*Advances in Consumer Research*
https://acr-journal.com/
Volume-2 | Issue-5 | October 2025

*Original Researcher Article*

# Behavioural Insights and Heuristics in Investment area: Role of Artificial Intelligence as an Influencer

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**Received:** 30/09/2025
**Revised:** 07/10/2025
**Accepted:** 22/10/2025
**Published:** 28/10/2025

**ABSTRACT**
***Introduction***: Investor's behavior is influenced by many factors during investment decision-making. Each investor's behavior is different based on his demographic background. His decision depends on his knowledge of the investment products and his risk perception, which is a subjective factor. AI is used by machines will give better output by implementing an algorithm to solve a problem or make a decision so that it yields an appropriate answer on a continual basis. ***Aim***: This study focussed on finding the gap between the actual decisions and influencing variables such as heuristics, and risk attitude which activate individual decisions of the armed forces as a stratified cluster and how Artificial Intelligence (AI) is a influencer. ***Method***: Armed forces personnel have been taken as a sample for the study to check the influence of the Behavioural pattern on their investment decisions. PLS-SEM has been used for Data validation and Regression tool for hypothesis check. ***Findings & Conclusion****:* Empirical evidence proved the cause and relationship of Demographic factors and Behavioural traits' influence on investment decisions. AI performs functions such as interactive, textual, analytical, and visual functions. These functions are applied to enhance the intelligence and capabilities to undertake correct invest decision.

**Keywords**: Artificial Intelligence, Investment, Behavioural Finance, Portfolio, Heuristics, Risk aversion

## INTRODUCTION:

The investment spectrum of present times is indeed wide due to the availability of different investment avenues. Individual investors have to be well aware of the options, to get optimal returns. However, an Investor's behavior is influenced by many factors during investment decision-making (Wilson, 2014) . Each investor's behavior is different based on his demographic background. There can be an attempt to know the profiles of the investor and also know the characteristic of the investors so as to know their preferences with respect to their investments and financial planning. His decision depends on his knowledge of the investment products and his risk perception, which is a subjective factor. Investment, its decisions and associated investment behaviour can be analysed from two points of view. Investment may be studied theoretically and empirically. The empirical and theoretical approaches to investment behaviour do not have much in common (Virlics, 2013). Behavioral Finance is an emerging science that coalesces conventional economic and traditional financial theories with behavioral and psychological modern facets to determine the irrational behavior of investors (H. Kent Baker et al., 2019). The emotions of investors when investing is usually in two parts, those are expected emotion and immediate emotion. Expected emotion is anticipated to occur to the investors when they are undertaking investment transactions like buying or selling stocks. Hence, expected emotion or feelings that are expected to happen to, post the result of the decision taken and has materialized but not at the time of decision making (Ady, 2018).

### 1.2 Artificial intelligence (AI) and Heuristics, Aversions

Artificial intelligence involves a wide range of leading-edge logic-based methods, associated applications, and analytics that imitate human behavior, their decision-making pattern based on their behavioural pattern, and processes the application including learning and problem-solving. AI capabilities integrate human requirement based on cognitive exhibits and make rational decision and develop business strategies, in order to expand the various business value chain (Nikolaos-Alexandros Perifanis, 2023). This study is undertaken as many Asset management committees have no idea about emotions, aspirations of armed forces as a group cluster, as their needs and constraints are different from any other citizens or employees. There is no research is exiting to be aware of this aspect. This study is only a initial step that may breach or narrow the gap, to explore, understand, and explain existing influences of this demographic cluster.

How to cite: Thogaram U. Behavioural insights and heuristics in investment area: Role of artificial intelligence as an influencer. *Advances in Consumer Research*. 2025;2(5):369–376.

Contrary to the intelligence used by humans, AI is used by machines will give better output by implementing an algorithm to solve a problem or make a decision as that it yields an appropriate answer on a continual basis (Waymond Rodgers, 2023). Artificial Intelligence also helps in examining Financial Behaviour to guide people to improve their financial wellbeing. It explores problems and potential effects of, specific technologies regarding the use of AI and machine learning. Hence, Technology driving the AI, Machine learning, cognitive computing and distributed ledger technologies are used to augment the investor experience and their returns (Mhlanga, 2020). Heuristic methods in AI are prepared based on cognitive science principles which move around the way humans think. Further, heuristic algorithms in AI or Machine Language **enable systems to produce approximate solutions rather than exact ones**. The impact of artificial intelligence on investment decisions based on behavioural pattern and heuristics can be observed in different ways.

## 2. Scope of the study

Present study focuses mainly on armed forces personnel of India as individual investors, their heuristics, decision-making pattern based on their thought processes, in order to understand their behaviour and investment pattern. Armed forces personnel have been taken as sample for the study to check influence of the Behavioural pattern on their investment decisions.

**Armed forces personnel - demographic attributes**

## 3. Influence of Demographic factors & Influence of personal traits of armed forces personnel on investment

3.1 Demographic factors such as gender, education, age, income etc have a considerable impact on taking decisions. Yet, little attention has been paid to demographic factors (Dinesh Vallabh & Osward Mhlanga., 2015). These demographic attributes have a certain level of effect on investors' personal traits and are associated with a financial risk tolerance, up to a particular level. The demographic variables with undervalued influence sets in psychographic variables such as individual investor biases (Yimer Ayalew et al., 2019). Personality characteristics shape up based on strong working/service culture, as such a system spells out rules on how people should behave. Any employee in an organization with a strong culture, develops certain values, codes of conduct, way of behaviour and exhibits the same in all facets of life (Tsai, 2011). Important Demographic factors influencing decision making are Rank, Residual Service to retire, and Marital Status. The investment decisions do get influenced by the organisational culture. Hence, armed forces is a unique organisation, their serving personnel have been taken as Sample for the study. The sample size is 434. Qualitative research carried out brought out the facts that, armed forces personnel constraints in the job profile based on organisation's requirements, that helped to make the questionnaire for the survey.

### 3.3 Theoretical framework based on behavioural parameters

Behavioural finance is based on cognitive psychology, suggesting that human decisions are subject to two groups cognitive illusions such as heuristic decision processes, and the other is illusions caused by the adoption of mental frames. The second one is grouped in the prospect theory.

**Figure 1: Relationship of Behavioural parameters- a framework.**

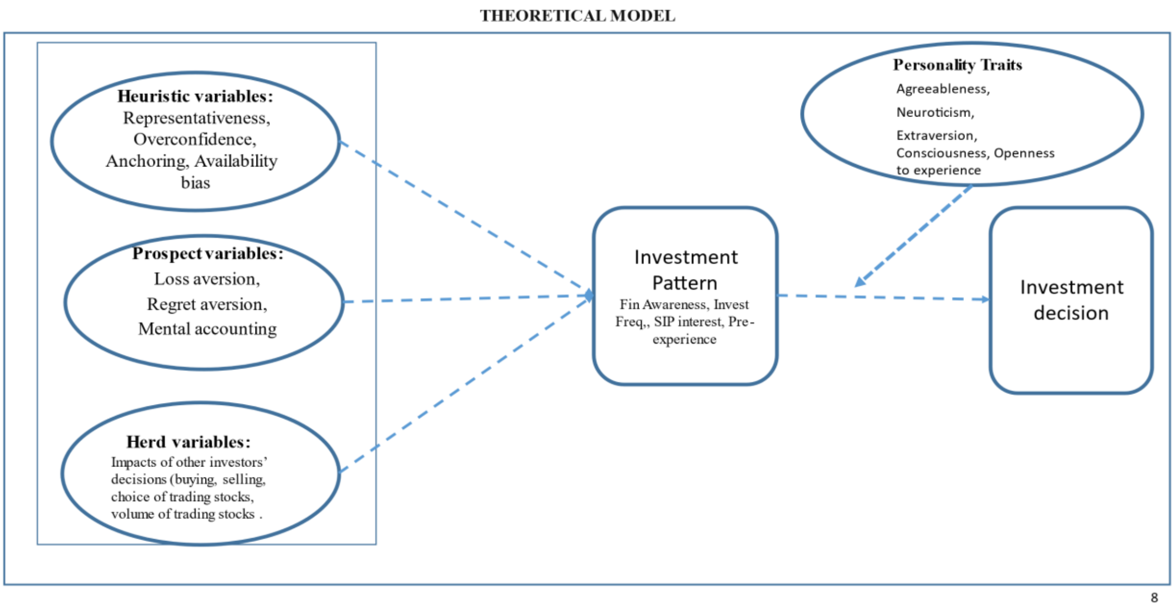


**Figure 1**

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4. **Hypothesis.** The hypothesis framed for the present study based on above stated study methodology is given under:

**H1: There is an impact of individual Investment behaviour on investment decisions, due to Heuristics, Prospects Theory and Herding through Personal Traits as moderating factor.**

**H2: There is a significant effect of demographic characteristic Rank is associated with on investment decisions.**

**H3: There is a significant effect of residual service of Individual Retirement time (retime) on investment decisions.**

**H4: There is a significant effect of the demographic characteristic Marital Status (MS) is associated with on investment decisions through behavioural patterns.**

4.1 **Hypothesis H1 Check**

The data has been modelled under the categories of Demographic, Personnel Traits, Heuristics, Prospect theory and Herd, with Personality traits as Moderating Factor to check the Hypothesis that : **There is an impact of individual Investment behaviour on investment decisions by heuristics, Prospects Theory and Herding through Personal Traits as moderating factor.** PLS-SEM has been used for data validity. The construct is given below:

**Figure 2. The complete relationship of first order constructs with the data variables - 1st stage Reflective- 2nd stage Formative:**

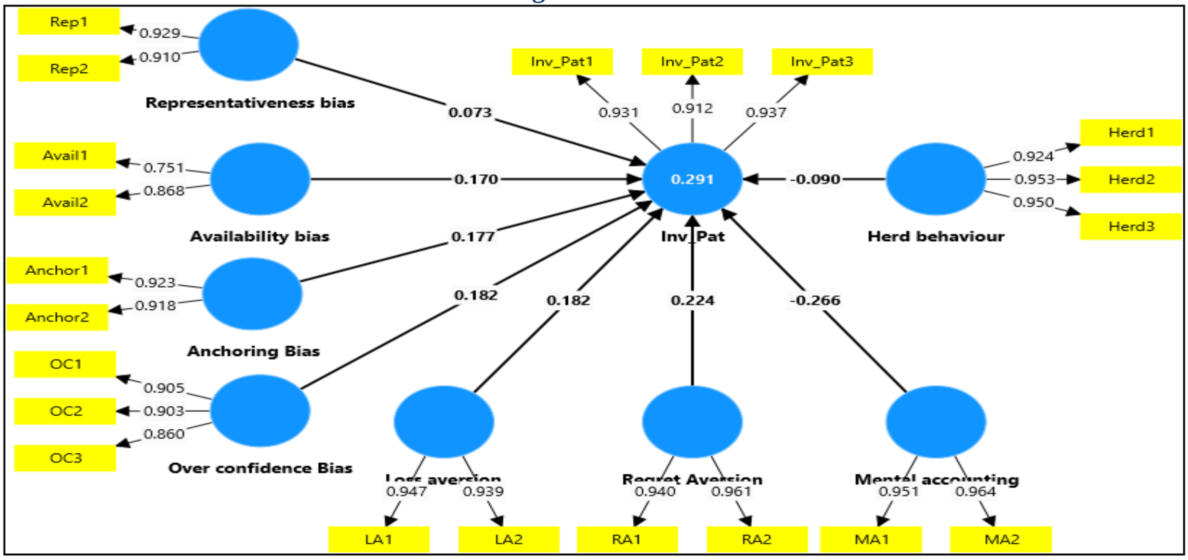


**Figure 2**

**Figure 3. The second order constructs with the data variables - Formative:**

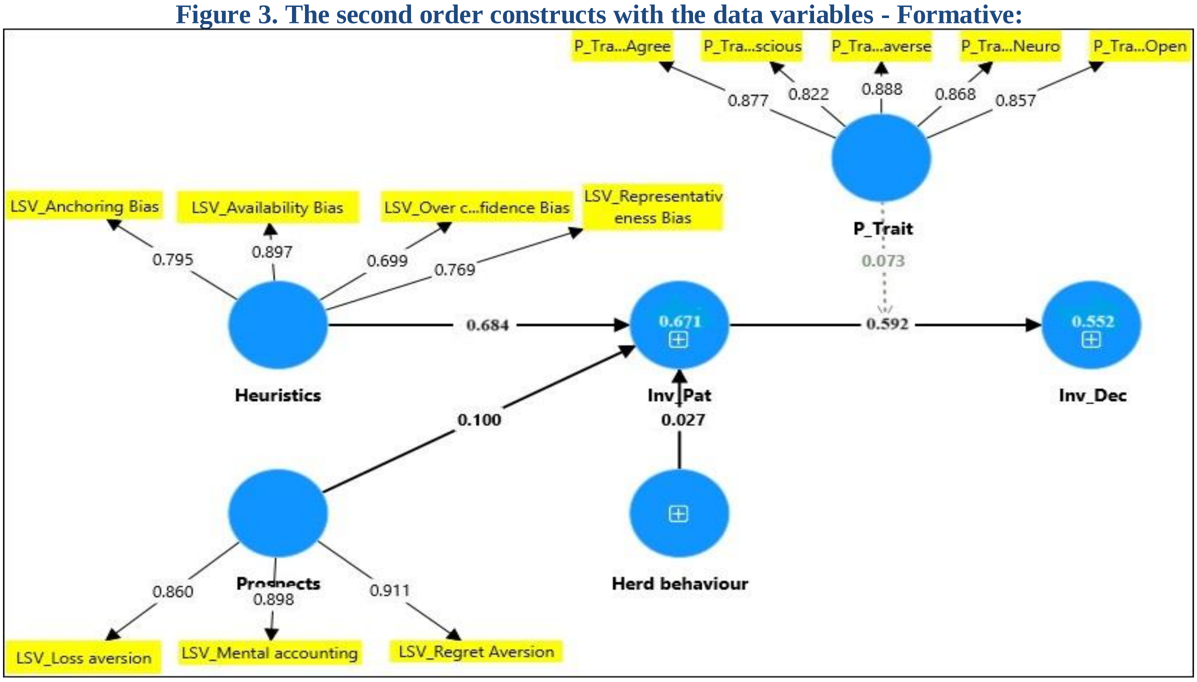


Figure 3

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**Construct reliability &Validity** :

**Table 1 : Construct Reliability Validity**

| Construct reliability &Validity | | | | |
|---|---|---|---|---|
| | Cronbach's alpha (internal consistency) | Composite reliability (rho_a) (adequate internal consistency) | Composite reliability (rho_c) (Overall reliability) | Average variance extracted (AVE) (Convergent Validity) |
| Heuristics | 0.8 | 0.813 | 0.871 | 0.629 |
| P_Trait | 0.9 | 0.917 | 0.936 | 0.744 |
| Prospects | 0.871 | 0.896 | 0.919 | 0.792 |

Table 1

4.2 Composite reliability that testifies Construct reliability gives out how reliable are the intended latent constructs of the measurement model has been verified through PLS SEM algorithm and the construct reliability and validity. Cronbach's Alpha values for all constructs ranged from 0.8 to 0.9, which are acceptable for exploratory research. Rho_A values exceeded 0.8 for all constructs, confirming internal consistency. Composite Reliability values ranged from 0.87 to 0.93, exceeding the threshold of 0.8, indicating high reliability. The AVE values were all above 0.62, supporting convergent validity. The results confirm that the constructs used in this study are reliable and valid. Indicators are consistent in measuring their respective constructs, and the constructs demonstrate strong convergent validity (Hair et al., 2020).

**Discriminant Validity (HTMT)**

If the HTMT value is below the threshold, a **Discriminant Validity** is established between the constructs. Discriminant validity indicates how much a construct is empirically different from another. It also measures the differences between overlapping processes. Discrimination can be assessed using the method of Fornell & Larcker and heterogeneity-monotropic trait (HTMT) correlations. A HTMT (heterogeneity-homogeneity ratio) of less than 0.90 is generally considered useful for establishing a discriminant relationship (Ab Hamid et al., 2017).

**Table 2: Discriminant Validity (HTMT)**

| Discriminant Validity (HTMT) | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Herd behaviour | Heuristics | Inv_Dec | Inv_Pat | P_Trait | Prospects | P_Trait x Inv_Pat |
| Herd behaviour | | | | | | | |
| Heuristics | 0.787 | | | | | | |
| Inv_Dec | 0.262 | 0.461 | | | | | |
| Inv_Pat | 0.351 | 0.565 | 0.418 | | | | |
| P_Trait | 0.535 | 0.888 | 0.394 | 0.388 | | | |
| Prospects | 0.64 | 0.786 | 0.354 | 0.401 | 0.55 | | |
| P_Trait x Inv_Pat | 0.173 | 0.131 | 0.008 | 0.103 | 0.172 | 0.092 | 1 |

Table 2

**Fornell-Larcker Criterion**

The Fornell-Larcker criterion evaluates the distinctiveness of constructs by comparing the square root of the average variance extracted (AVE) of a construct with the correlations between that construct and others. A higher Fornell-Larcker value signifies that the constructs are distinct and well-represented by their measurement scales. An AVE value exceeding 0.5 is deemed acceptable, indicating that a construct shares more dispersion with its indicators than with other constructs. (Ab Hamid et al., 2017).

**Table 3: Fornell-Larcker Criterion**

| Fornell-Larcker Criterion | | | | | | |
|---|---|---|---|---|---|---|
| | Herd behaviour | Heuristics | Inv_Dec | Inv_Pat | P_Trait | Prospects |
| Herd behaviour | 1 | | | | | |
| Heuristics | 0.691 | 0.793 | | | | |
| Inv_Dec | 0.662 | 0.642 | 1 | | | |
| Inv_Pat | 0.551 | 0.507 | 0.518 | 1 | | |
| P_Trait | 0.511 | 0.764 | 0.578 | 0.574 | 0.863 | |
| Prospects | 0.603 | 0.661 | 0.631 | 0.687 | 0.798 | 0.89 |

Table 3

Variation Inflation Factor (VIF) as less than 5 indicates less multi-collinearity, and the standardized root mean square residual (SRMR) value as less than 0.8 indicated model as Good fit.

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## 5. **Hypothesis Check**

**H1: There is an impact of individual Investment behaviour on investment decisions, due to Heuristics, Prospects Theory and Herding through Personal Traits as moderating factor.:**

Table 4 : Significance Testing of Hypothesis - H4

| | **Unstandardized coefficients** | **Standardized coefficients** | **SE** | **T value** | **P value** | **2.5%** | **97.5%** |
|---|---|---|---|---|---|---|---|
| **Inv_Pat** | **0.278** | **0.253** | **0.053** | **5.217** | **0** | **0.173** | **0.382** |
| **Herd** | **0.074** | **0.062** | **0.073** | **1.022** | **0.007** | **-0.217** | **0.069** |
| **Heuristics** | **0.354** | **0.236** | **0.095** | **3.724** | **0** | **0.167** | **0.541** |
| **Prospects** | **0.166** | **0.14** | **0.066** | **2.509** | **0.012** | **0.036** | **0.296** |
| **P_Trait x Inv_Pat** | **0.052** | **0.038** | **0.059** | **0.886** | **0.006** | **-0.063** | **0.167** |
| **Intercept** | **1.005** | **0** | **0.26** | **3.862** | **0** | **0.493** | **1.516** |

Table 4

The results show a significant positive relationship between the predictor variable and **investment patterns**, confirming that factors such as heuristics, aversions or personality traits positively influence irrational investment decisions. The standardized coefficient (0.253) suggests a moderate effect size. The **herd behaviour** demonstrated a significant relationship with the dependent variable. While the standardized effect size is small (0.06), the p-value (0.007) indicates that even small variations in herd behaviour could influence investment patterns. This finding aligns with previous studies suggesting that herd mentality may lead to more conservative or irrational investment behaviour. **P_Trait x Inv_Pat value** can also be considered significant based on P Value being below <0.05 and falls with in 2.5%- 97.5%, thus the cause and relationship is associated upto 95% of the model. As the P- value being significant, the Null Hypothesis rejected and proves that Heuristics, Prospects Herd bias, of investors, through Personality Traits as moderating factor is positively associated with the irrationality in investment decisions.

**H2: There is a significant effect of demographic characteristic Rank is associated with on investment decisions through behavioural pattern:**

The values of Investment decision (Inv_Dec) have been modelled by making two groups. One group is Personnel Below Officer Rank (PBOR), and the other group is Officer Rank. The t-test was conducted to examine the hypothesis that rank as a demographic characteristic (Officers vs. Personnel Below Officer Rank [PBOR]) is significantly associated with investment decisions through behavioural patterns.

**Table 5: Significance Testing of Hypothesis – H2**

| | Personnel below Officer rank | Officers |
|---|---|---|
| Mean | 3.508621 | 3.755 |
| Variance | 1.740185 | 1.59294 |
| Observations | 232 | 200 |
| Hypothesized Mean Difference | 0 | |
| df | 425 | |
| t Stat | 1.98117 | |
| P(T<=t) one-tail | 0.024108 | |
| t Critical one-tail | 1.648447 | |
| P(T<=t) two-tail | 0.048216 | |
| t Critical two-tail | 1.965561 | |

Table 5

**P value and statistical significance**:

The Average, officers have slightly higher scores (**3.75**) in terms of their behavioural patterns influencing investment decisions compared to PBOR (**3.5**). **T-Statistic = 1.98** indicated the difference between the means of the two groups in terms of standard error units. The two-tailed p-value is 0.04, showing that the difference between the two groups is statistically significant in a non-directional hypothesis at the 5% level of significance. The results of the t-test provide evidence to reject the null hypothesis at the 5% level of significance. Hence, the data testifies, the Rank is having significant effect, and the Investment decisions of the Officers is significantly different than Persons below officer rank.

**H3: There is a significant effect of residual service of Individual Retirement time (retime) on investment decisions:**

The retirement (retime) data is taken Ratio scales of having residual service<5 years, Residual service of 5 to 10 years, residual service of 10-15 years, residual service of 15-20 years and 20 years above. Hence One Way ANOVA Test used to check the statistical significance of the Hypothesis.

**One Way ANOVA test, using F distribution**

**Table 6: Significance testing of Hypothesis – H3**

| | | Groups based on Residual Service to Retirement | | | | |
|---|---|---|---|---|---|---|
| | | >20 years | 15-20 Years | 10-15 Years | 5-10 Yeras | < 5 years |
| N | 179 | 56 | 44 | 72 | 83 | 434 |
| ∑X | 626 | 227 | 167 | 275 | 279 | 1574 |
| Mean | 3.4972 | 4.0536 | 3.7955 | 3.8194 | 3.3614 | 3.627 |
| Std.Dev. | 1.2998 | 1.0517 | 1.231 | 1.3036 | 1.3844 | 1.29 |
| Variance | 1.68948 | 1.106073 | 1.515361 | 1.699373 | 1.916563 | 1.6641 |

Table 6

As the F-statistic indicates the ratio of between-group variance to within-group variance, higher F-value suggests greater variability between groups compared to within groups. The p-value is less than 0.05, indicating statistical significance at the 5% level. This suggests that there is sufficient evidence to reject the null hypothesis and conclude that the residual service categories have a significant effect on investment decisions. The result indicate that individuals' investment decisions are influenced by their stage of service, as measured by residual years left until retirement.

**H4: There is a significant effect of demographic characteristic Marital Status (MS) is associated with on investment decisions through behavioural pattern.**

A two-sample t-test was conducted to examine the hypothesis that marital status (Married vs. Unmarried) has a significant effect on investment decisions through behavioural patterns.

**Table 7: Significance Testing of Hypothesis -H4**

| t-Test: Two-Sample Assuming Unequal Variances | | |
|---|---|---|
| | Unmarried | Married |
| Mean | 3.778894 | 3.502146 |
| Variance | 1.79935 | 1.526935 |
| Observations | 199 | 233 |
| Hypothesized Mean Difference | 0 | |
| df | 407 | |
| t Stat | 2.216093 | |
| P(T<=t) one-tail | 0.013619 | |
| t Critical one-tail | 1.648606 | |
| P(T<=t) two-tail | 0.027238 | |
| t Critical two-tail | 1.96581 | |

Table 7

T-Statistic and Critical Values indicate that the computed t-statistic (2.21) is greater than the critical value for both the one-tailed test (1.648) and the two-tailed test (1.965). This indicates that there is sufficient evidence to reject the null hypothesis. The two-tailed p-value (0.027) is less than the standard significance level of 0.05 and the results indicate that marital status is a significant factor influencing investment decisions.

**Transformational Impact of AI as an influencer**

7. In present scenario of globalization and internationalization of financial markets, investor requirements have led the portfolio managers to adopt the automation and use of AI for the better services and returns of their investments (Serge-Lopez Wamba-Taguimdje, 2020). Artificial intelligence (AI) methods enhances psychotherapy with real- or close to real-time recommendations according to the individual's chosen responses (Patricia Gual-Montolio, 2022). Throughout the world, many organisations have significantly adopted the digitalization process through AI, which is

playing a pivotal role in the digitalization of data processing aimed at achieving any desired goals through flexible adaptation (Vidya S Athota, 2023). Many AI-based programs appear to be effective in addressing problems by engaging, the user and making it feasible to deliver a very effective cognitive behavior solution (Fredrik Ahs, 2020). Hence, based on individual investment knowledge, personality traits, demographic factors, AI can find solution and recommend the optimum choice for the effective return of the investor.

**Figure 3 : Interaction of AI Tools in Behavioural finance spectrum of investors**

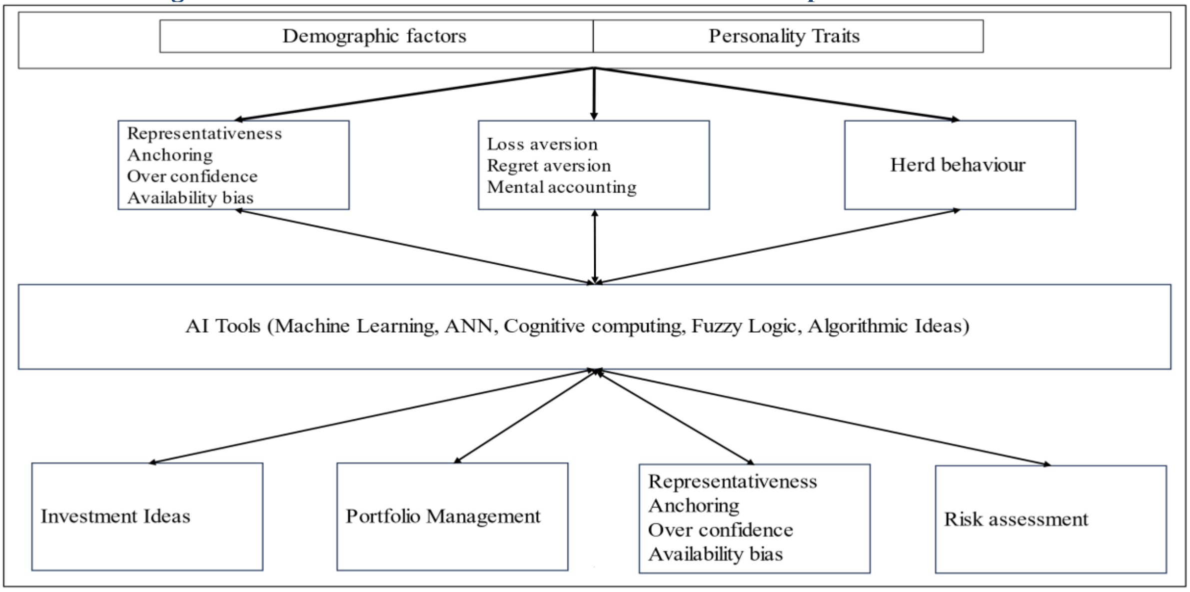


**Figure 3**

7.1 **Personalized Portfolio management services-** Artificial Intelligence increases the entire gamut of portfolio management and related investment services, and associated methods for the investor's portfolio management. Each customer's financial services, are tailormade to keep the customers and their distinctive requirements at the very core of their extremely optimized offerings (Gurinder Singh, 2020)

7.2 **Reduction in the cost- enhanced efficiency -** AI is a machine-driven process, and this has vastly improved customer orientation in all investment services providing a value addition to customers with enhanced efficiency. Hence, AI, has minimised the expenditure of economic services, and also, has created investment as extraordinarily convenient to resort to and avail the facilties in cost optimised mode (Fedyk, 2022).

7.3 **The AI monitoring data and pattern-** Systems modeled with Artificial intelligence play a significant role in building intelligent, and smart systems according to client's requirements and needs. In the investment arena, AI consists of continuous learning and re-learning of data patterns and data developments of the investment world. In order to solve real time investment issues, AI performs functions such as interactive, textual, analytical, and visual functions. These functions are applied to enhance the intelligence and capabilities of an application (Sarker, 2022).

Once introduced, AI can ensure investment methods and related portfolio services are updated and prepared to face the investment world. Artificial Intelligence, hence offers a new paradigm that combines intelligence fed to machines with human intellect, to resolve and remove the biases in the decision-making process. Several studies have already identified importance and significant use of AI and it's involvement in decision-making purposes. AI combines the human-artificial intelligence framework with data intelligence and analytics for effective decision-making purposes for businesses (Zahid Hasan, 2023).

7.4 **A I Tools**:
Systematic investors, focuses on generating alpha by maintaining an information advantage by using AI. The tools should aid to transform the way Investment decisions made, make Portfolio management rich and frequently do the Risk assessment. The AI techniques such as Algo -trading involving Artificial Neural Networks, Fuzzy logic, and Generic algorithms (GAs) are the popular tools used by Investment advisors. Tools and Methods, enhanced with AI Techniques tend to offer more accurate and highly precise results in the cognitive behaviour field for better financial management of investor's money as the AI made significant inroads into cognitive computing (Miltiadis D Lytras, 2021).

## CONCLUSION

8. Machine learning applications have superseded and exceeded human expert-judgement in many domains including that of Finance, investments arena too. Studies related to investor behaviour are found in abundance, wherein earlier studies focused on the investment pattern, gender indifferences and other demographic factors, in common to the general population without stratifying. Though few studies have

concentrated on the decision-making process and individual decisions concerning their investments but no studies have focussed on filling the gap between the actual decisions and influencing variables such as heuristics, and risk attitude which activate individual decisions of this armed forces as a stratified cluster. This study is undertaken to fine-tune the concept, that is necessary to empirically test in the Indian context using the psychological variables which intuit the decisions among armedforces as individual's respondents and how AI can be used as force multiplier, to enahce the Alpha - returns. Armedforces personnel have their own functional constraints and limits them to be inactive with rest of the world for days together. Their duties also forbid carrying mobile for days sometimes, owing to operational reasons. But in the process, it results in often ends up neglecting their finances. Further, the retirement age is different from other such Government employees, wherein other government employees retire at the age of 60 but, armedforces personnel retire at an early age starting from early forty years of age to early fifty years of age. Under such constraints, AI enabled investment research will be able to tailor made investment options for optimal returns.

**REFERENCES**


1. Abdellaoui, M., Bleichrodt, H., & Paraschiv, C. (2007). Loss aversion under prospect theory: A parameter-free measurement. Management science, 53(10), 1659-1674.
2. Ady, U. (2018). The Cognitive and Psychological Bias in Investment Decision-Making Behavior: (Evidence From Indonesian Investor's Behavior). *Journal of Economics and Behavioral Studies, 10*((1)), 86-100. doi:10.22610/jebs.v10i1.2092
3. Dinesh Vallabh, O. M. (2015). Influence of demographic factors on business performance in small to medium tourism enterprises (SMTEs). *African Journal of Hospitality, Tourism and Leisure, 4*((2)), 1-9. Retrieved from http//: www.ajhtl.com
4. Fedyk, A. H. (2022). Is artificial intelligence improving the audit process? *Review of Accounting Studies, 27*((1)), 938–985. Retrieved from https://doi.org/10.1007/s11142-022-09697-x
5. Fredrik Ahs, P. M. (2020). Artificial Intelligence Supported Cognitive Behavioral Therapy for Treatment of Speech Anxiety in Virtual Reality Environments. *European Conference on the Impact of Artificial Intelligence and Robotics - ECIAIR 2020* (pp. 1-10). virtual: ECIAIR .
6. Gurinder Singh, V. G. (2020). Application of Artificial Intelligenceon Behavioral Finance. *Recent Advances in Intelligent Information Systems and Applied Mathematics*, 342-353. Retrieved from DOI: 10.1007/978-3-030-34152-7_26
7. Hair Jr, J. F., Howard, M. C., & Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. Journal of business research, 109, 101-110.
8. Mhlanga, D. (2020). Industry 4.0 in Finance: The Impact of Artificial Intelligence (AI) on Digital Financial Inclusion. *International Journal of Financial Studies, 8*((3)), 1-45. Retrieved from https://doi.org/10.3390/ijfs8030045
9. Miltiadis D Lytras, A. V. (2021). Artificial Intelligence and Cognitive Computing: Methods,Technologies, Systems, Applications and Policy Making. *Sustainability, 13*((7)), 1-3. Retrieved from https://doi.org/10.3390/su13073598
10. Nikolaos-Alexandros Perifanis, F. K. (2023). Investigating the Influence of Artificial Intelligence on Business Value in the Digital Era of Strategy: A Literature Review. *Information, 14*((2)), 85-100. Retrieved from https://doi.org/10.3390/info14020085
11. Patricia Gual-Montolio, I. J.-B.-R. (2022). Using Artificial Intelligence to Enhance Ongoing Psychological Interventions for Emotional Problems in Real- or Close to Real-Time: A Systematic Review. *International Journal of Environmental Research and Public Health, 19*((13)), 7737-7748. doi:10.3390/ijerph19137737
12. Sarker, I. H. (2022). AI-Based Modeling: Techniques, Applications and Research Issues Towards Automation, Intelligent and Smart Systems. *SN Computer Science, 3*((1)), 158-176. Retrieved from https://doi.org/10.1007/s42979-022-01043-x
13. Serge-Lopez Wamba-Taguimdje, S. F. (2020). Influence of Artificial Intelligence (AI) on FirmPerformance: The Business Value of AI-basedTransformation Project. *Business Process Management Journal, 1*((1)), 1-34. doi:10.1108/BPMJ-10-2019-0411
14. Vidya S Athota, V. P. (2023). Overcoming financial planners' cognitive biases through digitalization: A qualitative study. *Journal of Business Research, 154*((1)), 1-4. Retrieved from doi.org/10.1016/j.jbusres.2022.08.055
15. Virlics, A. (2013). Investment Decision Making and Risk. *Procedia Economics and Finance, 6*((1)), 169-177. doi:10.1016/S2212-5671(13)00129-9
16. Waymond Rodgers, R. H. (2023). Modelling credit and investment decisions based on AI algorithmic behavioral pathways,. *Technological Forecasting and Social Change, 191*((1)), 1-13. Retrieved from https://doi.org/10.1016/j.techfore.2023.122471
17. Wilson, K. E. (2014). New Investment Approaches for Addressing Social and Economic Challenges. *OECD Science, Technology and Industry Policy, 15*((1)), 1-41. Retrieved from http://dx.doi.org/10.1787/5jz2bz8g00jj-en
18. Zahid Hasan, D. V. (2023). Can Artificial Intelligence (AI) Manage Behavioural Biases Among Financial Planners? *Journal of Global Information Management, 3*((12)), 1-18. Retrieved from DOI: 10.4018/JGIM.321728