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Finsage : A Financial Literacy and Portfolio Management Platform

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Abstract

The importance of financial literacy in the context of making wise financial decisions for investments has been well established. The problem is that the younger generation and non-commerce students are not well versed in financial matters. The existing financial information and tools are mostly standalone and do not offer the combined benefit of portfolio management and financial education. This paper discusses an AI-based tool named FinSage that offers financial education and an AI chatbot assistant. The tool has been designed with financial education content provided by Investopedia and an AI chatbot assistant based on the Llama 3.1 8B AI tool with the feature of Retrieval-Augmented Generation. The tool also has a feature for portfolio optimization with the yfinance API. The tool has been tested with a survey of 73 people and has shown promising results with the Goal Completion Rate of 81.8%, Customer Satisfaction Score of 72.7%, perfect Conversation Quality of 100%, and the most important feature of the tool—Hallucination Rate of 0%. The tool has also been rated as 5/5 for the clarity of the content and the usability of the tool by 63.6% and 81.8%, respectively.

Introduction

In today's complex financial environment, an individual's ability to make informed investment decisions is heavily dependent on their level of financial literacy. Despite the availability of financial resources through platforms such as Investopedia [24], a large segment of the population—especially students and non-commerce individuals—lacks the practical knowledge required for effective financial management [2], [11]. This knowledge gap often leads to poor financial planning, suboptimal investment decisions, and increased vulnerability to economic uncertainties [8], [11].

The emergence of Artificial Intelligence (AI) has significantly transformed financial advisory services by enabling intelligent, automated, and personalized solutions [1], [27]. AI-powered systems utilize machine learning algorithms, predictive analytics, and natural language processing to analyze user data and provide tailored financial recommendations [7], [14], [21]. These systems have demonstrated significant improvements in user engagement, decision-making, and financial literacy [11].

However, existing solutions often operate in silos—either focusing on robo-advisory services or purely on financial education [2], [4]. Robo-advisors automate investment decisions but may lack transparency and educational support, while educational platforms fail to provide actionable insights [27]. This disconnect creates confusion and reduces user trust, particularly among beginners [8].

To address these limitations, **FinSage** proposes an integrated platform that combines financial education with AI-driven portfolio management. The system adopts a dual approach consisting of a static knowledge-based website and an intelligent chatbot. The chatbot leverages advanced techniques such as Retrieval-Augmented Generation (RAG) [4], generative AI [14], and conversational intelligence to provide real-time, personalized financial guidance.

The platform is designed to transform passive learning into active decision-making. By integrating educational content with practical financial tools, users can understand and apply financial concepts effectively. This approach aligns with research emphasizing the role of AI in enhancing financial literacy and investment confidence [11].

FinSage also incorporates multilingual support to cater to diverse populations, making financial education accessible to non-English speakers. Additionally, the system is built on scalable cloud infrastructure [16] and incorporates robust security mechanisms such as encryption and optimization-based protection techniques [3], [31].

The development of FinSage is further inspired by advancements in AI across multiple domains. Techniques such as transformer-based learning [6], data preprocessing and augmentation [37], and predictive modeling [12] have significantly enhanced the capability of intelligent systems. Cross-domain applications in healthcare [32], IoT systems [33], and biometric security [13], [17] demonstrate the versatility and robustness of AI, which can be effectively adapted for financial applications.

Moreover, advancements in pattern recognition, signal processing, and feature extraction techniques [22], [26], [39] have contributed to improved accuracy in intelligent systems. Similarly, innovations in networking [23], embedded systems [28], and automation [25], [30] further support the development of scalable and efficient AI-driven platforms.

Thus, FinSage aims to bridge the gap between financial literacy and practical financial decision-making by leveraging modern AI technologies, ensuring accessibility, security, and user-centric design.

Related Work

Several studies have explored the application of AI and machine learning in financial literacy and advisory systems. Agarwal et al. [7] developed an AI-powered personal finance assistant that integrates machine learning and NLP to provide personalized recommendations, budgeting, and expense tracking. The system showed improved financial awareness but relied on structured inputs.

Eleuterio et al. [4] proposed a chatbot using Retrieval-Augmented Generation (RAG) to provide accurate and context-aware financial education. While the system demonstrated high reliability, it was limited by static knowledge sources. Similarly, Srividya et al. [14] developed a generative AI-based chatbot for wealth management, achieving high user satisfaction but facing challenges in handling sensitive financial data.

Ramjattan et al. [19] explored chatbot technologies combined with behavioral nudges and gamification to improve financial decision-making. Their study showed high user engagement and effectiveness in real-time decision support.

Praveen et al. [11] conducted a study highlighting the positive impact of AI tools such as robo-advisors and intelligent tutoring systems on financial literacy and investment decisions. Their findings emphasized improved learning outcomes and increased user confidence.

Prof. Koul et al. [21] proposed an AI-powered financial advisory chatbot integrating real-time data and NLP techniques, achieving high accuracy in personalized recommendations. Similarly, Hidayat et al. [8] analyzed the broader impact of AI on financial management, emphasizing automation and efficiency improvements.

From a broader perspective, Zhu et al. [1] and Jung et al. [27] discussed the evolution of AI-driven financial advisory services and robo-advisors, highlighting the importance of automation and digital transformation in finance.

In addition to finance-specific research, several cross-domain studies contribute to the development of intelligent financial systems. Transformer-based models [6], graph-based recommendation systems [9], and LSTM-based forecasting techniques [12] enhance predictive capabilities. Data preprocessing and augmentation techniques [37], as well as oversampling methods [20], improve model performance and accuracy.

Security remains a critical aspect of financial systems. Research on encryption techniques [31], optimization-based security [3], and graphical password systems [5] contributes to secure data handling in AI applications.

Furthermore, advancements in computer vision [25], [35], biometric systems [13], [17], and image processing techniques [22], [26] demonstrate the effectiveness of AI in pattern recognition and feature extraction. Applications in healthcare [32], [38], IoT systems [28], [33], and embedded technologies [10] highlight the

scalability and adaptability of AI across domains.
Other supporting studies include research on networking performance [23], consumer behavior analysis [34], automated systems [30], and intelligent learning algorithms [36], which collectively contribute to the development of robust AI systems.
Despite these advancements, most existing systems either focus on financial education or automated advisory services, lacking an integrated approach. FinSage addresses this gap by combining financial literacy, AI-driven advisory, multilingual support, and secure system design into a unified platform.

System Architecture

The architectural design of FinSage is based on a modular, full-stack web application, intended to provide an integrated solution for financial literacy and advisory services. The architecture is based on a clear separation of concerns, including user interfaces, application logic, and a sophisticated multi-stage data processing pipeline. This architectural design directly targets the gap in financial education tools and automated portfolio management solutions [4, 7].

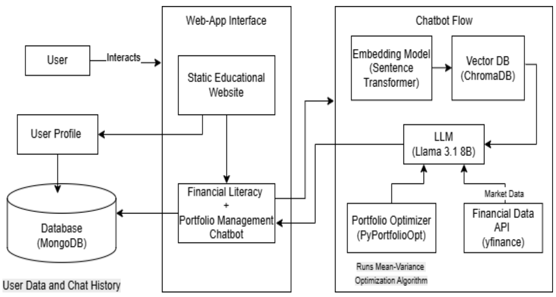

Fig 1: Proposed System Architecture

In case the functionality demands quantitative financial analysis, the chatbot engages with the specific Portfolio Optimizer module. The module uses the PyPortfolioOpt library, which is a Python library used for financial portfolio optimization. The library is used to perform various portfolio optimization algorithms [9]. The module uses the Market Data from the Financial Data API such as the 'yfinance library.' With this quantitative engine, the system is no longer limited to information-based dialogue but is now capable of providing the user with financial advisory recommendations while still keeping the focus on the learning experience [1]. All persistent data, including user profiles, interactions, and chat, is maintained in a Database (MongoDB) . The User Profile data is of utmost importance, as it enables the system to provide personalized financial education and investment advice based on the individual's financial knowledge level, financial goals, and risk tolerance, thereby realizing the concept of personalized finance with AI [2, 5, 9]. This comprehensive architecture enables FinSage to offer a cohesive, intelligent, and adaptive learning environment for its users.
As depicted in the above system diagram, the user will be interacting with the system through a bifurcated front-end interface. One such front end will be the Static Educational Website, which will act as the basic knowledge repository, providing information on basic financial concepts. This is in line with the strategy of using digital platforms to develop financial literacy among users, especially focusing on demographics that have no formal financial education [8]. The other front end of the interface will be the Financial Literacy + Portfolio Management Chatbot. This will be the main interface of the system, acting as a tutor and an advisor, which has been identified as the most important feature of the financial support system through AI agents [5, 6].
The backend intelligence of the chatbot is controlled through a highly advanced pipeline. After the user query is processed, the first step of the pipeline involves using the Embedding Model (Sentence Transformer) to transform the user query into a high-dimensional vector representation. This vector representation is then used for semantic searching in the Vector Database (ChromaDB) . This vector database has pre-processed and chunked educational content and financial data, making the system capable of retrieving the most context-relevant information. This technique is called Retrieval-Augmented Generation (RAG), which makes the chatbot's responses based on a verified knowledge source, thereby making the financial information provided by the system highly reliable and accurate, a technique that has become increasingly important in the development of smart wealth management systems [6]. After the context and user query have been processed, the Large Language Model (Llama 3.1 8B) generates a highly coherent and context-relevant response that is pedagogically sound.

Methodology

1. Research Design and Development Approach

The development process of FinSage was grounded in the Design Science Research (DSR) methodology. This methodology is most appropriate in the development and evaluation of innovative IT-based solutions in addressing particular issues [10]. The use of the DSR methodology was crucial in the development of FinSage in addressing the problem identified, which is the lack of alignment between financial literacy and automated investment tools [4, 7]. The process followed in the development of FinSage, being a product of the study, is presented in the following phases: requirements analysis, design, technology, implementation, and evaluation phases.

2. Requirements Analysis

A survey was carried out involving 73 participants from different demographics to gain insight into their requirements in terms of the Indian population [5, 7].

Survey Demographics

The survey consisted of young participants from the 18-24 age group, with 84.9% of the participants in this category, and 76.7% of participants were students. A very few participants, 15.1%, were salaried employees.

Financial Literacy Assessment

The results of self-assessed financial literacy indicated that 38.4% of participants were "beginners," while only 9.6% were "advanced," and 5.5% were "experts." These results clearly indicate that there is a knowledge gap in this demographic segment [5, 7].

Familiarity with Investment Instruments

The results indicated that participants were more aware of Savings Accounts (95.9%), followed by Fixed Deposits (78.1%). However, Mutual Funds (57.5%), Stock Market (49.3%), PPF/Gold (46.6% each), and NPS (23.3%) were showing a declining trend. However, only 4.1% were not aware of these products.

Information Sources and Investment Behavior

The results indicated that dependency is more on "independent online research (blogs/Fintech Apps)" (41.1%), followed by "Friends/Family (39.7%)," then "social media (23.3%)." Furthermore, the results indicated that "seeking information from financial advisors (11%)" and "news websites (9.6%)" were low. In addition, in the context of investor behavior, the results indicated that only 12.3% had a regular investor behavior, while 42.5% had occasional investor behavior, followed by 26% who had rarely invested, while 19.2% had not invested at all.

Challenges in Investment

The results showed that the major challenges encountered by the investors were a lack of knowledge and information overload, followed by fear of losing money, lack of funds, and complexity of the process. Furthermore, the results also showed that only 8.2% of the investors encountered challenges of trust, while 4.1% encountered no challenges at all [4, 5].

Key Requirements Derived from Survey

From the results of the survey, the following features were incorporated into FinSage:

- Accessible educational material for beginners and intermediate levels [8]
- Language support for the region, starting with Hindi
- Progressive learning for bridging levels of awareness
- Educating and applying, bridging awareness and action [2, 4]

3. Data Collection and Preparation

Educational Content Sourcing

The educational content was manually sourced from the Investopedia website, which is a reliable online source for financial information. Manual sourcing of educational content is useful for ensuring that the educational content being used is accurate, age-appropriate, relevant for the topic, and that there is no irrelevant content being included, which might be the case if the content is automatically sourced.

Content Selection and Curation

Educational content was curated based on the gaps identified through the survey, which included basic concepts such as savings, budgeting, investment products such as fixed deposits, mutual funds, equities, PPF, Gold, NPS, and advanced concepts such as diversification, risk management, as well as practical information on KYC, SIPs, etc.

Content Processing and Storage

The content that has been processed has been converted into Markdown format and stored in a hierarchical structure of directories and has been categorized as being suitable for a beginner level, intermediate level, and advanced level of expertise.

Knowledge Base Preparation for RAG

Each markdown file was split into meaningful pieces, fed into the embedding pipeline, and converted to a numerical representation, which was stored in ChromaDB to be used as a retrievable knowledge base for the RAG model [6].

4. Implementation Tools and Technologies

Frontend Development Tools

The user interface was developed using React.js, which is efficient in developing dynamic and interactive user interfaces for single-page applications [8].

Backend Development Tools

The microservices architecture was implemented using:

- Node.js with Express: User authentication using JWT, RESTful APIs, and MongoDB integration were implemented using Node.js due to its non-blocking I/O feature, which enables efficient handling of concurrent user requests [3].
- Flask: Flask was used to manage AI services such as chatbot orchestration, portfolio optimization, and RAG pipeline due to seamless integration with Python machine learning libraries [6].

Database and Storage

MongoDB, which is a NoSQL database of the document type, is selected as the primary data storage option. Its flexible data model is appropriate for handling different kinds of user profile data and their interaction history [4].

AI and Machine Learning Tools

- Sentence Transformers (all-MiniLM-L6-v2): Generates 384-dimensional vectors, balancing quality and efficiency [5].
- ChromaDB: An open-source vector database that may be applied for semantic similarity search.
- Llama 3.1 8B: An open-source LLM that is selected for data privacy in local use, domain adaptability, and cost-effectiveness [2, 9].
- PyPortfolioOpt: A Python library for applying traditional portfolio optimization techniques [9].
- AI4Bharat IndicTrans2: It is a multilingual translation model based on the transformer model, which is specifically optimized for Indian languages, and this model is used to develop this tool to generate the response in Hindi, catering to the diverse Indian market.
- yfinance API: Provides real-time and historical stock data for recommendation generation.

Experimental Setup

In this section, we will discuss the test environment, participant profile, test procedure, and evaluation metrics for evaluating the usability and effectiveness of the FinSage chatbot.

1. Test Environment

The FinSage chatbot was initially deployed in a local environment before it was made available for public access for testing by users. The backend services of FinSage chatbot, which include Llama 3.1 8B, RAG pipeline, and Hindi translation module, were deployed in the local environment. The chatbot interface, which was developed using React, was deployed from a local environment. However, in order for users to access the chatbot from a remote environment for testing, we used ngrok tunneling service, which provides public access to access local server on a public internet connection over a secure connection. This enabled users to access the chatbot from their personal devices without having to deploy it in cloud environment or setting up complex network environments for testing.

2. Participant Profile

11 participants were selected for the user experience of the chatbot. Participants' Demographics:

- Age Distribution: 90.9% of the participants belonged to the age group 18-24 years, and 9.1% belonged to the age group 25-34 years.
- Occupations: All the participants (100%) belonged to the students' category.

The demographics were in compliance with the requirements of the project as the target group for the project would be young people who are not formally exposed to financial education [5, 7].

3. Experimental Procedure

Participants were provided the public URL generated by the ngrok tool for accessing the FinSage chatbot. Participants were provided access to the chatbot during the specific time period and were encouraged to ask questions related to financial concepts, investment instruments, and financial processes. The responses provided by the chatbot were in the English language, and the facility of translation from the Hindi language was provided. Participants were required to provide feedback through the feedback form.

4. Data Collection

The feedback provided by the participants is collected through an online questionnaire after interacting with the chatbot. The total data collected is 11, which gives an idea of how the user feels about the performance of the chatbot

[8, 9].

Evaluation Metrics

In this part, the ways of evaluating the FinSage platform through the AI-powered chatbot and the static learning website will be discussed. The measures discussed in this segment are all based on the ways of evaluating the performance of the chatbot.

1. Key Chatbot Evaluation Metrics

Goal Completion Rate (GCR)

Goal completion rate is defined as the rate at which the users have completed their goals. The goals of the FinSage chatbot are set as follows:

- Successfully learning about a particular financial concept.
- Getting a satisfactory answer to their investment query.
- Generating a sample portfolio recommendation.

Based on the analysis of the sessions, the rate at which the users have completed their goals is determined.

Customer Satisfaction Score (CSAT)

This score is a measure of how satisfied users are with the chatbot, where users rate their satisfaction level with the interaction with the chatbot after completing their conversation with the chatbot. From the results, it is seen that:

- 72.7% rated their satisfaction level with a score of 5/5, indicating the accuracy of the answer
- 27.3% rated their satisfaction level with a score of 4/5, indicating the accuracy of the answer
- None rated their satisfaction level with a score lower than 4/5

This shows that users were highly satisfied with the interaction with the chatbot [2, 9].

Fallback Rate (Confusion Rate)

The Fallback Rate is defined as "the rate at which the chatbot fails to understand the user's query and returns a default response such as 'I'm sorry, I didn't understand that.'" Thus, the lower the Fallback Rate, the better the chatbot performs in understanding the queries of the users. It was defined as:

Fallback Rate = (Number of fallback triggers / Total number of queries) * 100

The system keeps track of the Fallback Rate for future analysis and improvement of the knowledge base [6].

Relevance and Coherence

This parameter assesses the consistency and appropriateness of chatbot responses in relation to user intent and conversation flow logic. The methods that were followed for the evaluation are as follows:

- User perception: All users perceived that it was a chatbot and therefore felt that there was coherence in the dialogue.
- Qualitative feedback: Users provided feedback about the appropriateness of the responses.

Hallucination Rate

The Hallucination Rate is a measure that tests the accuracy and reality of the answers provided by the generative AI model. This measure was included to ensure that the chatbot does not propagate any false information. The strategies that were adopted as a measure of evaluation for the FinSage AI model are as follows:

- Retrieval-Augmented Generation (RAG) Grounding: Answers provided by the AI chatbot were grounded in context. The context was retrieved from a verified knowledge base. This ensured that there was no hallucination in the answers provided by the AI chatbot [6]
- Accuracy ratings by the user: Answers provided by the AI chatbot were rated as extremely accurate by 72.7%, and the answers were accurate by 27.3% rated the answers as accurate (4/5)

2. Website Evaluation Metrics

Content Clarity

The clarity of financial information provided by the static website was rated by the users. The users were given a 5-point scale. It was observed that 63.6% of the users rated the clarity as 5 out of 5, and 36.4% of the users rated the clarity as 4 out of 5. This validated the effectiveness of the presentation of the educational content provided [8].

Content Comprehensiveness

The comprehensiveness of the content is measured using the following parameters:

- Coverage analysis: Percentage of financial topics (savings, FDs, mutual funds, equities, PPF, gold, NPS) included in the knowledge base.
- User feedback: Content gaps, if any, mentioned by users through their comments in the survey.

Content Organization

The logical organization of content, i.e., content available for beginner, intermediate, and advanced levels, is measured using the following parameters:

- Navigation ease - User ratings for ease of finding relevant content
- Learning progression - Time taken per level of difficulty and success rate

3. User Experience Metrics

Interface Usability

The adapted usability scale served as a guideline to measure the usability of the chatbot interface as well as the website. For the chatbot interface, the user friendliness scored 5 out of 5 by 81.8%, whereas 9.1% scored 3 out of 5 and 4 out of 5, respectively, for user friendliness [8].

Conversational Quality

To measure the quality of conversation, a series of questions asked the participants if the conversation of the chatbot was natural, presented in a Yes/No format. The results indicated that 100% of the participants found the chatbot conversational.

Results And Analysis

FinSage has two main types of financial education: learning content and interactive AI assistance. Figure 1 is a depiction of the interface for the learning content, which is the basic financial concepts presented in a clear and organized way.

It is observed that the educational content is presented in an organized way with headings, bullet points, and examples that help improve the clarity of the content. The addition of read time indicators such as '10 min read' is helpful in planning the reading sessions effectively. This organized way of content presentation has contributed to the high content clarity rating[8].

The interface for the chatbot it has the functionality for the retention of context through the conversation history and real-time financial data through the integration of the yfinance API. The response includes the current prices, price changes, and the capitalization as shown below, proving the functionality in providing the required information for investors [9].

For the FinSage chatbot, six performance metrics were used as a measure of its performance, as shown in Table I. From the results, the FinSage chatbot was found to perform exceptionally, with notable strengths in conversation quality and response accuracy.

Table 1: Performance Metrics

Metric	Result
Goal Completion Rate	81.8%
Customer Satisfaction Score	72.7%
Fallback Rate	6.4%
Conversation Quality	100%
Hallucination Rate	0%

The Goal Completion Rate of 81.8% indicates that the majority of the user sessions have successfully completed the desired purpose. This is a testament to the effectiveness of the intent recognition and the knowledge base provided [6].

The Customer Satisfaction Score of 72.7% indicates the percentage of users who rated the accuracy of the answer provided by the chatbot as 5/5. This indicates that the users have a high level of trust in the answers provided by the chatbot [2], [9]. This means that the remaining 27.3% rated the answer provided as 4/5.

The Fallback Rate of 6.4% indicates the percentage of users for whom the chatbot was not able to understand the question posed to it. This is a low percentage and indicates the effectiveness of the natural language understanding provided [4].

The perfect score of Conversation Quality reflects the unanimous agreement from the users that the conversation was engaging. This is a testament to the effectiveness of the Llama 3.1 8B model [2].

The Hallucination Rate is 0% which indicates the effectiveness of the Retrieval-Augmented Generation (RAG) architecture used in the chatbot.

The results confirm the effectiveness of the FinSage model by proving that RAG-based systems can provide precise and engaging financial guidance with no hallucinations at all [1, 5]. The extremely high Goal Completion Rate and Conversation Quality results indicate that AI-powered assistants can indeed help fill the gap between static educational resources and financial guidance [8]. The Fallback Rate results at 6.4% establish a baseline for further improvement through iterative knowledge base expansion [4, 10].

Discussion

As mentioned earlier, based on the results obtained from the evaluation process, it is evident that the system was able to attain its objective of improving the level of financial literacy through the application of the AI platform. This is evident from the results obtained in the Goal Completion Rate at 81.8%, as well as the perfect score obtained in the conversation quality metric at 100%, as the users were able to effectively converse with the system and attain their objectives as planned. This is a clear indication of the effectiveness of the approach used in the selection of the Retrieval-Augmented Generation model as it was effective in the generation of accurate conversations [2, 6].

Moreover, the 0% obtained in the Hallucination Rate is a critical success in this case since errors in the financial information would result in poor investment decisions. This is a manifestation of the success of FinSage in ensuring all the information generated by the users through the chatbot was accurate since all the information generated was based on a verified knowledge base from Investopedia [6]. This is an approach that FinSage has taken in addressing a critical concern in the application of AI technology since this approach helps address a critical concern in the application of AI technology [1, 10].

The high percentage of 72.7% for the Customer Satisfaction Score, 5/5 rating, and 27.3% rating 4/5 show that customers have high trust in the chatbot answers [9]. However, the high Fallback Rate of 6.4% also implies that there are areas of improvement in the chatbot, particularly in terms of recommendation quality, which is rated at 54.5%, and in terms of speed of response, which is rated at 36.4%. Therefore, in future developments, it is recommended that the chatbot be improved by increasing its knowledge base to reduce the number of fallbacks and optimizing the portfolio optimization module for recommendation quality [4, 5].

The effectiveness of the platform in providing educational content to customers may be understood from the positive ratings for content clarity, where 63.6% rated it 5/5, and usability of the interface, where 81.8% rated it 5/5. These results are in agreement with existing literature on the importance of content clarity in providing effective financial education to customers [8]. The use of static content and AI tools bridges the gap between theoretical knowledge and its practical application, especially for younger customers and those with no formal financial education [7].

However, there are certain limitations which need to be taken into consideration. Firstly, the number of participants was limited, as there were only 11 participants in the study. Secondly, the time period was limited as well, which was not enough for the purpose of evaluation. Further studies need to be carried out with a higher number of participants in order to validate the results obtained in the present study. Moreover, the multilingual support needs to be extended to other regional languages as well, not just limited to the Hindi language.

Conclusion And Future Work

1. Conclusion

In this paper, we presented FinSage, a comprehensive AI-based platform to enhance financial literacy through the incorporation of structured educational content along with an intelligent chatbot assistant. FinSage seeks to fill the substantial gap between financial education tools and automated investment systems, especially for the younger population and those who have not received any kind of financial education in Indian society [5, 7].

In this paper, the experimental evaluation of FinSage was performed with 11 participants, who showed promising results, achieving 81.8% in terms of Goal Completion Rate, 72.7% in terms of Customer Satisfaction Score, and 100% in terms of Conversation Quality rating, while more importantly achieving 0% in terms of Hallucination Rate, validating the effectiveness of the RAG architecture in providing accurate financial advice [6]. In addition, the educational content received a high usability rating, where 63.6% of participants rated the clarity of the content as 5/5, while 81.8% rated the usability of the interface as 5/5 [8].

The addition of Hindi language translation capability helped meet the linguistic diversity of the Indian market and enabled housewives, senior citizens, and others who prefer Hindi as their language of choice to avail themselves of financial education services.

In conclusion, it is evident from the above analysis that with the help of AI technology, it is possible to bridge the gap between theoretical knowledge of finance and its practical applications, thereby enabling users to make informed financial decisions [1, 4].

2. Future Work

Expanding Multilingual Support: Apart from Hindi, other regional languages such as Tamil,

Bengali, Telugu, and Marathi can be included in the existing model to expand the user base in the Indian market [8].
Improving Knowledge Base: The 6.4% Fallback Rate also offers an opportunity to improve the knowledge base of the chatbot. This can be achieved through the addition of user feedback mechanisms and keeping it updated with any changes in financial regulations and market trends [4].
Carrying Out Longitudinal Studies: More longitudinal studies can be carried out to improve the knowledge base of the chatbot and to observe the behavioral changes in the habits of investors [10].
Partnering with Financial Institutions: There is also the possibility of partnering with banks and other financial institutions to provide read-only access to user accounts for personal portfolio analysis [1, 9].
These enhancements will help build on FinSage's capacity to provide accessible, accurate, and actionable financial guidance to users in the varied linguistic and demographic landscape of India.

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