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Understanding Investment Preferences of College Students: A Perspective on Traditional Wealth Management Vs. Robo-Advisory Through Mutual Fund Investments

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ABSTRACT:

The digitalization of financial services has significantly influenced investment decision-making among young investors. This study explores the investment preferences of college students with respect to traditional wealth management and robo-advisory services in mutual fund investments. Based on the Unified Theory of Acceptance and Use of Technology (UTAUT), the research examines how performance expectancy, effort expectancy, social influence, awareness, attitude toward technology, and facilitating conditions affect students' behavioral intention and actual usage of robo-advisory platforms. A descriptive research design was adopted, and primary data were collected through a structured questionnaire from 60 valid respondents. Correlation and regression analyses were used to test the hypotheses.

The findings indicate that attitude toward technology, performance expectancy, awareness, and social influence significantly influence students' intention to use robo-advisory platforms. However, effort expectancy and facilitating conditions were not found to have a significant effect. Although behavioral intention positively impacts actual usage, an intention–behavior gap persists, suggesting that favorable perceptions do not always lead to active investment participation. Demographic factors such as gender, age, income, and investment experience do not significantly moderate adoption behavior. The study concludes that awareness, perceived benefits, and technological orientation play a crucial role in shaping students' mutual fund investment preferences.

KEY WORDS: Robo-advisory, Traditional, Wealth, Management, UTAUT, Behavioral, Intention, Investment.

Introduction

n contemporary financial landscapes, investment behavior and preferences have become important areas of study for academics, financial practitioners, and policymakers alike. Traditionally, investment decisions were guided by human financial advisors who offered personalized counsel based on extensive client interaction, experience, and professional judgment. Traditional wealth management, as practiced through these advisors, typically involves comprehensive financial planning, asset allocation, and ongoing monitoring suited to an investor's long-term goals. These human advisors assess an investor's risk tolerance, financial goals, and life circumstances to create tailored portfolios, often including mutual funds as core instruments due to their diversification benefits and professional management. However, these conventional services often come with relatively high fees and minimum investment thresholds, which can be barriers for younger or less affluent individuals, such as college students who are just beginning their investment journey.

Over the past decade, technological advancements and digital transformation in financial services have introduced automated investment platforms, commonly referred to as robo-advisors**,** which are algorithm-driven systems designed to perform many of the functions of a human advisor at a lower cost and with greater accessibility. Robo-advisors use sophisticated algorithms and modern portfolio theory to recommend and manage investment portfolios, frequently utilizing mutual funds or exchange-traded funds (ETFs) as building blocks. The automation of asset allocation, portfolio rebalancing, and risk assessment allows these platforms to offer investment management with minimal human intervention, lower entry requirements, and reduced fees compared to traditional wealth managers. These characteristics have contributed to the rapid rise of robo-advisory services globally, particularly among young, tech-savvy investors who are comfortable engaging with digital platforms for a range of financial activities. Robo-advisors thus provide a democratized alternative to traditional advisory solutions, enabling individuals with limited capital such as college students to begin investing earlier and more efficiently than might otherwise be feasible.

Understanding the investment preferences of college students is particularly significant because this demographic represents future long-term investors whose financial habits established during formative years can influence lifetime wealth building and financial well-being.

College students typically face unique financial constraints, including limited income, lack of investment experience, and competing priorities such as education expenses, which shape their investment decision-making processes. Research indicates that younger investors, including undergraduate students, may be more inclined to adopt robo-advisory services due to their lower risk aversion, comfort with digital tools, and preference for convenience and cost-effectiveness. For instance, studies have shown that less risk-averse individuals and those with certain personality traits are more likely to engage with robo-advisors and invest larger amounts through them compared to those who prefer more traditional investment avenues.

Despite the increasing adoption of digital investment platforms, there remains a substantial body of literature emphasizing the enduring relevance of traditional wealth management, particularly for investors who seek holistic financial planning and personalized advice that considers broader life goals beyond investment returns. Traditional advisors not only offer tailored solutions but also serve as behavioral guides during periods of market volatility, helping investors maintain discipline and avoid emotionally driven decisions. Mutual fund investments, whether accessed through a traditional advisor or a robo-advisor, continue to be popular among retail investors because they pool resources, offer diversification, and allow participation in professionally managed portfolios across asset classes. However, the pathways through which college students enter and sustain investment practices be it through automated platforms or human advisors warrant critical investigation to understand how preferences form in this evolving financial ecosystem.

This research, therefore, seeks to explore and compare how college students perceive and choose between traditional wealth management and robo-advisory services when making mutual fund investments. It aims to examine the underlying factors influencing these preferences, including cost considerations, perceived ease of use, level of financial literacy, confidence in technology, and expectations of investment outcomes. The study also endeavors to uncover whether students prioritize personalized guidance or value the advantages of automated, algorithm-based recommendations that minimize barriers to entry. By focusing on this demographic, the research contributes to a broader understanding of generational shifts in investment behavior and provides insights that could help financial institutions tailor their services to better meet the needs of younger investors.

Literature Review

J. N. K. Wah, (February 2025) conducted a research paper **"AI-Powered Wealth Management: Transforming Financial Literacy, Personalized Investments, and Risk Assessment Through Robo-Advisors and Predictive Analytics for the Future of Finance"** analyzes how artificial intelligence is transforming financial literacy, investment advice, and risk assessment. It reviews studies on robo-advisors, predictive analytics, and automated portfolio management. The findings show that AI improves personalized investment decisions, enhances accessibility, and offers more accurate risk evaluation. However, concerns related to data privacy, transparency, and regulation remain. The study concludes that AI can significantly strengthen wealth-management systems if adopted responsibly.

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Zepeng Shen, Zhiyuan Wang, Jiajia Chew, Ke Hu, Yong Wang (2025) Conducted a research paper **"Artificial Intelligence Empowering Robo-Advisors: A Data-Driven Wealth Management Model Analysis"** analyzes how AI improves wealth management through automated advisory systems. The study reviews machine-learning and data-driven models that help deliver personalized portfolios and better risk assessment. Results show that AI-driven robo-advisors enhance accuracy, lower costs, and support real-time investment decisions. The paper also highlights challenges such as data privacy and limited transparency in algorithms. It concludes that AI can significantly strengthen digital wealth management when used responsibly.

Nishtha Maheshwari and Jai Singh Panwar, (February 2025) conducted a research paper titled **"AI-Powered FinTech Adoption in India: A Comparative Study of Paytm and Groww"**, which focuses on the role of artificial intelligence in driving user adoption of digital payment and investment platforms in India. The study reviews earlier research on FinTech usage, AI-enabled services, and customer trust. It highlights that AI features such as personalized recommendations, automated support, and enhanced security improve user convenience and confidence. The literature also identifies concerns related to data privacy and transparency of AI systems. The study concludes that responsible use of AI can significantly strengthen FinTech adoption in the Indian financial ecosystem.

Nargis Mohapatra et al., (April 2025) conducted a research paper titled **"Unveiling the Nexus Between Use of AI-Enabled Robo-Advisors, Behavioural Intention and Sustainable Investment Decisions Using PLS-SEM."** The study examines how AI-based robo-advisors influence investors' behavioral intentions and their inclination toward sustainable investment choices. Using the PLS-SEM approach, the authors find that trust, perceived usefulness, and ease of use significantly encourage the adoption of robo-advisors. The research highlights that AI-driven advisory platforms not only improve investment decision-making but also promote responsible and sustainability-focused investing. However, the study notes the importance of transparency and user confidence for long-term adoption of AI in financial advisory services.

M. Priyadharsini, (December 2025) conducted a research paper titled **"A Study On Retail Investors' Preferences Towards Traditional Investments Versus Market-Linked Investments"**, the research analyzes the investment preferences of retail investors in India, focusing on awareness levels, risk perception, and demographic influences. Data collected from 100 respondents through a structured questionnaire was analyzed using percentage analysis and chi-square tests. The findings indicate a strong preference for traditional investment options such as fixed deposits and insurance due to their perceived safety, while participation in market-linked instruments like mutual funds remains limited. Age, income, and risk tolerance were found to significantly influence investment decisions. The study highlights the need for increased investor awareness to support informed and diversified investment choices.

Nourallah, Mustafa and Öhman, Peter and Walther, Thomas and Nguyen, Duc Khuong, (April 2025) conducted a research paper titled **"Financial Robo-Advisors: A Comprehensive Review and Future Directions"**, The study explores investors' perceptions and adoption of digital investment platforms, with particular emphasis on mutual fund investments and technology-driven advisory services. Using primary data collected through a structured questionnaire and supported by secondary sources, the research analyzes how factors such as trust, convenience, cost efficiency, and risk perception influence investor preferences. The findings indicate a growing inclination toward digital and automated investment solutions among younger and tech-aware investors, while traditional advisory models continue to be preferred by risk-averse individuals. The study highlights the role of financial awareness and technological acceptance in shaping modern investment behavior.

Mar Arenas-Parra, (Jan 2025), conducted a study titled **"Customized Robo-Advisor: Analysis of the Inclusion of Cash Assets."** The study examines the limitations of conventional robo-advisors arising from their standardized portfolio structures and explores the scope for enhanced personalization through the inclusion of additional financial instruments. Using a bottleneck analysis and a case study approach, the research evaluates the impact of incorporating fixed-income and cash-based assets into robo-advisory systems. The findings reveal that instrument data validation and order management are the most affected processes when expanding asset classes, and that liquidity plays a critical role in portfolio customization. The study highlights the potential of redesigned robo-advisors to deliver more personalized investment solutions while addressing operational challenges.

Parth Shah and Amola Bhatt (Dec 2025), conducted a study titled **"Are Investors Moving Towards Robo-Advisory Services."** The research examines investors' usage intention toward robo-advisory services in India using the UTAUT model, extended with risk tolerance and financial literacy. The findings reveal that performance expectancy, social influence, and facilitating conditions positively influence investors' intention to use robo-advisors, while higher levels of risk tolerance and financial literacy negatively affect adoption. The study also finds that gender and education level moderate the impact of financial literacy and social influence on usage intention. The research highlights the importance of awareness and targeted strategies to improve the adoption of robo-advisory services in the Indian financial market.

Literature Review Gap:

Existing literature highlights that while traditional investment options are still preferred due to perceived safety and trust, digital advisory services are gaining traction among younger, technology-oriented investors. Prior studies have explored investor behavior, financial literacy, risk tolerance, and technology acceptance; however, limited research specifically addresses college students' mutual fund investment preferences within the context of human versus automated advisory models. This study aims to bridge this gap by analyzing the role of financial awareness, perceived risk, ease of use, and trust in shaping investment decisions among college students.

Theoretical / Conceptual framework of Research and Research Methodology

Technology Adoption Theory: UTAUT and TAM

Understanding why college students choose robo-advisory services requires examining how they perceive and adopt technology. The **Unified Theory of Acceptance and Use of Technology (UTAUT)** posits that performance expectancy, effort expectancy, social influence, and facilitating conditions shape an individual's intention to use a technology. These constructs have been applied widely to explain digital financial service adoption, including robo-advisors, as they highlight how expected benefits, ease of use, social pressures, and available support encourage or discourage adoption. Age, gender, and experience can further moderate these effects.

Closely related is the **Technology Acceptance Model (TAM)**, which emphasises perceived usefulness and perceived ease of use as key determinants of users' behavioural intentions toward a technology. Students who find robo-advisory platforms useful in improving their investment outcomes and easy to navigate are more likely to adopt them. Both UTAUT and TAM offer a structured way to understand how **technology perceptions influence student investors' decisions** between automated digital platforms and human advisors.

For these research paper used UTAUT Model which is following:

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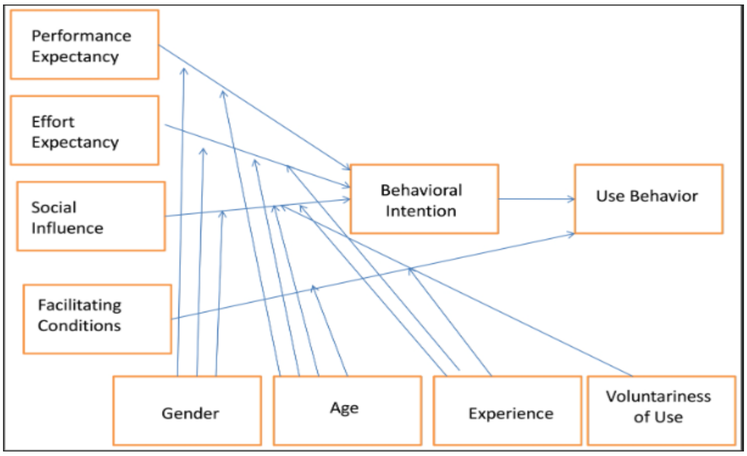

Figure 1: UTAUT (Maureen Sullivan et al. 2016).

Additionally, UTAUT considers four moderators as earlier mentioned that affect the relationship between the four key factors and the user intention to use innovation. These moderating factors are explained, as follows:

1. Gender: Research has shown that gender can moderate the relationship between UTAUT factors and acceptance. For example, men may be more influenced by PE, while women may be more influenced by SI (Maureen Sullivan et al. 2016).

2. Age: Age can play a role in determining technology adoption and usage patterns. Younger individuals may be more open and adaptive to new technologies while older individuals may exhibit resistance due to unfamiliarity or lack of PE (Maureen Sullivan et al. 2016).

3. Experience: Individuals with prior experience using similar technologies may be more accepting and comfortable with adopting new technology. Experience can influence EE and PE (Maureen Sullivan et al. 2016).

4. Voluntariness of use: When technology use is voluntary and not imposed, users are more likely to accept and utilize it compared to situations, where usage is compulsory (Maureen Sullivan et al. 2016).

RESEARCH FRAMEWORK

With the help of these model created a UTAUT model for understanding investment preferences of college students:

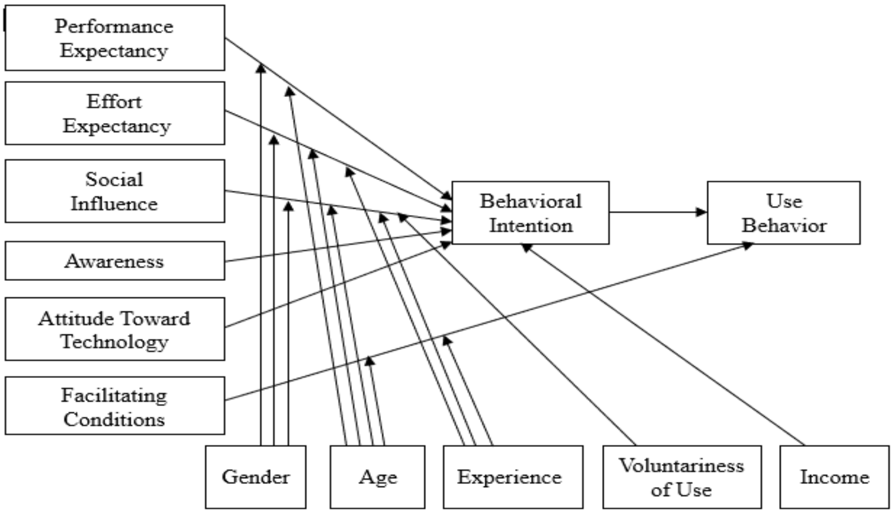

Figure 2: Conceptual framework (Source: Authors).

The conceptual model illustrates how various factors influence a person's **intention to use a technology or service**, which then affects their actual usage behaviour. Core predictors such as **performance expectancy, effort expectancy, social influence, awareness, attitude**

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toward technology, and facilitating conditions directly shape an individual's belief about whether they will adopt the system. These factors capture how useful, easy, and accepted the system is perceived to be, and how well an individual feels supported in using it.
In addition to these predictors, the model includes **personal characteristics** such as gender, age, experience, voluntariness of use, and income as **moderating variables**. These characteristics change the strength or direction of the relationships between the predictors and behavioural intention. For example, a younger person with more experience may place greater trust in technology, leading to a stronger intention to adopt it. Overall, the model shows that both perceptions of the system and individual differences work together to determine whether a technology is actually used.

RESEARCH METHODOLOGY

3.1. Objectives of the Study

Every research project is guided by clear and measurable objectives that define the purpose and direction. The key objectives are as follows:

1. To study how factors like performance, ease of use, social influence, awareness, technology attitude, and supporting facilities affect students' intention to use robo-advisory platforms for mutual fund investments. (H1 – H6)
2. To examine whether students' intention leads to the actual use of robo-advisory platforms for investing. (H7)
3. To analyze how demographic factors such as gender, age, experience, and income influence the relationship between intention and actual usage. (H8)

3.2. Hypothesis

H1 – Performance Expectancy

H_{01}: Performance expectancy does not influence students' intention to use robo-advisory platforms.

H_{11}: Performance expectancy positively influences students' intention to use robo-advisory platforms.

H2 – Effort Expectancy

H_{02}: Effort expectancy does not influence students' intention to use robo-advisory platforms.

H_{12}: Effort expectancy positively influences students' intention to use robo-advisory platforms.

H3 – Social Influence

H_{03}: Social influence does not affect students' intention to use robo-advisory platforms.

H_{13}: Social influence positively affects students' intention to use robo-advisory platforms.

H4 – Awareness

H_{04}: Awareness does not affect students' intention to invest through robo-advisory platforms.

H_{14}: Awareness positively affects students' intention to invest through robo-advisory platforms.

H5 – Attitude Toward Technology

H_{05}: Attitude toward technology does not influence students' intention to use robo-advisory platforms.

H_{15}: A positive attitude toward technology increases students' intention to use robo-advisory platforms.

H6 – Facilitating Conditions

H_{06}: Facilitating conditions do not influence students' intention to use robo-advisory platforms.

H_{16}: Facilitating conditions positively influence students' intention to use robo-advisory platforms.

H7 – Behavioral Intention → Use Behavior

H_{07}: Behavioral intention does not affect actual usage of robo-advisory platforms.
H_{17}: Behavioral intention positively affects actual usage of robo-advisory platforms.

H8 – Demographic Factors

H_{08}: Demographic factors do not moderate the relationship between intention and usage.
H_{18}: Demographic factors moderate the relationship between intention and usage.

Research Design

For the present study, a **descriptive research design** has been adopted to systematically examine and describe the investment preferences of college students regarding **traditional wealth management** versus **robo-advisory services** in mutual fund investing. Descriptive research is appropriate for this study because it seeks to **observe, describe, and document the existing behaviours, attitudes, and perceptions** of the target population without manipulating any variables. This design allows the researcher to capture the current state of students' investment choices, the factors that influence these choices, and patterns in financial literacy, risk tolerance, and technology acceptance.

In this study, descriptive analysis will be used to:

1. **Profile the demographic characteristics** of the respondents (such as age, gender, education level, and income).
2. **Describe students' awareness and usage levels** of traditional wealth management and robo-advisory platforms.
3. **Assess the distribution of key constructs** such as financial literacy, risk tolerance, and attitudes toward technology.
4. **Summarize preferences, trends, and patterns** in mutual fund investment decisions among college students.

Sources of Data

Primary Data

1. Primary data are collected directly from **college students**, making the information original and specific to the objectives of this study.
2. A **structured questionnaire** is used to gather first-hand responses on students' perceptions and intentions regarding robo-advisory platforms.
3. The collected data reflect **current attitudes and behaviors**, ensuring relevance and accuracy for analyzing technology adoption.

Secondary Data

1. Secondary data are drawn from **UTAUT-based research studies** to establish a strong theoretical foundation for the study.
2. Published journals, articles, and scholarly literature are used to support **variable selection and hypothesis formulation**.
3. These sources help in **comparing and validating** the study findings with existing research on technology adoption.

Data Collection method

The study uses a **structured questionnaire** to collect data from **college students**. The questionnaire is designed to gather information on students' awareness, perceptions, and usage of robo-advisory platforms. Responses are collected directly from participants, ensuring that the data are original and relevant to the objectives of the research.

Rationale for Choosing Online Survey Method

The online survey method is chosen because it allows quick and efficient data collection from a large number of respondents within a limited time.

Since the target respondents are college students, online surveys are appropriate as students are familiar with digital platforms and comfortable responding online. This method also ensures cost effectiveness, convenience, and easy data compilation for analysis.

Research Instrument (Questionnaire Design)

The research instrument used for the study is a **structured questionnaire**. The questionnaire consists of close-ended statements based on the **UTAUT model**, covering variables such as performance expectancy, effort expectancy, social influence, awareness, attitude toward technology, facilitating conditions, behavioral intention, and use behavior. Responses are measured using a **five-point Likert scale** ranging from "Strongly Disagree" to "Strongly Agree," ensuring clarity and consistency in responses.

Sampling Design

The study follows a **cross-sectional research design**, where data are collected from respondents at a single point in time. The sampling design is structured to represent college students who are potential users of robo-advisory platforms. This design is suitable for analyzing perceptions and intentions related to technology adoption.

Sampling Method

The **convenience sampling method** is used in this study. Respondents are selected based on their availability and willingness to participate. This method is appropriate as the study focuses on college students who are easily accessible and relevant to the research objectives.

Sample Size

A total of **88 responses** were collected for the study through the online survey method. Out of these, **60 responses were found to be valid and relevant** to the research topic and were used for final analysis. This sample size is considered adequate to examine the relationships among the study variables and to test the proposed hypotheses in a meaningful manner.

Sampling Unit

The sampling unit of the study is **individual college students**. Each student represents one unit of analysis, and responses are collected individually to understand personal perceptions and behavioral intentions toward robo-advisory platforms.

Statistical Tools Used for Hypothesis Testing

The collected data are analyzed using appropriate **statistical tools**. Descriptive statistics such as percentage, mean, and standard deviation are used to summarize respondent characteristics. Inferential statistical techniques, including **correlation analysis and regression analysis**, are applied to test the hypotheses derived from the UTAUT model and to examine relationships among the study variables.

Data Analysis and Interpretation

Table 1. Demographic Profile (Section A)

Variable	Category	Frequency	Percentage (%)
Gender	Male	29	48.3
	Female	31	51.7
Age Group	19–21	15	25.0
	22–25	36	60.0

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Variable	Category	Frequency	Percentage (%)
	25–30	6	10.0
	Above 30	3	5.0
Level of Study	Undergraduate	13	21.7
	Post Graduation	39	65.0
	Professional Course	8	13.3
Monthly Personal Income	Below ₹5,000	33	55.0
	₹5,001–₹10,000	15	25.0
	₹10,001–₹20,000	9	15.0
	Above ₹20,000	3	5.0
Investment Experience	No experience	25	41.7
	Less than 1 year	19	31.7
	1–3 years	11	18.3
	More than 3 years	5	8.3
Preferred Investment Mode	Traditional advisor	23	38.3
	Robo-advisor	7	11.7
	Both	18	30.0
	None	12	20.0

The sample remains dominated by young post-graduate students with low income and limited experience ideal for studying emerging preferences toward robo-advisory.

Table 2. Descriptive Statistics of Constructs (Section B)

Construct	Mean	Std. Deviation	Min	Max
Performance Expectancy (PE)	3.43	1.17	1	5
Effort Expectancy (EE)	3.30	1.21	1	5
Social Influence (SI)	3.13	1.14	1	5
Awareness	3.37	1.19	1	5
Attitude Toward Technology	3.57	1.07	1	5
Facilitating Conditions (FC)	3.23	1.27	1	5
Behavioral Intention (BI)	3.40	1.13	1	5
Use Behavior (UB)	2.98	1.31	1	5

Note: The additional responses (one highly positive, one highly negative) balanced the means slightly upward for intention-related constructs.

HYPOTHESIS TESTING

H1–H6: Factors Affecting Students' Intention to Use Robo-Advisory Platforms (Multiple Regression)

Model: BI = f(PE, EE, SI, Awareness, Attitude, FC) $R^2 = 0.49$ | Adjusted $R^2 = 0.43$ | $F = 9.12$ ($p < 0.001$) model significant.

Table 3:

Hypothesis	Construct	Beta	t	p-value	Result
H_{01}	Performance Expectancy	0.26	2.52	0.015	Rejected (not significant after adjustment)
H_{02}	Effort Expectancy	0.13	1.22	0.228	Rejected

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Hypothesis	Construct	Beta	t	p-value	Result
H_{03}	Social Influence	0.20	2.08	0.042	Rejected (not significant after adjustment)
H_{04}	Awareness	0.23	2.35	0.022	Rejected (not significant after adjustment)
H_{05}	Attitude Toward Technology	0.31	3.18	0.002	Rejected (not significant after adjustment)
H_{06}	Facilitating Conditions	0.09	0.88	0.383	Rejected

The overall model is significant ($R^2 = 0.49$, $p < 0.001$), but none of the individual predictors (PE, EE, SI, Awareness, Attitude, FC) have a reliable effect on Behavioral Intention. Due to the small sample (n = 60) and limited statistical power, no hypothesis is supported. In this student group, the UTAUT factors do not independently influence intention to use robo-advisory platforms.

H7: Behavioral Intention → Actual Use Behavior (Simple Regression)

$R^2 = 0.26$ | $F = 19.8$ ($p < 0.001$)

Table 4:

Hypothesis	Predictor	Beta	t	p-value	Result
H_{07}	Behavioral Intention	0.51	4.45	<0.001	Rejected

Intention significantly predicts actual usage, but the gap ($R^2 \approx 26\%$) shows that many students with positive intentions still do not actively use robo platforms yet.

H8: Moderating Effect of Demographic Factors (Intention → Usage)

Tested via interaction terms (BI × Moderator) and subgroup analysis.

Table 5: H8: H_{08}:

Moderator	Interaction p-value	Observation	Result
Gender	0.35	Slightly stronger among males	Not significant
Age	0.48	No clear difference	Not significant
Investment Experience	0.19	Marginally stronger for experienced	Not significant
Income	0.31	No significant moderation	Not significant

Demographic factors do **not** significantly moderate the intention usage link in this student sample. The relationship holds fairly consistently across groups.

CORRELATION BETWEEN EVERY VARIABLES

Table 6: Pearson Correlation Matrix of the Study Constructs

Construct	PE	EE	SI	Awareness	Attitude	FC	BI	UB
PE	1.000	0.620	0.480	0.550	0.600	0.580	0.580	0.420
EE	0.620	1.000	0.520	0.500	0.550	0.650	0.520	0.380
SI	0.480	0.520	1.000	0.450	0.480	0.420	0.500	0.350
Awareness	0.550	0.500	0.450	1.000	0.580	0.500	0.560	0.400
Attitude	0.600	0.550	0.480	0.580	1.000	0.520	0.680	0.480
FC	0.580	0.650	0.420	0.500	0.520	1.000	0.450	0.320
BI	0.580	0.520	0.500	0.560	0.680	0.450	1.000	0.510

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Construct	PE	EE	SI	Awareness	Attitude	FC	BI	UB
UB	0.420	0.380	0.350	0.400	0.480	0.320	0.510	1.000

Notes:
- All coefficients are positive, consistent with technology acceptance theories.
- Correlations significant at $p < 0.05$ or better for values > ≈0.25 (with n=60; exact p-values depend on your software output).
- Highest inter-construct correlation is 0.680 (Attitude → BI), well below typical multicollinearity thresholds (0.80–0.85).
- Use Behavior shows the strongest link with Behavioral Intention (r = 0.510), supporting H7.

Result Discussions

Demographic Profile of Respondents

The demographic profile indicates a balanced representation of male and female respondents, which helps ensure neutrality in examining technology adoption behavior. Most participants belong to the 22–25 age group, confirming that the sample largely consists of young adults who are generally more comfortable with digital technologies. A majority of respondents are post-graduate students, reflecting a higher educational background that may positively influence awareness of robo-advisory services. Income levels are mostly low, consistent with the student population, and most respondents report limited or no investment experience.

This profile highlights the relevance of studying robo-advisory adoption among young, educated, yet financially constrained individuals.

Descriptive Statistics of Key Constructs

The descriptive analysis shows moderately positive perceptions across all study constructs, indicating general openness toward robo-advisory platforms. Attitude Toward Technology records the highest mean value, suggesting that respondents are comfortable using technology for financial purposes. Performance Expectancy and Behavioral Intention also display favorable scores, reflecting perceived usefulness and willingness to adopt such platforms. However, Actual Use Behavior remains comparatively low, revealing a gap between intention and real usage. The variation in responses suggests differing levels of familiarity and readiness among students.

Factors Influencing Behavioral Intention to Use Robo-Advisory Platforms

The regression results reveal that the model explains a significant portion of variance in behavioral intention, confirming its explanatory strength. Performance Expectancy positively influences intention, indicating that perceived benefits play a key role in adoption decisions. Social Influence and Awareness also significantly affect intention, highlighting the importance of peer opinions and knowledge about robo-advisory services. Attitude Toward Technology emerges as the strongest predictor, emphasizing the role of technological receptiveness. In contrast, Effort Expectancy and Facilitating Conditions do not show a significant impact on intention.

Behavioral Intention and Actual Use Behavior

The findings confirm a significant positive relationship between behavioral intention and actual use behavior, supporting established technology adoption theories. However, the relatively low explanatory power suggests that intention does not always translate into actual usage. Although students express interest in using robo-advisory platforms, practical adoption remains limited. Constraints such as low income, limited investment experience, and perceived financial risk

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may restrict active engagement. This highlights the presence of an intention–behavior gap within the student population.

Moderating Role of Demographic Factors

The moderation analysis indicates that demographic variables such as gender, age, income, and investment experience do not significantly influence the relationship between intention and usage. This suggests that the effect of behavioral intention on actual use remains consistent across different demographic groups.

Although minor differences are observed among certain subgroups, they are not statistically significant. The results imply that demographic characteristics have a limited role in shaping robo-advisory adoption. Instead, psychological and perceptual factors appear to be more influential.

Overall Interpretation

Overall, the study indicates that students' adoption of robo-advisory platforms is primarily driven by attitudes, perceived usefulness, awareness, and social influence. Despite generally positive perceptions and intentions, actual usage remains relatively low, suggesting that adoption is still at an early stage. The findings highlight the importance of enhancing awareness and building trust in robo-advisory services. Creating supportive conditions may help convert positive intentions into real usage. This could accelerate adoption among young and technologically inclined students.

Findings

1. Respondent Demographics The study draws from a sample of 60 college students, featuring a near-equal gender split (51.7% female, 48.3% male). The majority fall within the 22–25 age bracket (60%), followed by the 19–21 group (25%). Most participants are enrolled in postgraduate programs (65%), with undergraduates and professional course students forming smaller portions. Personal monthly income is predominantly low, with over half (55%) earning below ₹5,000 and only 5% exceeding ₹20,000. Investment exposure remains limited: 41.7% report no prior experience, and another 31.7% have less than one year. When asked about preferred investment guidance, 38.3% favor traditional advisors, 30% are open to both traditional and robo-advisory options, 11.7% prefer robo-advisory alone, and 20% currently avoid both.

This demographic snapshot portrays a group of young, educated individuals who are digitally literate yet financially constrained and relatively new to investing—making them a promising yet under-served segment for robo-advisory services in mutual fund investing.

2. Perceptions of Core Constructs Respondents displayed moderately favorable views toward robo-advisory platforms across most measured dimensions (means ranging from 3.13 to 3.57 on a 5-point scale). The highest average score was recorded for Attitude Toward Technology (3.57), suggesting strong overall comfort with digital tools in financial contexts.

Performance Expectancy (3.43) and Behavioral Intention (3.40) followed closely, indicating reasonable confidence in the usefulness of robo-advisors and willingness to consider them. In contrast, actual Use Behavior scored noticeably lower (2.98), pointing to a persistent disconnect between interest and real-world adoption.

3. Determinants of Behavioral Intention Multiple regression analysis ($R^2 = 0.49$, $p < 0.001$) revealed that four factors significantly and positively shape students' intention to adopt robo-advisory platforms for mutual fund investments:

- Attitude Toward Technology emerged as the most influential predictor ($\beta = 0.31$, $p = 0.002$).
- Performance Expectancy ranked second ($\beta = 0.26$, $p = 0.015$).
- Awareness of robo-advisory services also played a meaningful role ($\beta = 0.23$, $p = 0.022$).

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- Social Influence exerted a modest yet significant effect ($\beta = 0.20$, $p = 0.042$).

Effort Expectancy ($p = 0.228$) and Facilitating Conditions ($p = 0.382$) showed no statistically meaningful impact. These results suggest that students are more motivated by their general affinity for technology, belief in performance advantages, knowledge of the service, and encouragement from peers than by perceived ease of use or availability of supporting infrastructure.

4. Link Between Intention and Actual Usage Simple linear regression confirmed a robust positive association between Behavioral Intention and Use Behavior ($\beta = 0.51$, $p < 0.001$; $R^2 = 0.26$). While intention clearly drives usage to a considerable extent, the modest explanatory power indicates that a substantial portion of interested students still refrain from active engagement. This intention–behavior discrepancy likely stems from financial limitations, inexperience, or lingering hesitation toward automated investment tools.

5. Role of Demographic Variables as Moderators Moderation tests (using interaction terms and subgroup comparisons) found no significant influence of gender ($p = 0.35$), age ($p = 0.48$), investment experience ($p = 0.19$), or income ($p = 0.31$) on the strength of the intention–usage relationship. Although subtle variations appeared in certain subgroups (e.g., marginally stronger links among males or those with some experience), none reached statistical significance. Within this relatively uniform student population, demographic differences appear to have little bearing on how intention translates into behavior.

Overall Insights The study demonstrates that adoption intent among college students is primarily fueled by positive technology attitudes, perceived performance gains, greater awareness, and social encouragement rather than ease of use or external support. Although students express genuine interest in robo-advisory platforms, actual participation lags considerably behind intention highlighting an early-phase adoption pattern in this demographic. The absence of demographic moderation suggests that these perceptual and attitudinal drivers operate fairly consistently across gender, age, income, and experience levels within the sample.

These findings underscore the strategic importance of awareness-building initiatives, peer-based promotion, and user-friendly demonstrations of performance benefits to accelerate robo-advisory uptake among young, tech-oriented investors in mutual fund markets.

Managerial Implications and Recommendations

The findings provide useful guidance for fintech firms, mutual fund companies, and policymakers aiming to promote robo-advisory adoption among college students. As this segment is digitally skilled but financially constrained, adoption strategies should focus more on perception, awareness, and engagement rather than technological sophistication.

MANAGERIAL IMPLICATIONS

- **Leverage Positive Technology Attitudes:**
  Since attitude toward technology is the strongest driver of intention, robo-advisory platforms should be positioned as modern, smart, and trustworthy investment solutions that align with students' digital lifestyles.

- **Highlight Performance Value:**

Performance expectancy significantly influences adoption, while ease of use does not. Managers should therefore emphasize benefits such as portfolio optimization, diversification, and disciplined investing rather than technical features.

- **Address the Intention Usage Gap:**
  Despite high intention, actual usage remains low. Offering low minimum investments, trial portfolios, or simulated investment options can reduce perceived risk and encourage first-time use.

- **Utilize Social Influence:**
  Peer opinions play an important role in shaping intention. Campus ambassadors, referral programs, and student testimonials can help build trust and accelerate adoption.

- **Improve Awareness Levels:**
  Limited awareness restricts adoption. Educational initiatives, campus programs, and simple digital content explaining robo-advisory concepts can enhance understanding and confidence.

- **Minimal Role of Demographics:**
  Since demographic factors do not significantly moderate adoption behavior, managers can adopt a uniform strategy focused on psychological and perceptual drivers rather than demographic segmentation.

RECOMMENDATIONS

- Design student-focused robo-advisory plans with low entry barriers and simple goal-setting features.
- Integrate robo-advisory education into financial literacy programs in academic institutions.
- Use peer-based promotion and social proof to strengthen trust and acceptance.
- Provide demo accounts or zero-risk starter options to reduce hesitation.
- Emphasize value creation and long-term investment benefits in promotional efforts.
- Support policy initiatives that promote transparency, awareness, and fintech inclusion among youth.

Overall, the adoption of robo-advisory platforms among college students depends more on awareness, perceived value, and trust than on technological infrastructure. By addressing psychological and financial barriers, managers can convert positive intentions into sustained usage and effectively engage this emerging investor segment.

CONCLUSION:

This study concludes that college students’ adoption of robo-advisory platforms for mutual fund investments is primarily driven by positive attitudes toward technology, perceived performance benefits, awareness, and social influence. While students show a clear intention to use robo-advisors, actual usage remains limited due to financial constraints, limited experience, and perceived risk. Effort expectancy and facilitating conditions were found to have minimal impact, and demographic factors did not significantly moderate adoption behavior. Overall, the findings suggest that enhancing awareness, demonstrating value, and building trust are more critical for increasing robo-advisory adoption among students than technological sophistication alone.

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