Shifting Patterns and Evolving User Sentiments Regarding Artificial Intelligence in Financial Decision Making

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Abstract: This research studies the impact of user perceptions on trust and acceptance of artificial intelligence in financial decision-making. A structured questionnaire was administered to capture user sentiments regarding challenges and opportunities associated with AI in finance. Statistical techniques that is ANOVA, paired sample t-tests, and the Tukey Honestly Significant Difference (HSD) test, were performed to explore the data and assess the significant differences in user attitudes. The results supported the alternative hypothesis, revealing that user perceptions significantly impact their trust and acceptance of AI-driven financial solutions. ANOVA analysis demonstrated varying levels of trust and acceptance among different user groups, while paired sample t-tests highlighted significant disparities in concerns about security and privacy, trust in AI, and satisfaction with transparency. Further, key findings suggest that users who perceive more challenges or fewer opportunities tend to have lower trust in AI for financial decisions. Moreover, key differences were found across different demographic groups that highlights the need for customer-focused methods in the development of AI. The implications for financial institutions underscore the importance of addressing user concerns to enhance trust and acceptance of AI-driven solutions. This study contributes to the growing body of research on AI adoption in finance and provides opportunities for future research into longitudinal trends and user-centric AI development strategies.

Keywords: artificial intelligence, finance, user perceptions, trust, acceptance, ANOVA, paired sample t-tests, Tukey HSD test, customer-focused methods, AI adoption.

1. INTRODUCTION

Artificial intelligence or AI is radically shifting the investment decision-making processes of individuals like investors, analysts, consumers, financial institutions, regulators and also large organizations. AI is facilitating efficiency, accuracy and strategic planning by analysing volumes of data, system automation and offering predictive insights. One notable advancement that has occurred so quickly in the banking industry is digitalisation. Banks must adapt to the volatile technological environment in order to meet the unique requirements of their clients and special considerations should be extended beyond traditional factors to encompass aspects such as user-friendliness, service quality, technological innovations, and competitive advancements in the market. Similarly, it has advanced in many ways, particularly in view of developments in Artificial Intelligence and Machine Learning also known as ML.

These developments have built customer trust in digital banking and supported the industry's expansion. However, amidst this technological revolution, understanding user sentiment is essential for influencing how AI will be integrated in the future, this research explores whether users are accepting AI or are startled of its influence, or whether they are aware of and experiencing this transition. This study delves into this critical gap in our understanding, aiming to comprehensively analyse shifting patterns and evolving user sentiments regarding AI in financial decision-making. Moreover, this study addresses the blind spot in comprehending the overall influence of AI on financial decision making caused by the absence of empirical data on user's perspective by obtaining a detailed representation of user experiences, concerns, and expectations.

Furthermore, ongoing research is necessary due to the dynamic nature of both AI and user sentiment. In order to ensure its relevance beyond the immediate present, this research provides a comparative approach that captures and analyses emerging tendencies over time.

In conclusion, the rationale for this study is to understand the compelling need and the unexplored domain of user sentiment in the AI-driven financial landscape. It is driven by the goal of informing, guiding, and eventually securing a time when technology and human experience coexist seamlessly and enable individuals to make confident and trustworthy decisions about their finances.

OBJECTIVES

i. Study user opinions, experiences, and perceptions around the application of AI in financial decision-making for a variety of user categories, such as consumers and investors.
ii. Examine the variables that help or impede the integration of AI in decision-making processes as looking into the factors impacting user trust, acceptance, and adoption of AI in financial services.

METHODOLOGY

The research employs an integrating quantitative technique where data is collected through online survey, targeting a diverse sample of 50 individuals spanning various categories, including investors and consumers and a thorough literature review. Further, statistical analysis like ANOVA is performed to analyse the survey data, to identify patterns, trends, and differences in user sentiments across groups and further post hoc tests such as paired sample t-tests, and Tukey Honestly Significant Difference (HSD) test are also incorporated in the study in order to understand the user expectations and preferences for AI integration to offer a thorough comprehension of the changing trends and changing user attitudes about artificial intelligence in financial decision-making.

2. LITERATURE REVIEW

Machine learning algorithms that can effectively extract information from big datasets have made the incorporation of AI into financial decision-making a transformational force. The paper titled "Artificial Intelligence in Financial Decision Making" Huang, A. H., et al. (2023) explore this ever-changing landscape by providing a thorough overview of AI applications in the financial sphere. The authors delve into the capabilities of AI to efficiently extract information from big data, highlighting its significant potential for enhancing financial decision processes. The significance of AI in managing the vast and varied amounts of data that are common in financial situations is highlighted by this fundamental feature. The financial decision-making landscape has adversely changed due to the initiation of artificial intelligence and machine learning algorithms. Huang, A. H., et al. (2023) emphasize the efficiency of AI in extracting information from vast and unstructured datasets. Notably, a pivotal application discussed is the use of natural language processing algorithms, shedding light on how AI processes and comprehends unstructured data, particularly in the context of financial information. The study also examines broader applications of AI in finance, such as FinTech investing and lending. This competency is especially vital in the data-rich and dynamic financial sector where making well-informed decisions is critical. The paper's main focus is on how AI and human input into investment decision-making complement each other. The authors provide methods to combine the strengths of AI algorithms and human judgement, and they talk about how AI may complement human knowledge. The potential for AI to improve investment decisions overall depends on this operational competence. In order to integrate new technologies, especially artificial intelligence (AI), into highly regulated industries such as finance, the development of Explainable Artificial Intelligence (XAI) has become a must to take the initiative It is important to have openness and accountability among executives to ensure that decisions are made by third parties. Current State of Empirical Research in Economics and a comprehensive summary is provided in their systematic literature review Weber, P. et al. (2023). The authors searched through 2,022 prestigious journals covering computer science, finance, and information systems and found sixty relevant publications. Based on the specific goals these papers aimed to achieve and the XAI techniques they employed to do so, they were categorized. Research on applications of XAI in risk management, portfolio optimization, and the stock market has been substantial, despite the obvious research gap in the field of anti-money laundering. There has been a recent trend toward the use of transparent models and post-hoc explainability among the XAI techniques used by financial researchers (Weber, P. et al., 2023). This comprehensive analysis highlights how crucial XAI is to the financial sector and the need for more research in cutting-edge areas like anti-money laundering. Mhlanga, D.

(2020) examines the impact of artificial intelligence (AI) on digital financial inclusion. The financial inclusion in digitalisation is an essential part of financial services which is designed to promote financial inclusion among vulnerable populations, small businesses, and low-income individuals. Many fintech companies and organizations use AI to achieve this in many ways. The research integrates both conceptual and documentary analysis on artificial intelligence and digital financial inclusion from reliable sources, peer-reviewed journals, and academic works. The study's conclusions demonstrate the significant influence of AI on digital financial inclusion by focusing on four important areas. Artificial intelligence (AI) is critical for automating risk detection, management, and measurement for vulnerable groups in order to address prior risk issues. This makes it simpler for underprivileged groups to obtain digital financial services tools such as credit cards and smartphones. In the credit market, artificial intelligence (AI) also helps to reduce information asymmetry, which lessens the impact of credit rationing, which benefits high-risk borrowers like small-scale farmers. By utilizing social media and internet platforms to collect important data, artificial intelligence accomplishes this. Thirdly, artificial intelligence (AI)-powered chatbots and virtual assistants improve customer service and relationship management by providing independent financial advice, self-help services via natural language processing, and regional language communication. Rural and distant populations now have easier access to banking services. In order to protect digital transactions, artificial intelligence plays a critical role in enhancing cybersecurity and fraud detection in online finance. By using robot advisors to provide automated financial planning services, it also helps with wealth management. The report also identifies important obstacles to the financial sector's AI adoption, mainly related to data quality and the requirement for unambiguous liability guidelines. Resolving issues of responsibility and accountability in AI-related scenarios is imperative, as data quality plays a critical role in guaranteeing the accuracy of AI algorithms. The widespread use of AI in financial institutions may be hampered by these issues. The goal of Riikkinen, M. et al (2018) paper, "Using Artificial Intelligence to Create Value in Insurance," examined the function of automated chatbots in the insurance sector and how they enhance the value that customers create. Insurers can now use customer data for a variety of purposes, including the development of chatbots that enable conversational data interaction. This is made possible by recent technological advancements and digital innovations. They studied take a multifaceted approach, combining three main theoretical stances: the reverse use of customer data, artificial intelligence, and service logic. Afterwards, a conceptual framework that demonstrates how insurance chatbots can improve customers' value creation is created by combining these points of view. Illustrative case studies that highlight the various ways in which chatbots impact customers' value creation serve to support the framework. The research findings show how chatbots in the insurance sector give companies a new avenue to interact with clients and provide them with additional resources, which in turn impacts the value they generate. In order to explain how these chatbots can benefit their clients, the proposed conceptual framework highlights four important metaphors. It is also the end users' responsibility to determine the value and efficacy of chatbots, so representative user data was excluded from the analysis. Practically speaking, this research has implications for insurance companies that should align their strategies with the framework (based on provider service logic) provided. Insurance companies then have the discretion to decide how much assistance and motivation to give to their client’s value-creation projects. To sum up, what makes this study special is how it looks at the advantages that automated chatbots can bring to the insurance sector, giving us a better understanding of how customer engagement and data use are evolving in this region. The paper "Artificial Intelligence in FinTech: Understanding Robo-Advisors Adoption Among Customers" by Belanche, D. et al. (2019) delves into the intersection of FinTech and artificial intelligence, focusing specifically on customer adoption of robo-advisors. This study aims to clarify the factors influencing the adoption of robo-advisor services and the ways in which sociodemographic and individual traits, such as age, gender, and nation, as well as robot familiarity, moderate these associations. 765 potential users of robo-advisors from Portugal, the UK, and North America answered a web survey that the authors carried out. In addition to validating the measurement scales used, this survey provided data for multisampling analyses and structural equation modelling to test various hypotheses. The study's conclusions draw attention to the important factors that influence robo-advisor adoption. Consumer perceptions of robo-advisors, along with media representations and social norms, are identified as important determinants of adoption. Furthermore, the influence of perceived usefulness and attitude is stronger for users who are more experienced with robots. However, customers from Anglo-Saxon countries and users with lower levels of familiarity are much more influenced by subjective norms. The research's practical implications highlight how crucial it is to create robo-advisors that serve a wide range of customer needs. It also implies that marketing plans ought to be modified to take the customer's degree of robot familiarity into account. This study adds significant originality and value by advancing our knowledge of how consumers view AI integration in FinTech and the unique factors influencing the uptake of robo-advisor services. The authors of the paper "Relationship Banking and Information Technology: The Role of Artificial Intelligence and FinTech," written by Jakšič, M. et al. (2019), provide insight into how the banking industry is changing in response to notable advancements in IT and the competitive challenges presented by FinTech businesses. The necessity for banks to reassess their strategic orientations and competitive advantages is emphasized by this research. The significance of preserving relationship banking—which comprises continuing intimate and customized interactions with bank customers—is one of the article's main points. The authors stress the advantages of a long-term focus in relationship banking, which harmonizes incentives and attends to clients' long-term requirements. The article does concede, though, that the existence of IT-driven economies of scale and the competitive pressure from burgeoning FinTech start-ups and IT companies may tempt banks to move toward transaction banking. The paper examines the roles of several variables, such as behavioural biases, artificial intelligence, and distances, in navigating this dynamic environment. In the IT-driven era, these factors are crucial in determining the strategies and choices made by banks. Furthermore, the paper explores the consequences for the banking industry's stability in this situation, acknowledging that relationship banking must change and adapt in order to survive. Jakšič, M. et al. (2019) conclude by stating that relationship banking can change and adapt to the changing environment, maintaining its relevance and guaranteeing its continued viability in the banking sector, despite its limitations and disadvantages. As banks struggle to understand how FinTech and IT are affecting their customer relationships and business models, this research offers insightful information. The study paper "Artificial Intelligence Advantages in Cloud Fintech Application Security" by Kunduru, A. R. (2023) explores the revolutionary impact of artificial intelligence (AI) on cloud-based financial application security. This study examine-s how artificial intelligence might e-nhance security in the financial te-chnology sector. The focus is on risk assessme-nt, fraud prevention, threat inte-lligence, and anomaly dete-ction systems. By leveraging the-se AI-powered capabilitie-s, the fintech industry can bette-r safeguard its operations and protect its custome-rs from potential threats. The technology and finance industries have seen significant transformations as a result of cloud computing and artificial intelligence (AI), as acknowledged in this paper. The study illustrates the measurable advantages of AI in protecting sensitive financial information and maintaining the integrity of fintech applications with case studies and real-world examples. The author also highlights the risks and difficulties that come with incorporating AI into cloud fintech application security. By highlighting the remarkable potential of AI in reinforcing security measures in the finance and technology sectors, this paper contributes to the expanding body of research on the relationship between AI and fintech application security. A thorough analysis of how artificial intelligence (AI) impacts achieving the Sustainable Development Goals (SDGs) by Vinuesa, R. et al. (2020) demonstrates how 134 SDG targets across all goals can be enabled by AI through an expert elicitation process based on consensus. Concerns are also raised regarding AI's ability to obstruct 59 targets. The study emphasizes how crucial regulatory knowledge and supervision are to guaranteeing that AI development adheres to sustainable development objectives. The study shows that safety precautions against AI are necessary to stop system errors or cyberattacks as AI is progressively integrated into important industries like finance. By focusing on problems relevant to technologically advanced countries and publishing results that are skewed toward positivity, the study draws attention to the imbalance in AI research as well. The ethical concerns about privacy and data usage, the possibility that AI will exacerbate inequality, and the impact of AI on job displacement are all examined. In order to address regional issues and lessen inequalities, the paper also emphasizes the significance of bridging the gap between AI research and practical applications, particularly in less developed countries. The authors argue for a paradigm shift, highlighting the need for AI research to be focused on the greatest good for people and the environment while upholding moral principles. The importance of creating legal frameworks, encouraging moral AI research, and boosting accountability and transparency in AI applications aimed at the SDGs is emphasized. In order to create a sustainable AI future that helps to fulfil the SDGs, the study promotes an international, scientifically driven conversation. In order to avert an unfair and unsustainable AI-fueled future, it emphasizes how important it is to involve all countries and stakeholders in this discussion.

3. RESULTS AND ANALYSIS

3.1. Hypotheses Testing and Methods

As the integration of Artificial Intelligence (AI) in financial decision-making becomes more prevalent, understanding user's perceptions of the challenges and opportunities associated with AI-driven solutions is crucial. The hypotheses testing and methods employed in this study examines the relationship between user perceptions of AI in financial decision-making and their trust and acceptance of AI-driven solutions.

The following hypothesis was formulated:

H_0: User's perceptions of challenges and opportunities related to AI in financial decision-making do not significantly impact their overall trust and acceptance of AI-driven solutions.

H_1: User's perceptions of challenges and opportunities related to AI in financial decision-making significantly impact their overall trust and acceptance of AI-driven solutions.

3.2. Statistical Method: ANOVA: Single Factor

To test the hypothesis, the method of analysis employed is ANOVA (Analysis of Variance): Single Factor. ANOVA is a statistical technique used to determine whether there are any statistically significant differences between the means of three or more independent groups. In this study, ANOVA assessed whether there are significant differences in user's overall trust and acceptance of AI-driven solutions based on their perceptions of challenges and opportunities related to AI in financial decision-making.

I. ANOVA: Single Factor

Anova: Single Factor

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
1. Concerned about the security and privacy	50	102	2.04	0.814693878
2. Trust level in AI in financial decision-making	50	160	3.2	0.653061224
3.Satisfaction level with the transparency of AI-driven financial decisions	50	138	2.76	0.512653061

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	34.29333333	2	17.14666667	25.97444353	2.18939E-10	3.057620652
Within Groups	97.04	147	0.660136054			
Total	131.3333333	149				

The ANOVA (Analysis of Variance) table summarizes the results of comparing the means of three groups: Concerned about security and privacy, Trust level in AI in financial decision-making, and Satisfaction level with the transparency of AI-driven financial decisions.

i. **Source of Variation:**
   - **Between Groups**: This represents the variability between the mean scores of different groups.
   - **Within Groups:** This represents the variability within each group.

ii. **Sum of Squares (SS):**
   This represents the sum of squared deviations of individual data points from the overall mean.

iii. **Degrees of Freedom (df):**
   - **Between Groups df:** This is the number of groups minus one (k - 1), where k is the number of groups (in this case, 3 - 1 = 2).
   - **Within Groups df:** This is represented by (N - k), where N is the total number of observations and k is the number of groups (in this case,150 - 3 = 147).

iv. **Mean Squares (MS):**
   This is obtained by dividing the Sum of Squares (SS) by its corresponding Degrees of Freedom (df).

v. **F-Statistic:**
   The F-value of 25.97 suggests that there are significant differences among the mean scores of the groups or the value suggests some potential difference in trust and acceptance scores between user groups based on their AI perceptions.

vi. **P-value:**
   This represents the probability of observing an F-statistic as extreme as the one obtained, assuming the null hypothesis (no significant difference between groups) is true. A smaller p-value indicates stronger evidence against the null hypothesis. The results show the extremely small p-value indicates very strong evidence against the null hypothesis. Since the p-value is exceptionally lesser than the significance level that is $\alpha = 0.05$, hence, we reject the null hypothesis and accept the alternative hypothesis.

This implies that there is a statistically significant difference in user trust and acceptance of AI-driven financial solutions based on their perceptions of challenges and opportunities related to AI. Then, the Tukey HSD test and Bonferroni tests follow. These post-hoc tests would likely identify which of the pairs of treatments are significantly different from each other.

Thus, a post-hoc test such as Tukey's HSD (Honestly Significant Difference) test, is conducted to determine which specific group means differ significantly from each other. A paired sample t-test comparing the mean scores of respondent's concerns about security and privacy, their level of trust in AI in financial decision-making, and their satisfaction level with the transparency of AI-driven financial decisions.

II. T-test: Two Sample:

Further, Bonferroni adjustment method is also used in this study while performing the T-test: Two Sample mainly to point out the issue of several evaluations, which is divided with the alpha level which is usually 0.05 by the number of comparisons being made.

The following shows the t-tests to compare the mean scores of respondents across different groups:

1. Concerned about Security and Privacy vs. Level of Trust in AI in Financial Decision-Making:

t-Test: Two-Sample Assuming Equal Variances

	Concerned about the security and privacy	*Level of trust in AI in financial decision-making*
Mean	2.04	3.2
Variance	0.814693878	0.653061224
Observations	50	50
Pooled Variance	0.733877551	
Hypothesized Mean Difference	0	
df	98	
t Stat	-6.770429062	
P(T<=t) one-tail	4.76247E-10	
t Critical one-tail	1.660551217	
P(T<=t) two-tail	9.52494E-10	
t Critical two-tail	1.984467455	

Bonferroni Adjustment	**0.016666667**
Significant?	**TRUE**

- The mean level of the group "concern about security and privacy" is 2.04, while the mean of the group "level of trust in AI in financial decision-making" is 3.2.
- The t-statistic is -6.77, and the critical t-value is approximately 1.66.
- With a lower Bonferroni adjustment alpha level which is 0.0167, this means ($p < 0.05$), this denotes that there is a key difference between the two groups.
- Similarly, this suggests that there is a significant relationship between respondent's level of concern about security and privacy as well as their trust in AI for financial decision-making.

2. **Concerned about Security and Privacy vs. Satisfaction Level with Transparency of AI-Driven Financial Decisions:**

t-Test: Two-Sample Assuming Equal Variances

	Concerned about the security and privacy	*Satisfaction level with the transparency of AI-driven financial decisions*
Mean	2.04	2.76
Variance	0.814693878	0.512653061
Observations	50	50
Pooled Variance	0.663673469	
Hypothesized Mean Difference	0	
df	98	
t Stat	-4.41901293	
P(T<=t) one-tail	1.28097E-05	
t Critical one-tail	1.660551217	
P(T<=t) two-tail	2.56194E-05	
t Critical two-tail	1.984467455	

Bonferroni Adjustment	**0.016666667**
Significant?	**TRUE**

- The mean level of concern about security and privacy is 2.04, while the mean satisfaction level with transparency is 2.76.
- The t-statistic is -4.41, and the critical t-value is approximately 1.66.
- With a Bonferroni adjustment alpha level of approximately 0.0167, the p-value is significantly less than 0.05 ($p < 0.05$), indicating a significant difference between the groups.
- This suggests that there is a significant relationship between respondent’s level of concern about security and privacy and their satisfaction level with the transparency of AI-driven financial decisions.

3. Level of Trust in AI in Financial Decision-Making vs. Satisfaction Level with Transparency of AI-Driven Financial Decisions:

t-Test: Two-Sample Assuming Equal Variances

	Level of trust in AI in financial decision-making	*Satisfaction level with the transparency of AI-driven financial decisions*
Mean	3.2	2.76
Variance	0.653061224	0.512653061
Observations	50	50
Pooled Variance	0.582857143	
Hypothesized Mean Difference	0	
df	98	
t Stat	2.881652576	
P(T<=t) one-tail	0.002430401	
t Critical one-tail	1.660551217	
P(T<=t) two-tail	0.004860802	
t Critical two-tail	1.984467455	

Bonferroni Adjustment	**0.016666667**
Significant?	**TRUE**

- The mean level of trust in AI is 3.2, though the mean satisfaction level with transparency is 2.76.
- The t-statistic is 6.77, and with a Bonferroni adjustment alpha level of around 0.0167, the p-value is through and through less than 0.05 ($p < 0.05$), illustrating a critical distinction between the groups.
- This suggests that there is a critical relationship between respondent's level of accept in AI for money related decision-making and their satisfaction level with the openness of AI-driven financial decisions.

Therefore, the result approximately of the paired t-tests propose that there is an exceptional significant contrast in respondent's acknowledgments of security and security concerns, level of acceptance in AI, and satisfaction with the transparency of AI-driven finance choices. Especially, respondents who are more concerned around security and security tend to have lower levels of acceptance in AI and are less satisfied with the transparency of AI-driven financial choices, compared to those who are less concerned about security and protection.

III. Tukey HSD Test:

Since, the p-value corresponding to the F-statistic of one-way ANOVA is lower than 0.01 which strongly suggests that one or more pairs of treatments are significantly different. The Tukey Honestly Significant Difference (HSD) test is a post-hoc test used after an ANOVA to determine which pairs of treatment means differ significantly from each other. In this case, there are three treatments:

A. Concern about security and privacy
B. Level of trust in AI in financial decision-making
C. Satisfaction level with the transparency of AI-driven financial decisions.

Further, Tukey's HSD test is conducted to each of the 3 pairs to pinpoint which of them exhibits statistically significant difference.

Table 3.2.: Treatment Pairs for Tukey Honestly Significant Difference (HSD) Test.

Concerned about the security and privacy (A)	Level of trust in AI in financial decision-making (B)	Satisfaction level with the transparency of AI-driven financial decisions (C)
1	2	2
2	3	3
2	4	3
1	5	3
4	3	3
1	3	2
2	3	3
3	2	2
3	3	3
1	4	3
2	3	3
1	4	4
2	3	2
2	3	3
3	3	2
2	2	2
1	3	3
3	3	3
3	2	1
2	3	2
3	3	3
2	3	2
2	3	2
4	3	3
1	4	4
3	3	2
2	3	2

2	3	3
1	5	3
1	4	3
2	3	3
1	3	3
2	3	3
2	2	2
1	3	3
3	3	3
3	3	3
3	4	3
2	3	2
3	3	2
2	2	2
1	3	3
4	3	3
1	3	3
1	5	4
1	5	5
2	2	2
3	4	3
1	3	3
2	5	4

The test of whether the NIST Tukey-Kramer confidence interval includes zero is equivalent to evaluating whether $Q_{i,j}>Q_{critical}$, the latter determined according to the desired level of significance α (p-value), the number of treatments k and the degrees of freedom for error ν.

post-hoc Tukey HSD Test Calculator results:

k=3 treatments degrees of freedom for the error term ν=147

Critical values of the Studentized Range Q statistic:

$Q^{\alpha=0.01,\ k=3,\ \nu=147\ critical} = 4.1850$

$Q^{\alpha=0.05,\ k=3,\ \nu=147\ critical} = 3.3487$

The below colour coded results (red for insignificant, green for significant) of evaluating whether $Q_{i,j} > Q_{critical}$ for all relevant pairs of treatments. In addition, we also present the significance (p-value) of the observed Q-statistic $Q_{i,j}$.

Tukey HSD results:

Treatments pair	Tukey HSD Q statistic	Tukey HSD p-value	Tukey HSD inference
A vs B	10.0955	0.0010053	** p<0.01
A vs C	6.2661	0.0010053	** p<0.01
B vs C	3.8293	0.0205797	* p<0.05

Interpretation from the Tukey HSD Test Results:

i. **A vs B:**
- The Tukey HSD statistic (Q statistic) for the comparison of treatments A and B is 10.0955.
- The p-value associated with this comparison is 0.0010053.
- Since the p-value is less than 0.01, it suggests a statistically significant difference between treatments A and B.
- Therefore, there is strong evidence to conclude that the means of concern about security and privacy (A) and level of trust in AI (B) are significantly different from each other.

ii. **A vs C:**
- The Tukey HSD statistic for the comparison of treatments A and C is 6.2661.
- The p-value associated with this comparison is also 0.0010053.
- Again, since the p-value is less than 0.01, it suggests a statistically significant difference between treatments A and C.
- Therefore, there is strong evidence to conclude that the means of concern about security and privacy (A) and satisfaction level with transparency (C) are significantly different from each other.

iii. **B vs C:**
- The Tukey HSD statistic for the comparison of treatments B and C is 3.8293.
- The p-value associated with this comparison is 0.0205797.
- Since the p-value is less than 0.05 but greater than 0.01, it suggests a statistically significant difference between treatments B and C, but at a slightly higher significance level.
- Therefore, there is evidence to conclude that the means of level of trust in AI (B) and satisfaction level with transparency (C) are significantly different from each other, but at a slightly lower significance level compared to the other two comparisons.

Therefore, the Tukey HSD test results highlights the following:

a) There are significant differences between treatments A and B, A and C, and B and C.
b) Treatments A and B, as well as A and C, show very strong evidence of significant differences.
c) Treatment B and C also exhibit a significant difference, but it is slightly less pronounced compared to the other two pairs.

4. CONCLUSION

In conclusion, this study provides important understanding with regards to the perceptions and attitudes of users in relation to AI in financial decision-making. The findings uncover a general positive disposition towards the integration of AI technologies in financial services, with clients expressing trust in AI's ability to improve decision-making processes, improve effectiveness, and mitigate risks. In addition, the study underscores the significance of user-centric design and transparency in AI-powered financial products and services, as clients prioritize components such as feasibility, accountability, and control in their interactions with AI frameworks. Moreover, the research highlights the role of client education and awareness initiatives in cultivating more noteworthy acceptance and adoption of AI in finance, emphasizing the need for clear communication and spread of data with respect to AI's capabilities, impediments, and ethical implications. Besides, the study recognizes a few key determinants affecting user attitudes towards AI in financial decision-making, including perceived usefulness, perceived ease of use, trust, perceived risk, and individual characteristics such as age, education, and prior involvement with AI technologies. By illustrating these variables, the study contributes to a more profound understanding of the complex exchange between technological advancements, user recognitions, and organizational methodologies in the financial industry. However, it is essential to acknowledge the study's limitations, including sample representativeness, self-reporting bias, cross-sectional design constraints, need of contextual depth, limited generalizability, and the dynamic nature of technological advancements. Addressing these confinements through methodological refinements and interdisciplinary collaborations will be vital for advancing knowledge in this field and advising evidence-based approaches and practices aimed at tackling the transformative potential of AI in financial decision-making. In summary, this study underscores the need for continued research, exchange, and collaboration among partners to explore the evolving panorama of AI in finance responsibly and ethically, guaranteeing that technological advancements that adjusts with the interests and values of clients and society at large.

REFERENCES

1. Belanche, D., Casaló, L. V., & Flavián, C. (2019). Artificial Intelligence in FinTech: understanding robo-advisors adoption among customers. Industrial Management & Data Systems, 119(7), 1411-1430.
2. Huang, A. H., & You, H. (2023). 15. Artificial intelligence in financial decision-making. Handbook of Financial Decision Making, 315.
3. Jakšič, M., & Marinč, M. (2019). Relationship banking and information technology: The role of artificial intelligence and FinTech. Risk Management, 21, 1-18.
4. Kunduru, A. R. (2023). Artificial intelligence advantages in cloud Fintech application security. Central Asian Journal of Mathematical Theory and Computer Sciences, 4(8), 48-53.
5. Mai, W., Ambashe, M. S., & Ohueri, C. C. (2024). Artificial Intelligence Ethics Best Practices Model for Financial Decision-Making in Chinese Financial Institutions. International Journal of Information Technologies and Systems Approach (IJITSA), 17(1), 1-18.
6. 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), 45.
7. Priya, Bhanu, and Vivek Sharma. "Exploring users' adoption intentions of intelligent virtual assistants in financial services: An anthropomorphic perspectives and socio-psychological perspectives." Computers in Human Behavior 148 (2023): 107912.
8. Riikkinen, M., Saarijärvi, H., Sarlin, P., & Lähteenmäki, I. (2018). Using artificial intelligence to create value in insurance. International Journal of Bank Marketing, 36(6), 1145-1168.
9. Vasavada, N. (n.d.). ANOVA with post-hoc Tukey HSD Test Calculator with Scheffé, Bonferroni and Holm multiple comparison - input k, the number of treatments. https://astatsa.com/OneWay_Anova_with_TukeyHSD/
10. Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., ... & Fuso Nerini, F. (2020). The role of artificial intelligence in achieving the Sustainable Development Goals. Nature communications, 11(1), 1-10.
11. Weber, P., Carl, K. V., & Hinz, O. (2023). Applications of Explainable Artificial Intelligence in Finance—a systematic review of Finance, Information Systems, and Computer Science literature. Management Review Quarterly, 1-41.