International Journal of Accounting and Economics Studies, 12 (8) (2025) 713-719

International Journal of Accounting and Economics Studies

Website: www.sciencepubco.com/index.php/IJAES
https://doi.org/10.14419/y3rdm113
Research paper

Modeling Risk Perception Through Investment Attributes: A CHAID-Based Analysis

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Received: November 17, 2025, Accepted: December 10, 2025, Published: December 21, 2025

Abstract

Individuals seek higher returns with minimum risk. Risk-taking ability is influenced by various factors, including demographics, upbringing, and culture; however, many behavioral factors are challenging to understand and quantify. In contrast, observable characteristics such as the mode of investment are comparatively easier to capture, and individuals can respond to such questions more accurately. The present study aims to link these observable characteristics, namely annual family investment, major earning source, preferred investment period, investment frequency, years of investment experience, and mode of investment, with the risk-taking ability of individual investors using the CHAID (Chi-square automatic interaction detection) tool.

Keywords: *Risk-Taking Ability; Risk Perception; Investor Profile; Investment Attributes; Behavioral Finance; CHAID Decision Tree.*

1. Introduction

Investors invest their money with the primary motive of capital gains. The economic environment of any country has a major effect on the businesses operating in that country and is affected by various other factors. In such risky conditions of a dynamic economic environment, the choices an investor may make or their reaction to a particular market condition are difficult to comprehend (Arrow, 1951). Investors are considered rational decision makers, and information is considered the basic necessity for making rational choices (Ricciardi, 2008). The changing environment thus presents risks for investors. Risk is the probability of incurring losses and can be understood as a 'mental representation of threats' (Renn, 1998).

Risk perception is affected by various factors, including demographics like gender, age, attitude, and emotions, cognitive biases, and heuristics (Saivasan and Lokhande, 2022). Investor personality and behavior are also seen as important factors that influence risk perception (Sachse et al., 2012; Dickason and Ferreira, 2018). Although actual and perceived risk differ, perceived risk holds greater significance in the decision-making process than actual risk (Ricciardi, 2008).

Conventionally, it was believed that stock prices in the market are self-correcting, incorporate all available information, and represent the true value of the firm. This theory was known as the “Efficient Market Hypothesis” (Fama, 1970). Various economic theories assume rationality. However, this hypothesis fails to explain real-world cases, as rationality is affected by market information, socio-cultural factors, national and global economic environments, and financial knowledge (Arrow, 1986). Another theory, Prospect Theory, established the importance of risk aversion in uncertain outcomes (Kahneman and Tversky, 1979). This theory marked the emergence of behavioral finance. Other research showed the presence of behavioral anomalies amongst investors that included overreaction, irrationality, and loss aversion (Bondt and Thaler, 1985).

2. Review of Literature

2.1. Theoretical foundations

A plethora of research has collectively contributed to a nuanced understanding of investment decision-making under risk. The Bounded Rationality Theory posits that investors’ rationality is limited by their information access and cognitive abilities (Simon, 1972). Investors thus cannot process or evaluate all available information and rely on simplified decision-making strategies.

A series of experiments shows that providing proper information and cognitive interventions can improve risk perception (Weber and Milliman, 1997). This aligns with the Risk Homeostasis Theory, where investors continuously monitor and adjust behaviors to maintain a personal risk level, influenced by social, cultural, and psychological factors (Wilde, 1998). This explains variability in risk attitudes.

The Security-Potential/Aspiration Theory offers a complementary view: investors balance logic with psychological criteria during decisions (Lopes and Oden, 1999). Similarly, the Behavioral Portfolio Theory emphasizes the role of emotions, mental accounting, and value perception in portfolio decisions (Shefrin & Statman, 2000).
Additionally, the Dual-System Theory posits that investment decision-making involves two systems: an intuitive, emotion-driven system shaped by past experiences, and a deliberate, analytical system that relies on adequate information and time to analyze it (Samson and Voyer, 2014).

2.2. Behavioral determinants of risk tolerance

Demographics interact with biases to shape risk attitudes. The influence of socio-demographic factors on investment decision-making has been studied extensively. Research shows gender-specific traits develop and influence behavior (Mathanika et al., 2018). Studies explore how factors such as age, gender, and income shape risk perception (Savage, 1992).
Grable (2000) demonstrated that demographic characteristics, individual attitudes, and socio-economic status interact in complex ways to affect financial risk tolerance. Booth and Nolen (2012) found that men are more likely to choose riskier options when higher returns are evident, highlighting gender's role. However, gender effects vary by context (Olsen, 2014).
Psychological biases amplify these effects. Olsen (2014) found strong correlations between perceived risk and factors such as downside potential, lower returns than target, domain expertise, and loss control. Weber and Milliman (1997) emphasized that risk preference varies with contextual changes and information availability, underscoring timely information.
Overconfidence and representativeness skew decisions among younger, single males (Kubilay & Bayrakdaroğlu, 2016). Lazanyi et al. (2017) reinforced gender and age's roles in risk attitudes. Singh and Bhattacharjee (2019) identified investment education, familiarity bias, market expertise, and financial literacy as key determinants in India. Synthesis: Personal traits dominate but are hard to measure objectively.

2.3. Investment attributes in risk perception

Observable behaviors offer practical alternatives to psychological measures. Despite such research, observable investment behaviors, including annual investment size, source of earnings, preferred investment horizon, frequency of investment, and mode of investment, have received limited empirical attention as determinants of risk-taking behavior.
Some studies have attempted to fill this gap. For instance, Corter and Chen (2006) showed that more experienced investors hold riskier portfolios aligned with their risk attitudes, suggesting that experience significantly shapes risk perception. Similarly, Klos, Weber, and Weber (2005) found that investment frequency affects how investors perceive risk; individuals who invest more frequently may perceive lower risk due to repeated exposure and a reduced probability of perceived losses over time. These behavioral indicators offer useful segmentation cues for investment advisors and financial planners.
Interactions among attributes (frequency, horizon, and mode) remain underexplored empirically.

2.4. Methodological gaps and CHAID justification

While many studies have explored how demographic and psychological factors affect investors' risk perception, there is limited research on observable investment behaviors like how often people invest, how long they invest, and how they invest, and how these relate to risk perception using robust predictive models. Most existing studies used traditional statistical tools like regression or correlation analysis, which often assume linear relationships and treat variables in isolation. These methods may not sufficiently capture the complex, interactive nature of risk-related behavior in real-world investment decisions.
Linear models miss non-linear interactions evident in real decisions (e.g., experience + frequency jointly predicting risk).
To address these limitations, the present study employs CHAID (Chi-square Automatic Interaction Detection), a classification tree technique that allows for non-linear, multi-way splits in the data. Unlike regression, CHAID can more effectively handle categorical variables and is better suited for identifying meaningful subgroups of investors based on combinations of investment attributes. Prior findings justify CHAID: complex interactions in attributes (Corter & Chen, 2006) demand tree-based methods for practitioner-interpretable results, filling the methodological void in behavioral finance segmentation.

3. Objective of The Study

The objective of this study is to analyze the relationship between investment characteristics and risk perception using CHAID to identify patterns in risk-taking behavior.

4. Research methodology

4.1. Nature of the study

The study is descriptive in nature. It examines how preferred investment period, investment frequency, investment experience, and mode of investment predict risk-taking capacity.

4.2. Sample

Primary data was collected using a structured questionnaire from investors in Indore. The questionnaire captured demographics, investor profile (annual family investment, major earning source, preferred investment period, investment frequency, investment experience, mode of investment), and risk-taking capacity via 5-point Likert scale items (1=Strongly Disagree, 5=Strongly Agree) (Singh and Bhattacharjee, 2019). Risk-taking capacity was computed by aggregating responses to multiple Likert items assessing willingness to accept investment risk. Items demonstrated excellent reliability (Cronbach's $\alpha = 0.979$). Total scores were dichotomized into high-risk (above median) vs. low-risk (below median) categories for CHAID analysis. Data was analyzed using SPSS 20.0.

4.3. Data collection

Using convenience sampling, 550 questionnaires were distributed; 507 returned (92.4% response rate); 488 were usable after excluding incomplete responses (19.4% rejection rate).

4.4. Statistical techniques

Questionnaire reliability: Cronbach's α = 0.979 (excellent).
Main analysis: CHAID examined the joint effects of investment attributes (annual family investment, major earning source, preferred investment period, investment frequency, investment experience, mode of investment) on risk-taking capacity. The model achieved 67.8% classification accuracy. Misclassifications primarily occurred among moderate-risk investors; future studies could incorporate behavioral biases or financial literacy measures.

5. Data analysis

5.1. Reliability test

To test the reliability of the data, Cronbach's alpha was used. As can be seen from the table, the value obtained is 0.979, which is greater than 0.7, and thus the questionnaire presents a reliable scale to measure the variables.

Table 1: Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.979	.979	37

Source: Author creation.

5.2. Effect of investor profile

Investor profile included annual family investment, major earning source, preferred investment period, investment frequency, number of years you have been investing from and mode of investment. CHAID was applied to study their effect on risk risk-taking capacity of an individual.
The independent variable used was annual family investment, major earning source, preferred investment period, investment frequency, number of years you are investing from and mode of investment, which were all categorical. Annual family investment was divided into 3 groups, i.e., up to 1 lakh, 1-3 lakhs, and above 3 lakhs. Major earning source was categorized into salary, business profits, return from investment, and rental income. The investment period was divided into up to 1 year, 1-3 years, 3-5 years, and above 5 years. Investment frequency was divided into weekly, monthly, quarterly, half-yearly, and yearly. Number of years you have been investing from had the options as since last 1 year, since last 2 years, and more than 2 years. The mode of investment was grouped into lump sum and SIP.
Risk risk-taking capacity of an individual was judged using statements on a Likert scale. The combined score of statements was then used to categorize the individuals as low-risk-taking or high-risk-taking individuals.

Table 2: Model Summary

Model Summary		
Specifications	Growing Method	CHAID
	Dependent Variable	Risk
	Independent Variables	Annual Family investment, Major earning source, From how many years are you investing, Investment frequency, Preferred Investment Period, Mode of Investment
	Validation	None
	Maximum Tree Depth	3
	Minimum Cases in Parent Node	100
	Minimum Cases in Child Node	50
Results	Independent Variables Included	Preferred Investment Period, Investment frequency, From how many years are you investing, Mode of Investment
	Number of Nodes	10
	Number of Terminal Nodes	6
	Depth	3

Source: Author creation.

Table 2 presents the results of the model. The model has a tree depth of 3, 10 nodes, and 6 terminal nodes. The input of the model had 6 independent variables, and the output of the model included 4 of them, i.e., preferred investment period, investment frequency, how many years are you investing, and mode of investment.

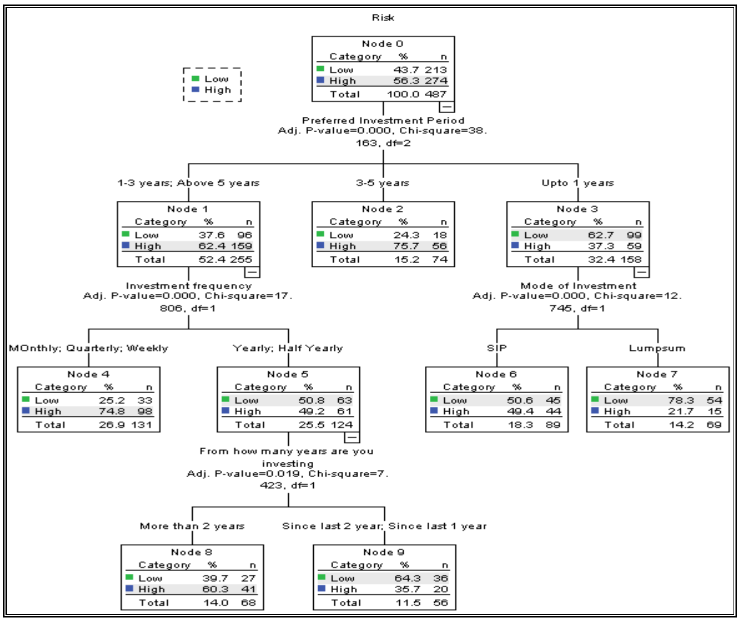

Fig 1: CHAID Decision Tree for Risk-Taking Capacity with Preferred Investment Period, Investment Frequency, Investment Experience, And Mode of Investment as Predictors.

Source: Author's Computation.

The resulting tree (presented in Fig. 1) has 10 nodes, where 6 are terminal nodes. A node in a decision tree basically represents a group or subgroup, while a terminal node represents a node that cannot be further classified on the basis of any other variable under study.

Node 0 is known as the parent node, which shows that the low risk-taking capacity of individuals is 43.7% while 56.3 % are high risk-taking individuals. Such a division is good to move further, as the number of individuals having low risk-taking capacity and those having high risk-taking capacity are almost equivalent in number.

Studies dependent variable, i.e. risks risk-taking capacity of individuals, thus serves as the parent node, and further division in the tree is on the basis of preferred investment period ($\chi^2 = 38.163$, df = 2, p-value = 0.000). The p-value is 0.000, which is less than 0.05 and thus is significant.

The first group or node 1 is of individuals whose preferred investment period is 1-3 years and above 5 years. Further analysis shows that 37.6% of such individuals are low-risk-taking individuals, while 62.4% are high-risk-taking. Node 2 is of individuals whose preferred investment period is 3-5 years. Further analysis shows that 24.3% of such individuals are low-risk-taking individuals, while 75.7% are high-risk-taking. Node 3 is of individuals whose preferred investment period is up to 1 year. Further analysis shows that 62.7% of such individuals are low-risk-taking individuals, while 37.3% are high-risk-taking.

The branch of node 1, which represents the preferred investment period, is 1-3 years and above 5 years is divided into 2 nodes ($\chi^2 = 17.806$, df = 1, p-value = 0.000). The p-value is 0.000, which is less than 0.05 and thus is significant. The node is divided into 2 nodes. Node 4 represents the individuals whose investment frequency is weekly, monthly, and quarterly. Further analysis shows that 25.2% of such individuals are low-risk-taking individuals, while 74.8% are high-risk-taking. Node 5 represents the individuals whose investment frequency is half-yearly and yearly. Further analysis shows that 50.8% of such individuals are low-risk-taking individuals, while 49.2% are high-risk-taking.

The branch of node 3, which represents the preferred investment period, is up to 1 year, is divided into 2 nodes ($\chi^2 = 12.745$, df = 1, p-value = 0.000). The p-value is 0.000, which is less than 0.05 and thus is significant. The node is divided into 2 nodes. Node 6 represents the individuals whose mode of investment is SIP. Further analysis shows that 50.6% of such individuals are low-risk-taking individuals, while 49.4% are high-risk-taking. Node 7 represents the individuals whose mode of investment is a lump sum. Further analysis shows that 78.3% of such individuals are low-risk-taking individuals, while 21.7% are high-risk-taking.

The branch of node 5, which represents investment frequency as half-yearly and yearly, is divided into 2 nodes ($\chi^2 = 7.423$, df = 1, p-value = 0.019). The p-value is 0.019, which is less than 0.05 and thus is significant. The node is divided into 2 nodes. Node 8 represents the individuals who have been investing for more than 2 years. Further analysis shows that 39.7% of such individuals are low-risk-taking individuals, while 60.3% are high-risk-taking. Node 9 represents the individuals who have been investing for the last 2 years and for the last 1 year. Further analysis shows that 64.3% of such individuals are low-risk-taking individuals, while 35.7% are high-risk-taking.

5.2.1. Accuracy assessment of the model

The performance of the model needs to be assessed to establish its accuracy. Tables 3 and 4 give basic information on the accuracy and robustness of the model.

Table 3: Risk

Risk	
Estimate	Std. Error
.322	.021
Growing Method: CHAID	
Dependent Variable: Risk	

Source: Author Creation.

Table 3 shows prediction risk expressed as a proportion of incorrectly categorised observations. The findings indicate that if the preferred investment period, investment frequency, from how many years you are investing, mode of investment of an individual are known, the likelihood that the individual would be incorrectly labelled in terms of risk bearing capacity (based on the complete sample) is 32.2%.

Table 4: Classification

Classification			
Observed	Predicted		
	Low	High	Percent Correct
Low	135	78	63.4%
High	79	195	71.2%
Overall Percentage	43.9%	56.1%	67.8%
Growing Method: CHAID			
Dependent Variable: Risk			

Source: Author Creation.

Table 4 presents a classification matrix that categorizes the individuals as high risk takers and low risk takers according to the model (predicted) and also lists the actual classification according to the data collected (observed). Overall accuracy of the model is 67.8% (135+195=288 individuals were classified accurately out of 488 responses collected).

6. Discussions

The purpose of this study was to use CHAID to identify investor groups based on investment profile variables (annual family investment, major earning source, investment experience, investment frequency, preferred investment period, and mode of investment) and to examine how these relate to risk-taking ability. The model shows that preferred investment period, investment frequency, investment experience, and mode of investment significantly influence risk-taking ability. Behavioral factors, in general, impact risk-carrying ability, although they are difficult to quantify. Understanding more complex behavioral features, such as decision-making style and risk preferences, requires a deeper assessment of personality traits, attitudes, habits, and perception-building processes. These dimensions are important for determining risk-bearing ability but are difficult and costly to measure in routine advisory practice. These criteria are critical in establishing an individual's risk-bearing ability, but they may necessitate more work to be appropriately assessed.

The information used in this paper to assess the risk-bearing capacity of an individual includes basic investment-related information such as mode of investment, investment experience, and preferred investment period. This information can be requested and evaluated during the initial meeting. It provides useful insights for portfolio managers and investment advisors when assessing an individual's risk-bearing capability and recommending products that match their needs.

Table 5: Conclusion of CHAID Model

Preferred Investment Period	Mode of Investment	Investment Frequency	Time from when individuals are investing	Risk-bearing ability of maximum individuals
3-5 years				High risk takers (75.7%)
upto 1 year	SIP			High-risk takers and low-risk takers are Equal.
	Lumpsum			Low risk Takers (78.3%)
1-3 years or above 5 years		weekly, monthly, quarterly		High risk takers (74.8%)
		half-yearly and yearly	more than 2 years	High risk takers (60.3%)
			for the last 1 year and for 2 years	Low risk Takers (64.3%)

Source: Author Creation.

To discuss, understand, and interpret the meaning of the CHAID tree, the terminal nodes are studied to understand the behaviour of the individuals. The analysis shows that a higher percentage of investors who have a preferred investment period of 3-5 years (Node 2, high risk-taking ability: 75.7%); a preferred investment period of 1-3 years or above 5 years and an investment frequency of weekly, monthly, or quarterly (Node 4, high risk-taking ability: 74.8%); and a preferred investment period of 1-3 years or above 5 years, an investment frequency of half-yearly or yearly, and investment experience of more than 2 years (Node 8, high risk-taking ability: 60.3%) are high-risk takers. This can be understood as individuals investing for a longer period, recognizing that market changes are inevitable, but that in the long term, the market tends to grow. These patterns are consistent with Prospect Theory, which suggests that investors with a longer investment horizon are more willing to tolerate short-term losses in anticipation of higher long-term gains. Frequent investors may also experience reduced loss aversion as repeated exposure to market fluctuations normalizes volatility. This is in line with Behavioral Portfolio Theory, which proposes that investors allocate more to growth-oriented "aspiration" layers of their portfolios when they have longer horizons and greater experience.

Further analysis shows that a higher percentage of investors who have a preferred investment period of up to 1 year and a mode of investment as lumpsum (Node 7, low risk-taking ability: 78.3%), and those whose preferred investment period is 1-3 years or above 5 years, whose investment frequency is half-yearly or yearly, and whose investment experience is since the last 1 or 2 years (Node 9, low risk-taking ability: 64.3%), are low-risk takers. This can be understood as individuals who are investing for a shorter period, such as up to 1 year, perceiving that the market may be high or low at the time when they redeem their investments. Similarly, individuals who have started their journey of investing recently, such as in 1 or 2 years, are novice investors and hence, although they may be investing for a longer period of 1-3 years or above 5 years, they are low-risk takers. The predominance of low-risk investors among those with short investment periods and lump-sum investments reflects strong sensitivity to potential short-term losses, a central feature of loss aversion in Prospect Theory. Novice investors with limited experience appear to emphasize capital preservation, which corresponds to the "safety layer" highlighted in Behavioral Portfolio Theory.

Further analysis also shows that investors who have a preferred investment period of up to 1 year and a mode of investment as SIP (Node 6, low risk-taking ability: 50.6%, high risk-taking ability: 49.4%) include both low-risk and high-risk investors. This can be attributed to the fact that individuals investing for up to 1 year are mostly low-risk takers, as the market may go up or down during this period, but SIP helps them to balance the risk and thus enables some of them to bear higher risk. The almost equal share of low and high-risk investors among short-horizon SIP users is somewhat unexpected, as SIPs are often promoted to more conservative investors. This suggests that SIPs may simultaneously appeal to cautious investors who seek to smooth market entry and to more risk-tolerant investors who use SIPs as a disciplined way to build higher-risk positions.

7. Conclusion

With increasing awareness among individual investors about capital market investment and their interest in achieving capital gains, the role of portfolio managers and advisors has become both important and challenging. This paper uses a CHAID-based decision tree to show that basic investment attributes (annual family investment, major earning source, investment experience, investment frequency, preferred investment period, and mode of investment) can classify investors into high- and low-risk-taking groups.

As per the data analysis, out of six factors considered for the study, four form the basis of the model, which include preferred investment period, investment frequency, from how many years you have been investing, and mode of investment. High-risk takers can be seen when the preferred investment period is 3-5 years. Market uncertainties cannot be ignored, but when investment is comparatively for a long period, the market tends to be uptrend, and individuals can earn profit from it. High risk takers are also seen when the preferred investment period is 1-3 years or above 5 years, and the investment frequency is weekly, monthly, and quarterly.

When the preferred investment period is 1-3 years or above 5 years, and investment frequency is half-yearly or yearly, categorizations of individuals as high risk takers and low risk takers involve one more parameter, i.e., time from when individuals are investing. If they are investing for more than 2 years, they understand the market in a better way as compared to novice investors and are also used to the highs and lows of the market and thus are high risk takers. Contrary to it, when they are novice investors and have embarked upon their journey of investment over the last 1 year or over the last 2 years, they are low risk takers.

Investors who invest for a comparatively short time period, like less than 1 year or up to 1 year, are more prone to market uncertainties and thus are mostly low risk takers. A difference can be seen due to the mode of investment, also. Individuals investing through a lump sum amount are low risk takers, while individuals investing through SIP (Systematic Investment Plan) can be divided almost equally into low risk takers and high risk takers.

8. Implications

Behavioral finance is closely connected to other fields such as communication, human psychology and behaviour, portfolio analysis, and investment advisory practice. The model proposed in this study has implications for several stakeholder groups. These implications are:

Implications for Government: India is on the path to becoming a five-trillion-dollar economy. Higher capital market participation by individuals can support economic growth. Appropriate policies to attract capital investment according to the risk appetite of the potential investors are necessary. In addition, strict legal norms and effective supervision by regulatory bodies are necessary.

Implications for Society: High risk appetite of individuals whose preferred investment period is between 3-5 years suggests a shift in society towards long-term investment rather than short-term speculation. This shift also explains that there is increasing financial awareness among individual investors regarding long-term planning and the potential benefits of remaining invested over longer horizons.

Implications for portfolio managers and advisors: Recognizing the factors that define an individual’s risk-taking ability will help portfolio managers and advisors recommend financial products that match the specific requirements of potential investors. The change in risk profile when the mode of investment shifts between lump sum and SIP suggests that the structure of investment itself influences investors’ risk-taking ability and their investment decisions.

9. Limitations and Future Scope

The findings of this study should be interpreted in light of certain limitations. First, the data were collected from investors in a single city (Indore), which may limit the generalizability of the results to other regions and market contexts. Future studies could focus on specific financial products and incorporate behavioural anomalies such as overconfidence or herding to examine how investor profiles relate to these biases.

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