b) LDA

It is generally believed that investors having higher income can afford to take a higher level of risk than their lower income counterparts but our study did not support this strongly. The reason for this is not well understood but could be associated with a number of other factors such as increased level of responsibilities, dependants, etc. We also did not see much dependence of the FRT on the number of dependents in the family and the reason for this could be in the perception of the dependents in the minds of the investor. If the dependents are perceived by an investor as family members irrespective of whether they are also earners, this could easily mislead the data implication.

5. Research Implications

The findings of this study can be useful to the financial investment agencies/advisors in identifying their potential clients living in the cities of Kolkata, Asansol and Durgapur who are likely to make investments through risky instruments such as stocks, shares, etc. based on demographic factors such as gender, profession, age and education. However, for better accuracy of prediction, the study would require the inclusion of more demographic details such as information on the number of earners in the family, ethnic origin, marital status, etc.

6. Conclusion and Future Scope

In this article, we have made an attempt to investigate the influence of six independent demographic factors which may influence the financial decision of the individual retail investors residing in the three major cities of the Indian state of West Bengal. The study specifically focuses to forecast the probability of investment (through risky instruments such as stocks, shares and mutual funds) of a retail investor based on his/her demographic information such as income, gender, age, number of dependents, education and profession for retail investors residing in the cities of Kolkata, Asansol and Durgapur. We use the multi-logistic regression analysis to determine the influence of these factors which revealed that gender and profession are the two demographic factors that have the most significant impact on the FRT of the retail investors whereas income and number of dependents have negligible impact. Also, our multi-logistic regression analysis predicted the number of investors with high FRT (risk takers) with up to 81.2 % accuracy.

The study does suffer from certain limitations. From the perspective of data collection, some investors may refuse to answer certain questions which can cause difficulty in classification and in turn introduce some biases in the data. Another problem regarding demographic variables is the fact that certain groups are overall more risk seeking or risk averse, but this does not necessarily mean that the questioned individual always acts in coherence with this group. Men for example are considered more risk tolerant than women, but there are definitely other women as well who are more risk tolerant than the average man. So the problems of certain exceptions always pertain. According to Jianakoplos&Bernasek (2006), there is even a difference between actual risk tolerance and stated risk tolerance as they found that many men verbally claiming to be more risk tolerant were actually non risk taker when measured by their actual investments. Market volatility and political instability may also have a strong impact on the financial risk decision of an informed retail investor and thus is a limitation of the current research.

It is worth noting that demographics alone may not be sufficient to classify retail investors into different categories since the socio-economic and attitudinal factors may also influence the financial risk decision of an investor (Grable &Joo, 2004). Financial education of the investor is another parameter that may be included in future studies. More sampling from a larger number of respondents with information on additional demographic factors such as marital status, number of earners in the family, financial education, ethnicity, family background, personality, etc., would establish a more generalised model for predicting the retail investors' risk category. Such studies may be extended to retail investors residing in other parts of India and can also be compared with institutional investors based on the same demographic factors.

References

Alquraan, T., Alqisie, A., & Al Shorafa, A. (2016). Do behavioral finance factors influence stock investment decisions of individual investors?(Evidences from Saudi Stock Market). *American international journal of contemporary research*, 6(3), 159-169.

Alwahaibi, S. S. O. (2019). Is demographic information influence risk tolerance/aversion in investment decision? Evidences from literature review. *International Journal of academic research in accounting, finance and management sciences*, 9(1), 111-122.

Ateş, S., Coşkun, A., Şahin, M. A., &Demircan, M. L. (2016). Impact of Financial Literacy on the Behavioral Biases of Individual Stock Investors: Evidence from Borsa Istanbul. Business & Economics Research Journal, 7(3), 1-19.

Barber, B.M., and Odean, T. (2013). The behavior of individual investors, in Constantinides, G.M., Harris, M., and Stulz, R.M. (Eds), Handbook of the Economics of Finance, Elsevier, Amsterdam, 1533-1570.

Bayer, P. J., Bernheim, B. D., &Scholz, J. K. (2009). The effects of financial education in the workplace: Evidence from a survey of employers. Economic Inquiry, 47(4), 605-624. https://doi.org/10.1111/j.1465-7295.2008.00156.x

Biswas, S., Bandyopadhyay, G., Guha, B., & Bhattacharjee, M. (2019). An ensemble approach for portfolio selection in a multi-criteria decision making framework. Decision Making: Applications in Management and Engineering, 2(2), 138-158.

Chakkaravarthy, S. E., Tanty, G., Priyadarshini, E. (2021). Study on the financial risk profile of investors in Chennai. EEO, 20(5), 5161-5167. http://doi.org/10.17051/ilkonline.2021.05.578

Chavali, K., & Mohan Raj, P. (2016). Impact of demographic variables and risk tolerance on investment decisions: An empirical analysis. *International journal of economics and financial issues,* 6(1), 169-175.

Chen, H., & Volpe, R. P. (1998). An analysis of personal financial literacy among college students. Financial services review, 7(2), 107-128.

Choudhary, K., Kamboj, S., Mehta, S. (2021). Financial literacy, investment behaviour and socio-demographic variables: evidence from India, International Journal of Behavioural Accounting and Finance, 6(3), 243 – 261. http://doi.org/10.1504/IJBAF.2021.116167

Cook, W, and Whittle, R. (2015). Do individuals' risk and time preferences predict entrepreneurial choice?,Munich Personal RePEcArchive, Manchester Metropolitan University, MPRA Paper No. 66674.

Croson, R., &Gneezy, U. (2009). Gender differences in preferences. Journal of Economic literature, 47(2), 448-474.

Dangi, M., and Kohli, B. (2018). Role of Behavioral Biases in Investment Decisions: A Factor Analysis, Indian Journal of Finance, 12(3), 121997. 10.17010/ijf/2018/v12i3/121997

Dash, M. K. (2010). Factors influencing investment decision of generations in India: An econometric study. Int. J. Buss. Mgt. Eco. Res, 1(1), 15-26.

Deaves, R., Lüders, E., &Schröder, M. (2010). The dynamics of overconfidence: Evidence from stock market forecasters. Journal of Economic Behavior & Organization, 75(3), 402-412.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., & Wagner, G. G. (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. Journal of the European Economic Association, 9(3), 522-550.

Ezekiel, A., & Oshoke, A. P. (2020). The influence of demographic factors on investment behaviour of individual investors: a case study of Edo State, Nigeria. Economy, *7*(1), 69-77. https://doi.org/10.20448/journal.502.2020.71.69.77

Gautam, S., &Matta, M. (2016). A study of socio-demographic and attitudinal factors on consumer behavior by individual investors in the Indian context. Indian Journal of Finance, 10(7), 48-59.

Geetha, N., & Ramesh, M. (2012). A study on relevance of demographic factors in investment decisions. *Perspectives of Innovations, Economics & Business*, 10 (1), 14-27.

Goo, Y. J., Chen, D. H., Chang, S. H. S., &Yeh, C. F. (2010). A study of the disposition effect for individual investors in the Taiwan stock market. Emerging Markets Finance and Trade, 46(1), 108-119.

Grable, J. E. (2000). Financial risk tolerance and additional factors that affect risk taking in everyday money matters. Journal of business and psychology, 14(4), 625-630.

Grable, J. E., &Joo, S. H. (2004). Environmental and biophysical factors associated with financial risk tolerance. Journal of Financial Counseling and Planning, 15(1), 73-82.

Grable, J., & Lytton, R. H. (1999). Financial risk tolerance revisited: the development of a risk assessment instrument☆. Financial services review, 8(3), 163-181.

Gupta, S., Bandyopadhyay, G., Bhattacharjee, M., & Biswas, S. (2019a). Portfolio selection using DEA-COPRAS at risk–return interface based on NSE (India). International Journal of Innovative Technology and Exploring Engineering (IJITEE), 8(10), 4078-4086.

Gupta, S., Bandyopadhyay, G., Biswas, S., &Upadhyay, A. (2019b). A hybrid machine learning and dynamic nonlinear framework for determination of optimum portfolio structure. In Innovations in Computer Science and Engineering (pp. 437-448). Springer, Singapore.

Hallahan, T., Faff, R., & McKenzie, M. (2003). An exploratory investigation of the relation between risk tolerance scores and demographic characteristics. Journal of multinational financial management, 13(4-5), 483-502.

Heena, T. (2015). Risk tolerance dependent on what? Demographics or personality type: Findings from an empirical research. *Journal of Marketing and Consumer Research*, 6, 48-56

Holt, C. A., and Laury, S. K. (2002).Risk aversion and incentive effects. American Economic Review, 92(5), 1644-1655.

Isidore, R. R., and Christie, P. (2018). Investment Behavior of Secondary Equity Investors : An Examination of the Relationship Among the Biases, Indian Journal of Finance, 12(9), 131556. 10.17010/ijf/2018/v12i9/131556

Jianakoplos, N. A., and Bernasek, A. (1998). Are women more risk averse?. Economic Inquiry, 36(4), 620-630.

Junkus, J. C., and Berry, T. C. (2010). The demographic profile of socially responsible investors, Managerial Finance, 36(6), 474-481.

Jonsson, S., Soderberg, I.L., and Wilhelmsson, M. (2017). An investigation of the impact of financial literacy, risk attitude, and saving motives on the attenuation of mutual fund investors' disposition bias. Managerial Finance, 43(3), 282-298.

Kannadhasan, M. (2015). Retail investors' financial risk tolerance and their risk-taking behavior: The role of demographics as differentiating and classifying factors, IIMB Management Review, 27, 175–184.

Karmakar, P., Dutta, P., & Biswas, S. (2018). Assessment of mutual fund performance using distance based multi-criteria decision making techniques-An Indian perspective. Research Bulletin, 44(1), 17-38.

Kumar, S., and Goyal, N. (2016). Evidence on rationality and behavioural biases in investment decision making. Qualitative Research in Financial Markets, 8(4), 270-287.

Lan, Q., Xiong, Q., He, L., & Ma, C. (2018). Individual investment decision behaviors based on demographic characteristics: Case from China. *PloS one*, 13(8), e0201916.

Lin, H. W. (2011). Elucidating rational investment decisions and behavioral biases: Evidence from the Taiwanese stock market. African Journal of Business Management, 5(5), 1630-1641.

Lutfi, L. (2011). The relationship between demographic factors and investment decision in Surabaya. Journal of Economics, Business, & Accountancy Ventura, 13(3), 213-224.

Madition, D. I., Sevic, Z., &Theriou, N. G. (2007). Investors' behavior in the Athens stock exchange. Studies in Economics and Finance, 24(1), 32- 50.

Mutswenje, V. S. (2009). A survey of the factors influencing investment decisions: the case of individual investors at the NSE (Doctoral dissertation, University of Nairobi).

Nosita, F., Pirzada, K., Lestari, T., Cahyono, R. (2020). Impact of demographic factors on risk tolerance. Journal of Security and Sutainability Issues, 9(4), 1327-1336. http://doi.org/10.9770/jssi.2020.9.4(18).

Paramashivaiah, P. Puttaswamy and Ramya, S. K,(2014), Changing Risk Perception of Women Investors: An Empirical Study. Indian Journal of Finance, 8(6), 22-33.

Pašalić, S., Mastilo, Z., Đurić, A., & Marković, D. (2020). Demographic Trends and the Educational System of the Republic of Srpska. Economics, 8(1), 93-113.

Prosad, J. M., Kapoor, S., &Sengupta, J. (2015). Behavioral biases of Indian investors: a survey of Delhi-NCR region. Qualitative Research in Financial Markets, 7(3), 230-263.

Raut, R. K., and Das, N. (2015). Behavioral Prospects of Individual Investor Decision Making Process: A Review, Indian Journal of Finance, 9(4), 71457. 10.17010/ijf/2015/v9i4/71457

Sapienza, P. Zingales, L. and Maestripieri, D. (2009). Gender differences in financial risk aversion and career choices are affected by testosterone, Proceedings of the National Academy of Science (USA), 106(36), 15268–15273.

Schindler, M. (2010). Rumors in Financial Markets: Insights into Behavioral Finance. West Sussex, UK: John Wiley & Sons Ltd.

Schooley, D. K., & Worden, D. D. (1999). Investors' asset allocations versus life-cycle funds. Financial Analysts Journal, 55(5), 37-43.

Shtudiner, Z. (2019). Risk Tolerance, Time Preference and Financial Decision-Making: Differences between Self-employed People and Employees, http://dx.doi.org/10.2139/ssrn.3269877.

Takeda, K., Takemura, T., and Kozu, T. (2013). Investment literacy and individual investor biases: survey evidence in the Japanese stock market. Review of Socionetwork Strategies, 7(1), 31-42.

Tekçe, B., Yılmaz, N., &Bildik, R. (2016). What factors affect behavioral biases? Evidence from Turkish individual stock investors. Research in International Business and Finance, 37, 515-526.

Thaler, R. H. (2005). Advances in Behavior Finence (Vol. 2). USA: Princeton university press.

Toma, M. (2015). Behavioral biases of the investment decisions of Romanian investors on the Bucharest Stock Exchange. Procedia Economics and Finance, 32, 200-207.

Tversky, A., &Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. science, 185(4157), 1124-1131.

Undirwade, A., & Das, S. (2021), Image Anonymization Using Deep Convolutional Generative Adversarial Network (Chapter 17), Machine Learning Algorithms and Applications (Srinivas, M., Sucharitha, G., Matta, A., Chatterjee, P. (Editors)), Wiley. https://doi.org/10.1002/9781119769262.ch17

Weber, M., Weber, E. U., & Nosić, A. (2013). Who takes risks when and why: Determinants of changes in investor risk taking. Review of Finance, 17(3), 847-883.