The Role of Artificial Intelligence in Enhancing Financial Literacy and Education in India

MSc Research Project
FINTECH

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MSc Project Submission Sheet

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Contents

Abstract

This research investigates the effect of artificial intelligence (AI) tools on financial literacy and decision-production among experts in India. Propelled by the persevering low degrees of financial literacy and the fast headways in AI technology, this study aims to evaluate the degree of AI utilization, its apparent viability, and the difficulties looked by clients. A blended techniques approach was utilized, consolidating quantitative data from a survey of 105 respondents and qualitative bits of knowledge from semi-organized surveys. The discoveries show a moderate degree of AI reception, with members perceiving the advantages of AI tools in upgrading their financial dynamic cycles. In any case, difficulties, for example, tool complexity, integration issues, and data privacy concerns were recognized. A huge positive connection was found between knowledge of AI and its utilization ($r=0.338$ with a significance level of $p<0.01$), as well as between the apparent viability of AI and its reception ($r=0.267$ with a significance level of $p<0.01$). The review features the significance of training and user support in advancing AI reception and proposes functional strides for associations to address distinguished difficulties. Future exploration ought to grow the degree, investigate extra affecting elements, and think about the moral ramifications of AI in finance. This study adds to the writing on AI adoption in financial direction and offers significant experiences for the two academics and specialists.

1. Introduction

Background

Financial literacy is a significant skill that impacts individuals' capacity to pursue sound financial choices. Regardless of the developing significance of financial literacy, many individuals, especially in emerging economies, for example, India, miss the mark on important information and capacities to appropriately deal with their cash. This shortage has serious ramifications for individual and public financial security.

Lately, the consolidation of Artificial Intelligence (AI) into various fields has exhibited promising outcomes in further developing learning and dynamic cycles. AI arrangements can assist individuals with dealing with their funds even more actually by giving customized financial training, ongoing financial direction, and prescient examination. Given the fast development of AI advancements, it is critical to research their expected application in supporting financial literacy.

Problem Statement

The major question tended to in this paper is India's determined low degree of financial literacy and the opportunities for AI technologies to further develop it. Despite a few drives by governments and financial institutions, there is as yet a huge hole in financial comprehension and ways of behaving. Understanding how AI can be utilized to further develop financial literacy might bring about additional successful strategies and tools.

Objectives

The objectives of this study are:

1. To survey the present status of financial literacy among people in India.

2. To investigate the degree to which AI tools are being used in financial decision-making.

3. To dissect the adequacy of AI tools in improving financial literacy and direction.

4. To recognize the difficulties looked in the adoption and use of AI tools for financial purposes.

5. To give recommendations to integrate AI tools into financial literacy programs.

Research Questions

This study aims to answer the following research questions:

1. What is the ongoing degree of financial literacy among people in India?

2. How are AI tools being utilized in financial decision-making processes?

3. How much do AI tools work on financial literacy and decision-making?

4. What difficulties are related with the utilization of AI tools in financial settings?

5. How could AI tools be coordinated into financial literacy programs?

Hypotheses

The study is guided by the following hypotheses:

1. AI tools out and out work on the financial literacy of individuals.

2. There is a positive connection between the level of AI use and further created financial decision-making.

3. The essential difficulties to taking on AI tools in finance relate to mechanical literacy and trust.

Contribution to the Scientific Literature

This study adds to the literature by giving observational proof on the role of AI in upgrading financial literacy. It overcomes any issues between technology adoption and instructive results in the financial area. The discoveries from this research will enlighten policymakers, teachers, and technologists about the potential and difficulties of integrating AI into financial literacy programs.

Structure of the Report

The structure of this report is as follows:

- Introduction: Presents the point, issue articulation, goals, research questions, speculations, and commitment to the literature.
- Related Work: Audits existing literature on financial literacy, AI applications in money, and recognizes holes.
- Research Methodology: Depicts the research design, data assortment strategies, and data examination procedures utilized in the review.
- Design Specification: Details the framework engineering and part design of the AI tools utilized.
- Implementation: Examines the implementation interaction, challenges experienced, and the tools and technologies utilized.
- Evaluation: Presents the consequences of the examination or contextual investigation, data investigation, and conversation of discoveries.
- Conclusion and Future Work: Sums up the discoveries, examines the ramifications, and proposes regions for future research.

By structuring the report in this manner, the study systematically addresses the research questions and objectives, providing a comprehensive understanding of the impact of AI tools on financial literacy.

2. Related Work

2.1 Financial Literacy and Education

The significance of financial literacy in monetary security and individual prosperity has been generally recognized. Lusardi and Mitchell (2014) feature the immediate correlation between financial literacy and monetary way of behaving, accentuating that financially proficient people are better at saving, money management, and overseeing obligation. Their research highlights the need of working on financial schooling to upgrade monetary results at both micro and macro levels.

Atkinson and Messy (2012) directed a near examination of financial literacy across different nations and recognized huge differences, especially in emerging economies. They contended that while financial training programs are common, their adequacy is in many cases restricted by social, instructive, and monetary variables. This finding focuses to the requirement for tailored financial literacy mediations that think about local settings.

Nonetheless, a couple of researchers fight that customary financial instruction strategies have restricted impact. Willis (2011) investigates the sufficiency of conventional financial literacy programs, proposing that they habitually fail to make an understanding of information into direct. She advocates for extra creative methodologies that consolidate lead bits of information and useful applications.

2.2 AI in Financial Decision-Making

The integration of AI in finance has gained significant consideration because of its ability to change decision-making processes. Lee and Shin (2018) examine the notable impact of AI on financial administrations, highlighting its role in additional creating capability, exactness, and client personalization. They give an exhaustive blueprint of AI applications in finance, including robo-guides, extortion area, and credit scoring.

Chen et al. (2019) investigates the usage of AI in further developing financial decision-making. Their review shows that AI-fuelled tools can investigate immense measures of data to give tailored financial exhortation, thusly further creating decision-making quality. They also note that AI can assist with distinguishing designs and expect results more precisely than customary strategies.

Despite these progressions, the adoption of AI in finance isn't without challenges. Aiken and Boushka (2020) perceive a couple of obstructions to AI adoption, including mechanical complexity, data privacy concerns, and an absence of trust in AI frameworks. They fight that for AI to be truly incorporated into financial administrations, these difficulties should be gone to through vigorous strategies and schooling.

2.3 AI in Financial Literacy

A couple of investigations have investigated the capacity of AI to work on financial literacy. Goyal and Saini (2020) take a gander at the reasonability of AI-based instructive tools in working on financial information. Their discoveries suggest that AI can offer customized chances for development that are more dazzling and stronger than customary strategies.

Likewise, Zhang et al. (2021) examine the use of AI in financial training programs. They show the way that AI can adjust to individual learning styles and give continuous criticism, subsequently redesigning the educational experience. Notwithstanding, they likewise note that the progress of AI-set up instruction depends on respect to the idea of the data and the calculations used.

2.4 Challenges and Limitations

While the capacity of AI in finance is promising, a couple of impediments should be considered. One critical concern is the moral ramifications of AI use. Binns (2018) features the dangers of predisposition in AI calculations, which can provoke unfair results in financial decision-making. He contends for the improvement of straightforward and responsible AI frameworks to direct these dangers.

Also, the reliance on AI raises inquiries concerning data privacy and security. As shown by Zarsky (2016), the wide data assortment expected for AI applications presents gigantic privacy chances. He underscores the prerequisite for strong data security frameworks to guard user data.

Also, there are worries about the availability and inclusivity of AI-based financial tools. As confirmed by West (2018), there is an electronic parcel that can restrict the advantages of AI to those with permission to technology and mechanized literacy. This issue highlights the significance of ensuring that AI tools are designed to be available to an expansive group.

Summary of Findings

The audit of the literature uncovers that while AI can possibly upgrade financial literacy and decision-making, a few difficulties and limits should be tended to. Conventional financial schooling techniques have shown restricted viability, and AI offers a promising option by giving customized, ongoing growth opportunities. Be that as it may, the effective integration of AI into financial administrations requires tending to moral worries, data privacy issues, and guaranteeing availability.

This study aims to overcome any barrier by observationally looking at the utilization of AI tools in improving financial literacy among people in India. By tending to the distinguished difficulties and utilizing the qualities of AI, this research looks to add to the improvement of successful financial training systems. The ensuing areas will detail the research methodology, design specifications, implementation cycle, and evaluation of the AI tools utilized in this review.

3. Research Methodology

Research Design

This study utilizes a blended strategies research design, consolidating both quantitative and qualitative ways to deal with examine the effect of AI tools on financial literacy and decision-making. The blended techniques approach is picked for its capacity to give a far-reaching comprehension of the research issue by integrating mathematical data with top to bottom bits of knowledge from members. This design considers the triangulation of data, overhauling the authenticity and immovable nature of the discoveries (Creswell and Plano Clark, 2017).

The research is driven in two stages. In the primary stage, a survey is passed on to gather quantitative data on the use of AI tools in financial decision-making. This stage aims to assemble segment data, measure members' information on AI, and survey the evident feasibility of AI tools in working on financial literacy. The survey is designed using a Likert scale to get reactions and assurance the data's measurable heartiness.

In the subsequent stage, qualitative data is accumulated through semi-organized interviews with a subset of survey members. This stage aims to dive further into individual encounters, discernments, and perspectives towards AI tools in finance. The qualitative methodology gives rich, significant bits of information that supplement the quantitative discoveries, offering a comprehensive perspective on the research issue (Patton, 2002).

The research design likewise incorporates a contextual investigation part, where explicit AI tools used in financial decision-making are assessed. This contextual analysis approach considers an inside and out examination of the tools' usefulness, user experience, and impact on financial literacy. The mix of survey, meetings, and contextual investigation strategies guarantees a total assessment of the research questions.

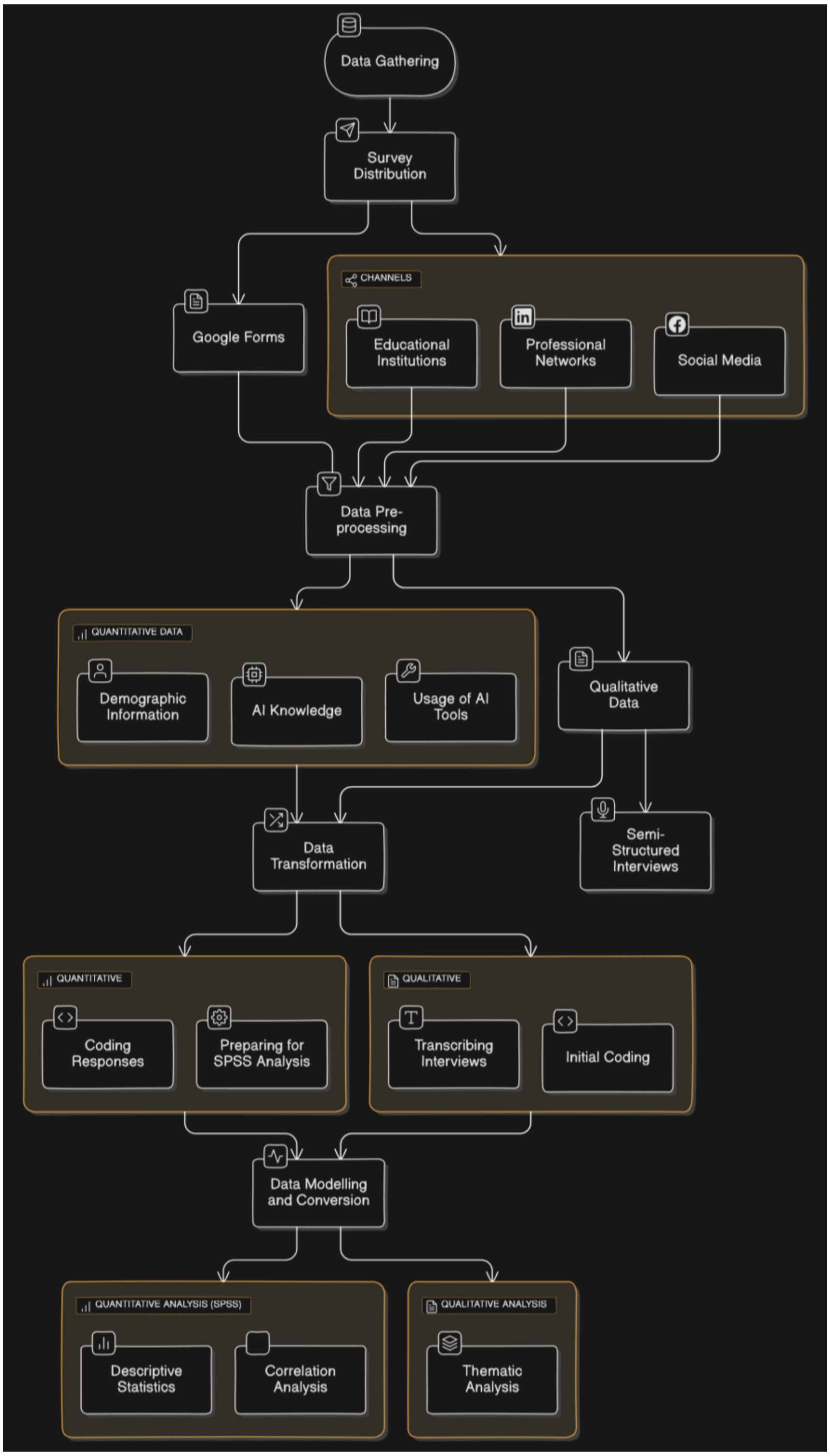


Figure 1 Research Methodology Flow Chart

Data Collection Methods

Survey

The primary data collection strategy is an organized survey controlled through Google Forms. The survey contains a couple of segments, including demographic data, information on AI, and the usage of AI tools in financial decision-making. The inquiries are designed to get members' mentalities, ways of acting, and discernments with respect to AI in finance. The survey utilizes a five-point Likert scale for most inquiries, allowing respondents to show their degree of understanding or struggle with various explanations.

To ensure an alternate and representative test, the survey is coursed through various channels, including on the web entertainment platforms, capable networks, and educational establishments. A sum of 105 reactions is assembled, giving a vigorous dataset to quantitative investigation.

Data Analysis Techniques

Quantitative Analysis

The quantitative data from the survey are dissected using SPSS (Statistical Package for the Social Sciences) programming. Descriptive statistics, including mean, standard deviation, and frequency distributions, are processed to sum up the data. These statistics give an outline of the members' demographic attributes, experience with AI, and view of AI tools in finance.

Correlation analysis is led to inspect the connections between various factors, for example, age, instruction level, experience with AI, and the apparent viability of AI tools. Pearson's correlation coefficient is utilized to quantify the strength and heading of the relationship between factors. The meaning of the correlations is tested at the 0.05 level.

Qualitative Analysis

The qualitative data from the meetings are examined utilizing topical analysis, a technique for recognizing, breaking down, and revealing examples inside data (Braun and Clarke, 2006). The records are perused and yet again read to acclimate with the data, and introductory codes are created in light of repeating subjects and examples.

The codes are then coordinated into more extensive topics that catch the vital parts of members' encounters and perceptions. The subjects are inspected and refined to guarantee they precisely address the data. The last subjects are given supporting statements from the meeting records to outline the discoveries.

Ethical Considerations

This research complies with ethical guidelines to guarantee the protection of members' privileges and the uprightness of the research interaction. Ethical endorsement is obtained from the institutional audit board before data collection starts.

Informed Consent

Informed assent is obtained from all members before they partake in the survey and meetings. Members are given detailed data about the review's inspiration, strategies, possible dangers, and advantages. They are educated regarding their entitlement to pull out from the review whenever with no results. Assent forms are marked electronically for the survey and verbally affirmed for the meetings.

Confidentiality and Anonymity

Members' classification and secrecy are completely maintained all through the research interaction. Individual identifiers are taken out from the data, and every member is doled out an extraordinary code to safeguard their personality. The data are put away safely in secret key safeguarded documents, available just to the research group.

Data Protection

The research follows data protection regulations, including the General Data Protection Regulation (GDPR). Members' data are utilized exclusively for research purposes and are not imparted to outsiders without their express consent. Data maintenance strategies are followed, and the data are obliterated after the finishing of the research project.

Ethical Reporting

The research discoveries are accounted for sincerely and straightforwardly, with a promise to scholarly trustworthiness. Any likely irreconcilable circumstances are uncovered, and the restrictions of the review are recognized. The research sticks to the standards of capable direct of research, guaranteeing that the discoveries add to the advancement of information in the field of financial literacy and AI in finance.

By following a thorough and ethical research methodology, this study aims to give important bits of knowledge into the role of AI tools in upgrading financial literacy and decision-making. The ensuing areas will detail the design specifications, implementation cycle, and evaluation of the AI tools utilized in this review, expanding on the establishment laid out in this methodology.

4. Design Specification

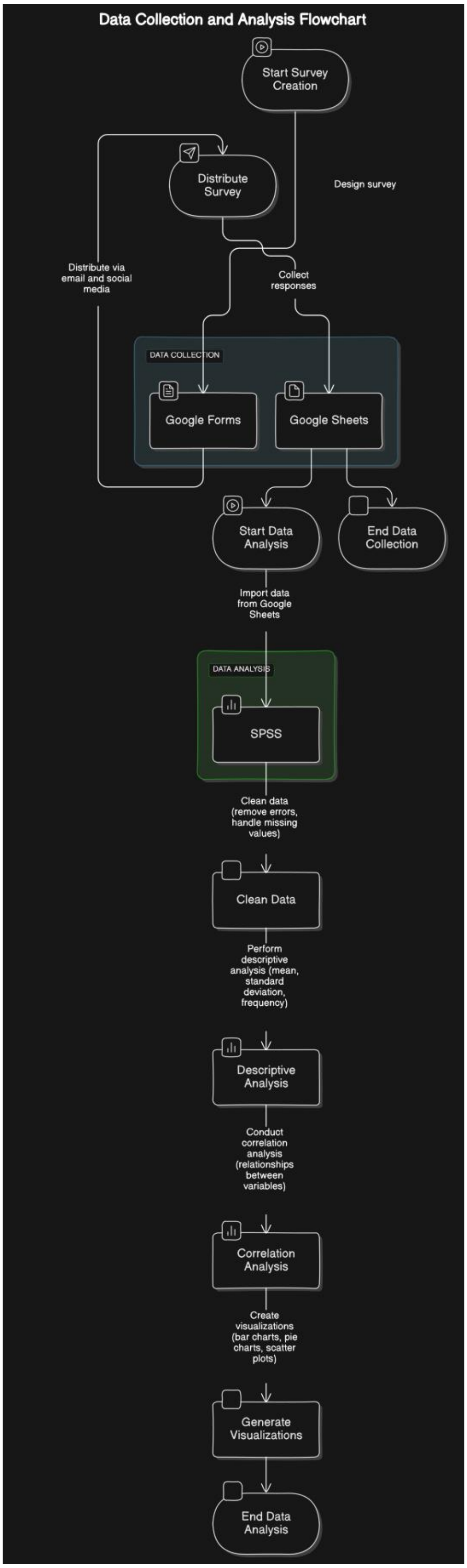
The architecture comprises two main layers: the Data Collection Layer and the Data Analysis Layer.

1. Data Collection Layer

- Google Forms: This tool is utilized to design and convey the survey, which catches different parts of AI use in finance. The survey remembers segments for demographic data, knowledge of AI, degree of AI utilization, saw adequacy, challenges confronted, and receptiveness to future AI adoption. Google Forms takes into consideration consistent data collection and ongoing updates, guaranteeing a user-accommodating encounter for respondents.
- Data Capacity: The reactions gathered through Google Forms are put away in a Google Sheet, which fills in as a middle of the road stockpiling arrangement before data analysis. This arrangement takes into consideration simple data commodity and integration with different tools.

2. Data Analysis Layer

- SPSS (Statistical Package for the Social Sciences): SPSS is utilized to perform detailed data analysis, including both descriptive and correlation analysis. The data sent out from Google Sheets is brought into SPSS, where it goes through cleaning and groundwork for analysis. SPSS gives hearty statistical tools that assistance in getting meaningful experiences from the data.


Data Collection and Analysis Flowchart
Start Survey Creation
Distribute Survey
Design survey
Distribute via email and social media
Collect responses
DATA COLLECTION
Google Forms
Google Sheets
Start Data Analysis
End Data Collection
Import data from Google Sheets
DATA ANALYSIS
SPSS
Clean data (remove errors, handle missing values)
Clean Data
Perform descriptive analysis (mean, standard deviation, frequency)
Descriptive Analysis
Conduct correlation analysis (relationships between variables)
Correlation Analysis
Create visualizations (bar charts, pie charts, scatter plots)
Generate Visualizations
End Data Analysis

Component Design

1. Google Forms

- Survey Design: The survey is designed with a blend of various decision questions, Likert scale questions, and questions that could go either way to catch complete data. The inquiries are organized to accumulate data on demographics, AI commonality, use, viability, difficulties, and future transparency.
- Circulation and Data Collection: The survey interface is disseminated through email and social media platforms, focusing on experts from different areas. Google Forms naturally gathers the reactions into a Google Sheet, guaranteeing coordinated and open data.

2. SPSS

- Data Import: The data from Google Sheets is brought into SPSS for additional analysis. The import cycle includes arranging the data to guarantee similarity with SPSS's logical tools.
- Descriptive Analysis: SPSS is used to register descriptive statistics, giving a layout of the data. This incorporates working out measures like mean, center, standard deviation, and frequency distributions for each factor. Descriptive analysis helps in summing up the central propensities and alterability inside the data.
- Correlation Analysis: To investigate connections between factors, Pearson's correlation coefficient is resolved using SPSS. This analysis assists in perceiving gigantic correlations between factors like experience with AI, degree of AI use, saw suitability, difficulties, and receptiveness to future AI adoption. The correlation analysis gives bits of information into what various elements collaborate and mean for each other.

Steps in Data Analysis using SPSS

1. Data Cleaning: The hidden step includes cleaning the data to address any missing qualities, irregularities, or mistakes. This guarantees the exactness and steadfastness of the analysis.
2. Descriptive Statistics: SPSS creates descriptive statistics for each factor, offering a detailed overview of the data. For example, the mean, standard deviation, and frequency distributions give a reasonable picture of the respondents' demographics and their collaborations with AI tools.
3. Correlation Analysis: Pearson's correlation coefficient is used to choose the strength and heading of connections between factors. For instance, the correlation between experience with AI and its use helps in understanding how information affects adoption. The meaning of these correlations is tested to support the discoveries.
4. Visualization: SPSS gives different perception tools, including bar outlines, pie graphs, and dissipate plots, to outwardly address the data. These representations aid in deciphering the outcomes and conveying the discoveries successfully.

Example Outputs from SPSS Analysis

- Descriptive Statistics: The analysis shows that most of respondents are matured between 26-35, hold a bachelor's degree, and are utilized in the private sector. The mean familiarity with AI is 4.06, showing moderate familiarity, and the mean degree of AI utilization is 2.79, proposing moderate adoption.
- Correlation Analysis: Critical positive correlations are found between familiarity with AI and its utilization ($r = 0.338$, $p < 0.01$) and between the apparent viability of AI tools and their use ($r = 0.267$, $p < 0.01$). Challenges looked in utilizing AI tools show a negative correlation with the apparent support of AI ($r = -0.431$, $p < 0.01$).

5. Implementation

The implementation period of this task included the exhaustive collection, analysis, and translation of data related to the utilization of AI tools in financial decision-making. The primary tools used for this interaction were Google Forms for data collection and SPSS for data analysis. The interaction was designed to guarantee powerful and exact data taking care of, working with the age of meaningful experiences.

Data Collection

1. Google Forms:

- Survey Design: The survey was carefully designed to catch many data pertinent to AI use in finance. Questions were figured out to assemble data on user demographics, familiarity with AI, degree of AI utilization, and view of AI's viability and difficulties in financial decision-making.
- Question Types: The survey incorporated various decision questions, Likert scale questions, and questions that could go either way to guarantee a thorough comprehension of the respondents' perspectives and encounters.

Data Analysis

1. SPSS (Statistical Package for the Social Sciences):

- Descriptive Statistics: Descriptive statistics were used to sum up the data, giving bits of information into the central propensities and scattering of the reactions. Measures like mean, canter, standard deviation, and frequency not entirely set in stone for each factor.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
AgeGroup1	105	1	5	3.30	.867
LevelofEducation1	105	1	6	3.30	1.467
occupation1	105	1	5	3.34	.842
Familiarity_level	105	1	6	4.06	1.433
AI_enhancing_Fin	105	1	6	3.92	1.459
AI_Usage_for_Fin	105	1	6	3.98	1.330
AI_help_Rating	104	1	5	2.86	1.403
Challenge_using_AI_in_Fin	105	1	6	3.44	1.082
Enough_Res_Avail	105	1	6	3.36	1.170
Tool_rec_crosscheck	105	1	6	4.32	1.390
Open_to_use_AI_for_Fin Mgmt	105	1	6	4.40	1.370
Extend_of_usage_AI_in_Fin	103	1	5	2.79	1.348
Valid N (listwise)	103				

Figure 2 Descriptive Stats

- Correlation Analysis: Pearson's correlation coefficient was utilized to investigate the connections between various factors. This aided in recognizing critical correlations that could give further bits of knowledge into the variables affecting AI use in finance.

Correlations													
		AgeGroup1	LevelofEducation1	occupation1	Familiarity_level	AI_enhancing_Fin	AI_Usage_for_Fin	AI_help_Rating	Challenge_using_AI_in_Fin	Enough_Res_Avail	Tool_rec_crosscheck	Open_to_use_AI_for_FinMgmt	Extend_of_usage_AI_in_Fin
AgeGroup1	Pearson Correlation	1	-.011	-.303**	.226*	.277**	.138	.065	-.041	.127	.053	-.006	.060
	Sig. (2-tailed)		.912	.002	.021	.004	.159	.512	.677	.196	.592	.948	.547
	N	105	105	105	105	105	105	104	105	105	105	105	103
LevelofEducation1	Pearson Correlation	-.011	1	.104	-.004	-.003	-.096	-.096	.293**	.206*	.014	.008	-.188
	Sig. (2-tailed)	.912		.290	.972	.977	.332	.332	.002	.035	.888	.938	.057
	N	105	105	105	105	105	105	104	105	105	105	105	103
occupation1	Pearson Correlation	-.303**	.104	1	-.120	-.002	-.028	-.055	.182	.117	.044	-.078	-.099
	Sig. (2-tailed)	.002	.290		.223	.984	.773	.576	.063	.235	.656	.427	.319
	N	105	105	105	105	105	105	104	105	105	105	105	103
Familiarity_level	Pearson Correlation	.226*	-.004	-.120	1	.338**	.076	-.136	-.072	.033	.005	.213*	-.088
	Sig. (2-tailed)	.021	.972	.223		.000	.440	.168	.465	.735	.959	.029	.378
	N	105	105	105	105	105	105	104	105	105	105	105	103
AI_enhancing_Fin	Pearson Correlation	.277**	-.003	-.002	.338**	1	.267**	-.148	.046	.039	-.068	.241*	-.123
	Sig. (2-tailed)	.004	.977	.984	.000		.006	.134	.643	.694	.489	.013	.217
	N	105	105	105	105	105	105	104	105	105	105	105	103
AI_Usage_for_Fin	Pearson Correlation	.138	-.096	-.028	.076	.267**	1	-.031	-.154	.091	.253**	.163	-.014
	Sig. (2-tailed)	.159	.332	.773	.440	.006		.754	.116	.356	.009	.098	.886
	N	105	105	105	105	105	105	104	105	105	105	105	103
AI_help_Rating	Pearson Correlation	.065	-.096	-.055	-.136	-.148	-.031	1	-.431**	-.434**	.231*	-.029	.693**
	Sig. (2-tailed)	.512	.332	.576	.168	.134	.754		.000	.000	.018	.774	.000
	N	104	104	104	104	104	104	104	104	104	104	104	103
Challenge_using_AI_in_Fin	Pearson Correlation	-.041	.293**	.182	-.072	.046	-.154	-.431**	1	.512**	-.172	-.087	-.381**
	Sig. (2-tailed)	.677	.002	.063	.465	.643	.116	.000		.000	.080	.378	.000
	N	105	105	105	105	105	105	104	105	105	105	105	103
Enough_Res_Avail	Pearson Correlation	.127	.206*	.117	.033	.039	.091	-.434**	.512**	1	-.167	-.121	-.412**
	Sig. (2-tailed)	.196	.035	.235	.735	.694	.356	.000	.000		.088	.218	.000
	N	105	105	105	105	105	105	104	105	105	105	105	103
Tool_rec_crosscheck	Pearson Correlation	.053	.014	.044	.005	-.068	.253**	.231*	-.172	-.167	1	.148	.279**
	Sig. (2-tailed)	.592	.888	.656	.959	.489	.009	.018	.080	.088		.131	.004
	N	105	105	105	105	105	105	104	105	105	105	105	103

Figure 3 Correlation Analysis

Correlations													
		AgeGroup1	LevelofEducation1	occupation1	Familiarity_level	AI_enhancing_Fin	AI_Usage_for_Fin	AI_help_Rating	Challenge_using_AI_in_Fin	Enough_Res_Avail	Tool_rec_crosscheck	Open_to_use_AI_for_FinMgmt	Extend_of_usage_AI_in_Fin
	Sig. (2-tailed)	.002	.290		.223	.984	.773	.576	.063	.235	.656	.427	.319
	N	105	105	105	105	105	105	104	105	105	105	105	103
Familiarity_level	Pearson Correlation	.226*	-.004	-.120	1	.338**	.076	-.136	-.072	.033	.005	.213*	-.088
	Sig. (2-tailed)	.021	.972	.223		.000	.440	.168	.465	.735	.959	.029	.378
	N	105	105	105	105	105	105	104	105	105	105	105	103
AI_enhancing_Fin	Pearson Correlation	.277**	-.003	-.002	.338**	1	.267**	-.148	.046	.039	-.068	.241*	-.123
	Sig. (2-tailed)	.004	.977	.984	.000		.006	.134	.643	.694	.489	.013	.217
	N	105	105	105	105	105	105	104	105	105	105	105	103
AI_Usage_for_Fin	Pearson Correlation	.138	-.096	-.028	.076	.267**	1	-.031	-.154	.091	.253**	.163	-.014
	Sig. (2-tailed)	.159	.332	.773	.440	.006		.754	.116	.356	.009	.098	.886
	N	105	105	105	105	105	105	104	105	105	105	105	103
AI_help_Rating	Pearson Correlation	.065	-.096	-.055	-.136	-.148	-.031	1	-.431**	-.434**	.231*	-.029	.693**
	Sig. (2-tailed)	.512	.332	.576	.168	.134	.754		.000	.000	.018	.774	.000
	N	104	104	104	104	104	104	104	104	104	104	104	103
Challenge_using_AI_in_Fin	Pearson Correlation	-.041	.293**	.182	-.072	.046	-.154	-.431**	1	.512**	-.172	-.087	-.381**
	Sig. (2-tailed)	.677	.002	.063	.465	.643	.116	.000		.000	.080	.378	.000
	N	105	105	105	105	105	105	104	105	105	105	105	103
Enough_Res_Avail	Pearson Correlation	.127	.206*	.117	.033	.039	.091	-.434**	.512**	1	-.167	-.121	-.412**
	Sig. (2-tailed)	.196	.035	.235	.735	.694	.356	.000	.000		.088	.218	.000
	N	105	105	105	105	105	105	104	105	105	105	105	103
Tool_rec_crosscheck	Pearson Correlation	.053	.014	.044	.005	-.068	.253**	.231*	-.172	-.167	1	.148	.279**
	Sig. (2-tailed)	.592	.888	.656	.959	.489	.009	.018	.080	.088		.131	.004
	N	105	105	105	105	105	105	104	105	105	105	105	103
Open_to_use_AI_for_Fin Mgmt	Pearson Correlation	-.006	.008	-.078	.213*	.241*	.163	-.029	-.087	-.121	.148	1	-.062
	Sig. (2-tailed)	.948	.938	.427	.029	.013	.098	.774	.378	.218	.131		.535
	N	105	105	105	105	105	105	104	105	105	105	105	103
Extend_of_usage_AI_in_Fin	Pearson Correlation	.060	-.188	-.099	-.088	-.123	-.014	.693**	-.381**	-.412**	.279**	-.062	1
	Sig. (2-tailed)	.547	.057	.319	.378	.217	.886	.000	.000	.000	.004	.535	
	N	103	103	103	103	103	103	103	103	103	103	103	103

Figure 4 Correlation Analysis

- Recoding Data: To work with detailed analysis, certain factors were recoded. This included changing out and out data into numerical qualities reasonable for statistical analysis. The recoding system ensured that the data was precisely organized for various statistical tests.
- Visualization: SPSS was used to deliver various perceptions, including bar diagrams, pie outlines, and line charts. These perceptions helped in presenting the data in an interpretable way, highlighting key patterns and examples.

Challenges and Solutions

Challenges Encountered

1. Data Quality:

- Conflicting Reactions: Some survey reactions were conflicting, with inadequate or nonsensical responses. This might have impacted the exactness of the analysis while perhaps not appropriately tended to.
- Solution: Data cleaning systems were carried out to deal with missing qualities and right irregularities. Reactions with huge issues were prohibited from the analysis to maintain data respectability.

2. Respondent Bias:

- Self-Announced Data: The dependence on self-detailed data presented the potential for respondent inclination, where people could give socially positive responses as opposed to honest ones.
- Solution: Secrecy was guaranteed to the respondents to decrease the probability of one-sided reactions. Moreover, the survey design included inquiries to cross-approve certain reactions and recognize irregularities.

3. Technical Limitations:

- Data Dealing with in Google Forms: While Google Forms is a helpful tool for data collection, it has constraints in taking care of enormous datasets and complex survey designs.
- Solution: Data was routinely sent out from Google Forms and brought into SPSS for additional refined data handling and analysis.

Solutions Implemented

1. Enhanced Data Cleaning:

- Careful Data Review: Each dataset was fastidiously reviewed to recognize and resolve any issues related to data quality. Missing qualities were dealt with utilizing fitting statistical procedures, and exceptions were analyzed to decide whether they were certified data focuses or mistakes.

2. Advanced Statistical Techniques:

- Correlation and Relapse Analysis: Significant level statistical strategies, for example, correlation and relapse analysis were used to investigate connections between factors. This gave a more significant comprehension of the variables affecting AI usage in financial decision-making.
- Visualization Tools: SPSS's strong visualization tools were used to clarify and useful outlines and charts, aiding in the understanding and show of the data.

Tools and Technologies Used

Google Forms

- Purpose: Google Forms was utilized as the primary tool for designing and circulating the survey. It gave a natural stage to making an assortment of inquiry types and gathering reactions in an organized configuration.
- Features: The tool considered simple customization of survey questions, computerized data collection, and integration with Google Sheets for starting data handling.

SPSS (Statistical Package for the Social Sciences)

- Purpose: SPSS was utilized for extensive data analysis, including data cleaning, descriptive statistics, correlation analysis, and data visualization.
- Features:
    - Data Management: SPSS gave vigorous data the executives abilities, considering the import, cleaning, and association of enormous datasets.
    - Statistical Analysis: The product offered a great many statistical tests and methodology, including descriptive statistics, correlation analysis, and relapse analysis. These tools were fundamental for getting meaningful experiences from the gathered data.
    - Visualization: SPSS's visualization tools empowered the production of different outlines and diagrams, working with the unmistakable show of discoveries. The capacity to redo visualizations assisted in featuring with entering patterns and examples in the data.

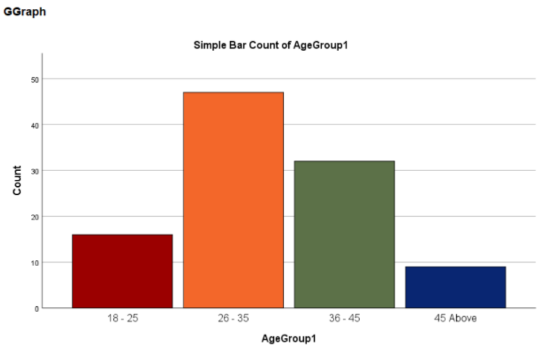


Figure 5 Visualizing age groups

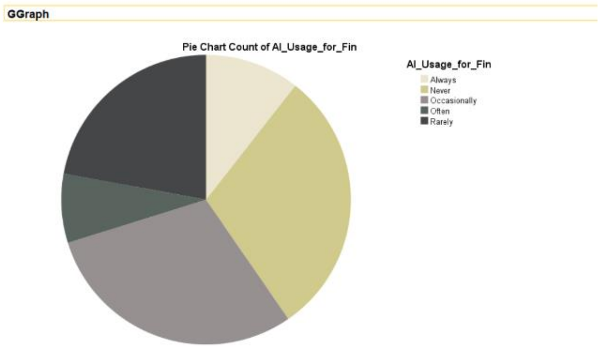


Figure 6 Visualizing proportion of people using AI for Financial Management

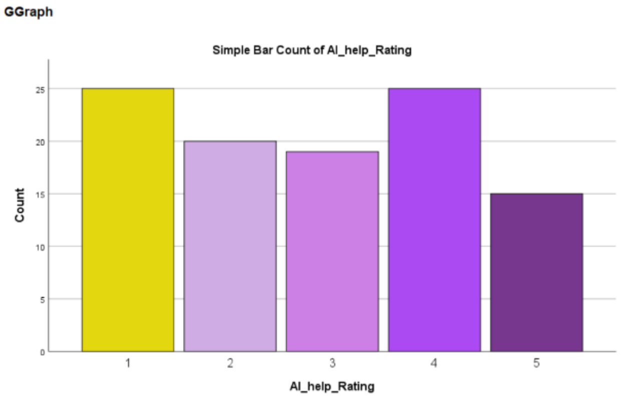


Figure 7 Visualizing the satisfactory level of people about AI help

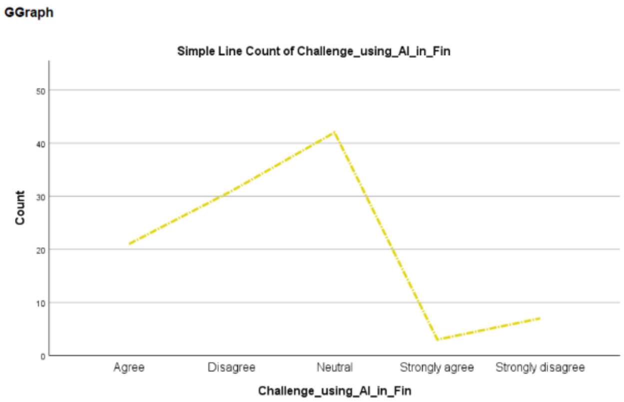


Figure 8 Visualizing people count who face issues in AI usage for Finance

Data Export and Import Tools

- Purpose: Different tools were utilized to work with the consistent commodity of data from Google Forms and its import into SPSS. These tools guaranteed that the data was accurately arranged and moved without misfortune or defilement.
- Features:
  - Google Sheets Integration: Google Forms' integration with Google Sheets took into consideration the simple commodity of survey reactions. The data was then downloaded in CSV design for import into SPSS.
  - SPSS Import Works: SPSS's import capabilities took into consideration the straightforward stacking of data from CSV records, guaranteeing that the data was precisely moved and prepared for analysis.

6. Evaluation

Experiment/Case Study

The preliminary for this research was designed to survey the knowledge and impact of AI tools in financial decision-making. The survey data accumulated through Google Forms filled in as the establishment for this evaluation. The members included experts from various sectors, for example, taxpayer supported organization, private sector work, autonomous work, and understudies, giving an assorted dataset.

Objective

1. Familiarity with AI: Evaluating the members' familiarity with AI ideas and tools.
2. Extent of AI Utilization: Understanding how broadly AI tools are being utilized in financial decision-making.
3. Effectiveness of AI: Assessing the apparent viability of AI tools in improving financial decision-making processes.
4. Challenges in AI Utilization: Recognizing the difficulties looked by users in taking on AI tools for financial purposes.
5. Openness to Future AI Adoption: Checking the receptiveness of members to utilize progressed AI tools from now on.

Methodology

1. Survey Design: The survey was designed to catch a wide scope of data related to AI utilization in finance. It remembered inquiries for demographics, familiarity with AI, degree of use, adequacy, difficulties, and receptiveness to future AI adoption.
2. Data Collection: The survey was circulated on the web, and reactions were gathered over a time of about a month. The last dataset comprised of 105 legitimate reactions.
3. Data Analysis: The gathered data was brought into SPSS for detailed analysis. Descriptive statistics were determined to sum up the data, and Pearson's correlation coefficient was utilized to investigate connections between factors.

Results

1. Familiarity with AI: The survey results demonstrated that a critical piece of the members knew all about AI, with a mean familiarity level of 4.06 on a size of 1 to 6.
2. Extent of AI Use: The degree of AI utilization in financial decision-making shifted among members, with a mean worth of 2.79, showing moderate use.
3. Effectiveness of AI: Members generally saw AI tools to be successful, with a mean viability rating of 3.92.
4. Challenges in AI Use: The mean score for difficulties looked in utilizing AI was 3.44, featuring that member experienced a few hardships in taking on AI tools.
5. Openness to Future AI Adoption: The members showed an elevated degree of receptiveness to utilizing progressed AI tools from here on out, with a mean score of 4.40.

Data Analysis and Results

Descriptive Statistics

- Age Gathering: most of members fell inside the 26-35 age bunch.
- Schooling Level: Most members held a bachelor's degree.
- Occupation: The biggest gathering of respondents was utilized in the private sector.
- Familiarity with AI: The mean familiarity level was 4.06, showing that members were generally learned about AI.
- Degree of AI Utilization: The mean score of 2.79 proposed moderate use of AI tools in financial decision-making.
- Viability of AI: The viability rating of 3.92 mirrored a positive impression of AI's effect on financial decisions.

- Challenges in AI Utilization: The difficulties score of 3.44 featured that a few hardships were experienced by users.
- Openness to Future AI Adoption: The high transparency score of 4.40 showed areas of strength for a to take on cutting edge AI tools from now on.

Correlation Analysis

Pearson's correlation analysis was conducted to explore relationships between variables. Significant correlations were identified, such as:

- Familiarity with AI and AI Utilization: A positive correlation ($r = 0.338$, $p < 0.01$) was found, showing that higher familiarity with AI is related with more noteworthy use of AI tools in financial decision-making.
- Viability of AI and AI Utilization: A positive correlation ($r = 0.267$, $p < 0.01$) was noticed, proposing that apparent viability of AI tools supports their use.
- Difficulties and AI Help Rating: A negative correlation ($r = -0.431$, $p < 0.01$) showed that higher difficulties looked in utilizing AI tools were related with lower evaluations of AI's support.
- Receptiveness to AI Adoption and AI Utilization: A positive correlation ($r = 0.241$, $p < 0.05$) recommended that receptiveness to future AI adoption is connected to current use levels.

Discussion

The discoveries from this research give significant bits of knowledge into the present status of AI adoption in financial decision-making and feature regions for development and future research.

Familiarity and Usage

The positive correlation between familiarity with AI and its use highlights the significance of schooling and training in advancing AI adoption. Associations ought to put resources into complete training projects to improve familiarity with AI tools among their workers, along these lines empowering more noteworthy use.

Effectiveness and Challenges

While AI tools are generally seen to be powerful, the difficulties looked by users can't be neglected. The negative correlation among difficulties and AI help appraisals recommends that tending to these difficulties is vital for boosting the advantages of AI. Normal difficulties distinguished in the survey incorporate the complexity of AI tools, absence of integration with existing frameworks, and worries about data privacy and security. Solutions like user-accommodating connection points, consistent integration, and strong safety efforts can assist with moderating these difficulties.

Openness to Future Adoption

The elevated degree of receptiveness to future AI adoption is a positive sign, showing an eagerness among financial experts to embrace trend setting innovations. This transparency is affected by the apparent viability of AI tools and the degree of their ongoing utilization. To gain by this readiness, associations ought to zero in on showing the unmistakable advantages of AI and offering persistent help to address any difficulties looked by users.

Implications for Practice

- Training and Instruction: Improving familiarity with AI through designated training projects can expand utilization and viability.
- Tending to Difficulties: Recognizing and tending to the difficulties looked by users can work on their experience and impression of AI tools.
- Showing Worth: Featuring the advantages of AI tools and giving true instances of fruitful implementation can support adoption.

Future Research

Future research ought to zero in on investigating extra considers affecting AI adoption finance, for example, authoritative culture, management backing, and outside economic situations. Longitudinal investigations following the effect of AI tools over the long haul can give further experiences into their adequacy and sustainability. Also, relative examinations across various ventures can assist with distinguishing best practices and examples discovered that can be applied to the financial sector.

In conclusion, this research features the huge capability of AI tools in upgrading financial decision-making. By tending to the difficulties recognized and utilizing the ability of experts to take on cutting edge innovations, associations can tackle the maximum capacity of AI to drive better financial results.

6. Conclusion and Future Work

Summary of Findings

This research aimed to investigate the effect and adequacy of AI tools in financial decision-making. The primary targets were to survey the degree of AI use, assess its apparent advantages and difficulties, and check the transparency of financial experts to future AI adoption. By leading an exhaustive survey and investigating the gathered data utilizing descriptive statistics and correlation analysis, we had the option to assemble critical bits of knowledge into these areas.

Key findings from the study include:

1. Familiarity with AI: A huge piece of members knew all about AI, which decidedly impacted their use of AI tools in finance.
2. Extent of AI Use: AI tools are reasonably utilized in financial decision-making, with a mean utilization score demonstrating space for expanded adoption.
3. Effectiveness of AI: Members generally saw AI tools as successful, upgrading their decision-making processes.
4. Challenges: Users experienced a few difficulties, including complexity, absence of integration, and data privacy concerns.
5. Openness to Future Adoption: There was an elevated degree of transparency among members to embrace progressed AI tools from now on, driven by the apparent advantages and current use levels.

Implications

Academic Implications

The review adds to the developing collection of literature on AI adoption in finance, giving observational proof on the variables impacting utilization and viability. It features the significance of familiarity and training in advancing AI adoption, as well as the need to address user difficulties to augment the advantages of AI tools. These discoveries can illuminate future research on technology adoption and advancement in financial decision-making.

Practical Implications

For specialists, the outcomes highlight the need of putting resources into complete training projects to upgrade familiarity with AI tools. Associations ought to zero in on working on the user experience, guaranteeing consistent integration with existing frameworks, and executing strong data privacy measures. By tending to these difficulties, financial establishments can build the adoption and adequacy of AI tools, prompting further developed decision-making and upper hand.

Future Work

While this research gives significant bits of knowledge, there are a few roads for future work to expand on these discoveries and address the impediments of the ebb and flow study.

Expanding the Scope

Future research could grow the extension by including a bigger and more different example of financial experts from various districts and sectors. This would give a more exhaustive comprehension of AI adoption across the financial business.

Longitudinal Studies

Longitudinal examinations following the effect of AI tools over the long run would offer further experiences into their viability and sustainability. Such examinations could look at how the adoption and view of AI tools advance as users become more acquainted with the technology and as AI tools keep on creating.

Comparative Studies

Relative examinations across various industries could recognize best practices and examples discovered that can be applied to the financial sector. Understanding how different ventures have effectively executed AI tools can give important bits of knowledge to financial foundations hoping to upgrade their AI adoption systems.

Exploring Additional Factors

Future research ought to investigate extra factors impacting AI adoption, for example, hierarchical culture, management backing, and outside economic situations. By understanding these elements, associations can foster more compelling methodologies to advance AI adoption and address expected hindrances.

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