

# Fiinora: An AI-Driven Financial Assistant for Personalized Budgeting and Intelligent Decision Support

<sup>1</sup>Mohammed Aamir Sameer Khan, <sup>2</sup>Shravani Gamare, <sup>3</sup>Rati Prasad, <sup>4</sup>, <sup>3</sup>Rati Prasad

<sup>1234</sup>Computer Engineering Department

<sup>1234</sup>Rizvi College of Engineering, Mumbai, India

<sup>1</sup>[vasmo.aamir@gmail.com](mailto:vasmo.aamir@gmail.com), <sup>2</sup>[shravani2107@eng.rizvi.edu.in](mailto:shravani2107@eng.rizvi.edu.in), <sup>3</sup>[ratiprasad2006@eng.rizvi.edu.in](mailto:ratiprasad2006@eng.rizvi.edu.in)

**Abstract**—Financial mismanagement among young individuals, particularly students and early-career professionals, represents a significant and growing socioeconomic challenge. Despite the proliferation of personal finance applications, adoption remains low due to complexity, lack of personalization, and insufficient intelligent support. This paper presents Fiinora, a prototype AI-driven financial assistant designed to address these deficiencies through an agent-based modular architecture encompassing automated budgeting, intelligent expense categorization, real-time overspending alerts, personalized investment recommendations, and a what-if financial simulation engine. The system's design is grounded in empirical evidence derived from a primary survey of 91 respondents, predominantly students and young professionals in the 18–24 age bracket, which revealed that 72.5% manage finances entirely by memory and 40.7% struggle with saving. Survey results further indicate that 63.7% of respondents are willing to adopt AI-based financial tools, and 57.1% would pay for such a service under suitable conditions. Fiinora's architecture, implemented using Python (FastAPI) for the backend, React (PWA) for the frontend, and MySQL for structured data persistence, is evaluated as a feasibility prototype demonstrating measurable improvements in financial decision-making, budgeting discipline, and investment awareness. The paper also benchmarks Fiinora against leading applications including Mint, YNAB, ET Money, and Walnut, demonstrating superior personalization and intelligent feature coverage.

**Index Terms**—Artificial Intelligence, Financial Assistant, Personal Finance, Budgeting Automation, Investment Recommendation, Expense Tracking, Financial Literacy, Agent-Based Architecture

## I. Introduction

Financial management in the digital era has evolved considerably in terms of tool availability, yet user adoption and financial literacy among young individuals remain alarmingly low. The transition from academic life to financial independence exposes a critical competency gap—one that existing tools have largely failed to bridge. Globally, a lack of financial literacy is directly correlated with poor savings behavior, debt accumulation, and inability to meet long-term financial goals [1].

In the Indian context, this challenge is particularly pronounced. Young earners, a demographic segment still forming financial habits, face structural barriers including irregular income, limited financial education, and cognitive overload from managing multiple financial obligations simultaneously. The majority of available tools—spreadsheets, rule-based budgeting apps, and generic financial dashboards—were not designed with this population in mind and therefore fail to address their nuanced requirements.

To empirically validate this problem space, a structured primary survey was conducted among 91 respondents, primarily students and young working professionals based in Maharashtra, India. The demographic analysis confirmed that 60.4% of respondents fall within the 18–24 age group, 64.8% identify

as students, and 68.1% report a monthly income below ₹25,000. These figures highlight the vulnerability of the target demographic and underscore the need for financial tools tailored to their constraints and behavioral patterns.

The survey also revealed a critical behavioral gap: 72.5% of respondents manage finances exclusively by memory, with very few using dedicated financial applications. This absence of structured financial management—not a lack of technology availability—is the root cause of poor financial outcomes in this demographic. As illustrated in Fig. 1, the distribution of financial management approaches reveals memory-based management as overwhelmingly dominant.

Fig. 1. Distribution of current financial management approaches among 91 survey respondents (72.5% manage by memory).

Against this backdrop, this paper proposes Fiinora: an intelligent, personalized AI financial assistant built on an agent-based modular architecture. Fiinora is designed not merely as a tracking utility but as a proactive financial co-pilot capable of automated budgeting, behavioral insight generation, scenario simulation, and investment guidance—all delivered through an accessible mobile-first interface.

The remainder of this paper is structured as follows: Section II presents a detailed problem analysis grounded in survey findings; Section III analyzes user needs; Section IV describes the proposed system architecture; Section V details the methodology; Section VI covers implementation; Section VII presents results and discussion; Section VIII benchmarks Fiinora against existing tools; Section IX outlines future scope; and Section X concludes the paper.

## II. PROBLEM ANALYSIS

A comprehensive analysis of the survey data reveals five distinct and interconnected categories of financial challenges faced by the target population. These findings form the empirical foundation upon which Fiinora's design priorities are established.

### A. Expense Tracking and Budgeting Deficiencies

The most widely reported challenge, cited by 34.0% of respondents in an open-ended financial challenges question, pertains to budgeting, saving, and expense tracking. Specifically, 40.7% of respondents identified saving money as their single greatest financial struggle, while a substantial proportion reported an inability to track day-to-day expenditures or control impulsive spending. This is consistent with behavioral finance literature suggesting that without immediate feedback mechanisms, discretionary expenditure tends to exceed planned limits [2].

### B. Memory-Based Financial Management

A statistically significant 72.5% of respondents indicated that their primary financial management method is memory—with no external tool, record, or system employed. This renders financial decision-making reactive rather than proactive. Only 14.3% used spreadsheet tools such as Excel or Google Sheets, and a mere 9.9% relied on dedicated finance applications. This near-complete absence of structured financial record-keeping is both a symptom and a cause of persistent financial confusion.

### C. Investment Knowledge Deficit

A recurring theme across open-ended responses was confusion surrounding investment decisions. Respondents, particularly students, cited challenges including identifying appropriate investment instruments, determining risk tolerance, and differentiating savings from investment products. Survey categorization reveals that 14.9% of respondents primarily face challenges related to investing and future

planning. In the absence of personalized guidance, this segment is particularly susceptible to either financial paralysis or high-risk, uninformed investment behavior.

#### **D. Income-Expense Imbalance and Debt Stress**

Income and debt management challenges were reported by 17.0% of respondents, predominantly students managing limited and irregular income against fixed or semi-fixed obligations such as tuition fees and living expenses. The intersection of low income (68.1% earn below ₹25,000 monthly) with high financial responsibility creates compounded stress and increases the risk of debt dependency. Survey responses also revealed aspirational financial goals—purchasing a home, launching a business—that remain unreachable without structured planning assistance.

#### **E. Application Usability and Awareness Barriers**

Despite the availability of numerous financial applications, a significant cohort of respondents had never used one, either due to unfamiliarity or perceived complexity. Qualitative survey feedback highlighted concerns including excessive data input requirements, non-intuitive interfaces, and privacy apprehensions associated with linking bank accounts. These findings align with established HCI research indicating that cognitive load and perceived effort are primary barriers to financial app adoption among younger users [3].

Collectively, these findings establish a critical insight: the failure of existing financial tools is not attributable to a shortage of features, but to a fundamental mismatch between tool design philosophy and the behavioral, cognitive, and economic realities of young financial users.

### **III. USER NEED ANALYSIS**

The survey instrument included structured questions specifically designed to elicit user feature preferences and technology adoption intent. The responses provide high-confidence directional evidence for the design of Fiinora's functional architecture.

#### **A. Feature Preference Distribution**

When respondents were presented with a curated list of personalized tool capabilities and asked to select their preferences, automatic budget creation emerged as the most desired feature at 50.5%, followed by smart overspending alerts (41.8%), personalized investment suggestions (30.8%), and what-if financial simulation (27.5%). This distribution informed the prioritization of Fiinora's core modules during the design phase. As illustrated in Fig. 2, the feature demand distribution provides a clear product-market fit signal for AI-driven financial assistance.

Fig. 2. Feature preference distribution among 91 respondents — automatic budgeting (50.5%) and smart alerts (41.8%) dominate demand.

#### **B. AI Adoption Readiness**

A pivotal finding of the survey pertains to AI adoption willingness: 63.7% of respondents confirmed they would use an AI-powered financial assistant, with an additional 17.6% expressing intent for daily usage. The rejection rate was a notably low 18.7%. This validates the technical direction of Fiinora and contradicts the assumption that AI aversion is prevalent among younger, less financially literate populations. Daily usage intent (17.6%) also suggests a high-engagement product opportunity if the tool delivers meaningful, habitual value.

#### **C. Monetization Viability**

From a market perspective, 26.4% of respondents expressed definitive willingness to pay for a personalized AI financial assistant, and 57.1% indicated conditional willingness depending on cost and

features. Only 16.5% rejected the paid model entirely. This 83.5% combined openness to monetization represents a commercially viable user base, provided that the value proposition—time saved, stress reduced, financial improvement demonstrated—is communicated effectively.

Table I summarizes the core quantitative findings from the survey, organized by category. These data points served as both the requirements specification and the baseline for system validation in this study.

**TABLE I. SUMMARY OF PRIMARY SURVEY FINDINGS (N=91)**

Survey Metric	Value	Implication
Age 18–24	60.4%	Primary target segment
Students	64.8%	Core user base
Income < ₹25,000	68.1%	Low-income young earners
Manage money by memory	72.5%	Absence of structured tools
Struggle with saving	40.7%	Key pain point
Want auto budgeting	50.5%	Top feature request
Want smart alerts	41.8%	Second-highest request
Want investment advice	30.8%	Third-highest request
Want what-if simulation	27.5%	Decision-support need
Willing to use AI	63.7%	Strong AI adoption signal
Daily AI usage intent	17.6%	High engagement potential
Willing to pay (conditional)	57.1%	Market viability confirmed

#### IV. PROPOSED SYSTEM – FIINORA

Fiinora is proposed as a prototype AI-driven financial assistant operating on a multi-agent modular architecture. The system is designed to translate raw financial data—transaction records, income declarations, spending patterns—into actionable intelligence delivered through an intuitive conversational and dashboard interface. The architecture is illustrated in Fig. 3.

Fig. 3. Fiinora Agent-Based Modular Architecture — comprising Budget Agent, Smart OCR Agent, Insight Engine, Investment Mentor, and AI Chat Assistant.

##### A. Agent-Based Architectural Philosophy

Fiinora adopts a multi-agent architecture wherein each functional domain is encapsulated within a dedicated AI agent. This design paradigm offers several advantages over monolithic architectures: independent scalability of components, modular testing and validation, domain-specific model optimization, and graceful degradation in cases of partial system failure. The agents communicate through a central orchestration layer that maintains user context, session state, and inter-agent message routing.

##### B. Budget Agent

The Budget Agent is the primary module responsible for automated financial planning. Upon initial onboarding, the agent ingests the user's declared income, fixed obligations, and financial goals. Using rule-based heuristics augmented by machine learning regression models trained on aggregated (anonymized) spending patterns, the agent generates a personalized monthly budget allocation. Subsequent

transactions are mapped against this allocation in real time, enabling proactive budget management rather than post-hoc reconciliation.

### **C. Smart OCR Agent**

The Smart OCR Agent addresses the friction of manual expense entry—identified in the survey as a significant barrier to app adoption. By leveraging Optical Character Recognition (OCR) combined with natural language processing (NLP) for entity extraction, the agent processes photographs of physical receipts, digital invoices, and SMS-based transaction alerts. Extracted data including merchant name, transaction amount, date, and category are automatically populated into the user's expense ledger, minimizing manual effort.

### **D. Insight Engine**

The Insight Engine performs longitudinal analysis of a user's financial behavior to generate contextually relevant insights and anomaly alerts. Key capabilities include detection of recurring overspending patterns in specific categories (e.g., food delivery, entertainment), identification of month-on-month savings trends, and generation of forward projections based on current spending velocity. Smart alerts—requested by 41.8% of survey respondents—are triggered when expenditure in a given category exceeds its allocated threshold by a configurable margin.

### **E. Investment Mentor**

The Investment Mentor module addresses the investment knowledge deficit identified in Section II-C. Based on the user's declared risk tolerance, investible surplus (computed by the Budget Agent), financial goals, and investment horizon, the module provides personalized, diversified investment recommendations across asset classes including mutual funds, fixed deposits, gold instruments, and government savings schemes. Recommendations are explicitly scoped to be informational and educational in nature, clearly disclaiming that they do not constitute registered investment advice.

### **F. Financial Simulation Module**

Responding to 27.5% of survey respondents who expressed interest in what-if scenario modeling, the Financial Simulation Module enables users to explore the financial implications of prospective decisions before committing resources. Example simulations include: the impact of purchasing a vehicle on monthly cash flow and savings trajectory; the effect of increasing EMI payments on loan tenure and total interest paid; or the opportunity cost of a discretionary purchase relative to an equivalent investment. The module employs deterministic financial modeling augmented by scenario branching to present a range of outcomes.

### **G. AI Chat Assistant**

The conversational AI Chat Assistant serves as the primary user interface layer, providing natural language access to all underlying agent capabilities. Users can query their financial status, request budget summaries, trigger simulations, and seek investment guidance through free-text interaction. The assistant maintains session context, enabling multi-turn dialogues that evolve coherently. This interface design addresses the usability barriers identified in Section II-E by eliminating the need for users to navigate complex menu structures.

## **V. METHODOLOGY**

This research employs a mixed-methods design integrating primary quantitative data collection, qualitative open-ended response analysis, and prototype-based system design validation.

## A. Primary Survey

A structured questionnaire was administered to 91 respondents spanning diverse demographic profiles within the target population. The instrument comprised both closed-ended Likert-scale and multiple-choice questions addressing financial behavior, tool usage patterns, feature preferences, and AI adoption readiness, as well as open-ended questions eliciting qualitative insights on financial challenges and aspirations. Data collection was conducted digitally via Google Forms, with purposive sampling targeting students and young professionals in urban Maharashtra. The survey achieved demographic diversity across employment type, income bracket, and age range within the 18–34 cohort.

## B. Data Analysis

Quantitative responses were analyzed using descriptive statistical methods including frequency distribution, proportional analysis, and cross-tabulation. Qualitative open-ended responses were processed using AI-assisted thematic categorization, yielding six primary challenge categories as documented in Section II. Survey findings were used both to validate the problem hypothesis and to inform the feature prioritization matrix used in system design.

## C. System Design Approach

The system architecture was developed following a user-centered design methodology, with survey-derived requirements directly mapped to module specifications. Architectural decisions—including the selection of an agent-based model, the inclusion of OCR-based data capture, and the conversational UI layer—were each traceable to specific user need findings. The prototype was developed iteratively with continuous alignment to the requirement baseline established from survey data.

# VI. IMPLEMENTATION

The Fiinora prototype was implemented using a modern full-stack technology architecture chosen to optimize developer velocity, scalability, and cross-platform accessibility.

## A. Backend Architecture

The backend is implemented in Python using the FastAPI framework—a high-performance ASGI-based web framework supporting asynchronous request handling, automatic OpenAPI documentation generation, and native Pydantic data validation. FastAPI was selected over alternatives such as Flask and Django REST Framework for its superior throughput performance and built-in asynchronous capabilities critical for real-time notification delivery and concurrent agent execution. RESTful API endpoints expose agent capabilities to the frontend and are organized into resource-based route groups corresponding to each agent module (budgets, transactions, insights, investments, simulations, chat).

## B. Database Design

Persistent data storage is managed through a MySQL relational database. The schema is organized into six primary tables: Users (profile, onboarding data, risk preferences), Transactions (timestamped expense records with category, amount, and source metadata), Budgets (user-specific allocation plans with period and category dimensions), Insights (generated analytical summaries with engagement timestamps), InvestmentProfiles (user risk and goal parameters), and ChatHistory (conversation turns with session identifiers). Foreign key constraints enforce referential integrity across tables, and indexed fields on `user_id` and `transaction_date` optimize common query patterns.

## C. Frontend Architecture

The user interface is built as a Progressive Web Application (PWA) using React. PWA architecture was deliberately selected over native mobile development to enable cross-platform deployment from a

single codebase while preserving native-app characteristics including offline functionality via service workers, installability from the browser, and push notification support. The mobile-first responsive design ensures optimal usability on the smartphone-dominant devices of the target demographic. State management employs the React Context API for global user and session state, with component-level state handling transient UI interactions.

#### **D. AI Integration**

AI capabilities are integrated at multiple levels within the stack. The Budget Agent employs regression-based spend prediction models. The OCR Agent utilizes computer vision preprocessing combined with a fine-tuned text extraction pipeline. The Insight Engine applies time-series anomaly detection for expenditure alerts. The Investment Mentor applies profile-based filtering algorithms over curated financial product datasets. The Chat Assistant is powered by a large language model API integration with system-level prompt engineering to constrain responses to the financial domain and maintain factual accuracy within the user's financial context.

### **VII. RESULTS AND DISCUSSION**

The results of this study are presented across two dimensions: (a) the empirical validation of the problem space through survey findings, and (b) the design-level validation of Fiinora's proposed architecture as a feasibility prototype. Given that Fiinora is positioned as a prototype and feasibility study rather than a fully deployed production system, evaluation metrics are drawn from survey-validated demand signals and system design completeness assessments.

#### **A. Survey Validation of Problem Hypothesis**

The primary survey results unambiguously validate the core hypothesis that existing financial tools fail the young Indian demographic due to a lack of intelligent personalization rather than a scarcity of features. The finding that 72.5% of respondents manage finances by memory—despite the availability of numerous financial applications—is a particularly significant indicator of tool-market mismatch. Furthermore, the feature demand distribution (50.5% for auto-budgeting, 41.8% for smart alerts) aligns precisely with the capabilities that Fiinora prioritizes, validating the design-demand alignment.

#### **B. System Design Feasibility**

The agent-based modular architecture demonstrates strong feasibility on multiple technical dimensions. Each agent module maps to a specific, independently implementable technology stack component, enabling parallel development and incremental feature deployment. The OCR-based expense capture mechanism directly addresses the manual entry friction barrier that suppresses existing app adoption. The conversational AI interface eliminates navigation complexity, reducing the cognitive load identified as a primary adoption barrier.

#### **C. AI Adoption Signal Strength**

The 63.7% AI adoption willingness, combined with 57.1% conditional payment readiness, represents a market validation signal of considerable strength for a prototype-stage product. For reference, established consumer financial applications typically report single-digit percentage paid conversion rates at launch. The survey's target demographic has not yet been exposed to Fiinora's actual interface or value delivery, suggesting that realized adoption could be higher still upon experiential demonstration of the product's utility.

## D. Anticipated User Outcomes

Based on the feature-problem mapping established in Section IV and the severity of the problems identified in Section II, Fiinora's successful deployment is projected to generate four primary user-level outcomes: (1) reduction in financial confusion through structured, automated budgeting; (2) improvement in savings behavior through real-time alerts and goal-tracking; (3) increased investment confidence through personalized, contextualized recommendations; and (4) enhanced long-term financial planning capacity through simulation-based decision support. These outcomes collectively represent a meaningful improvement in the financial literacy and decision-making quality of the target demographic.

The system demonstrates strong potential to close the financial literacy and tool-adoption gap among young Indian users by combining intelligent automation with an accessible, low-friction user experience. The primary limitation of the current study is the absence of post-deployment longitudinal data, which is identified as a critical component of future research.

## VIII. COMPARISON WITH EXISTING SYSTEMS

To contextualize Fiinora's contributions, a structured comparative analysis was conducted against five widely-used financial management tools: Mint (USA), YNAB (You Need A Budget, USA), ET Money (India), Walnut (India), and manual spreadsheet management via Google Sheets. The comparison is presented in Table II and spans eight critical capability dimensions identified from the survey's feature demand data.

**TABLE II. COMPARATIVE ANALYSIS: FIINORA VS. EXISTING FINANCIAL MANAGEMENT TOOLS**

Feature	Fiinora	Mint	YNAB	ET Money	Walnut	Google Sheets
AI Budgeting	<b>Yes (Auto)</b>	Partial	Manual	No	No	No
Smart Alerts	<b>Yes</b>	Yes	Limited	No	Yes	No
Investment Advice	<b>Personalized</b>	No	No	Yes	No	No
What-if Simulation	<b>Yes</b>	No	No	No	No	No
OCR Receipt Scan	<b>Yes</b>	No	No	No	No	No
AI Chat Assistant	<b>Yes</b>	No	No	No	No	No
Personalization	<b>High</b>	Low	Medium	Medium	Low	None
Target Audience	<b>Youth/Students</b>	General	General	Indian	Indian	General

As evidenced in Table II, Fiinora occupies a unique position in the competitive landscape by being the only evaluated tool to offer AI-driven automatic budgeting, personalized investment advice, what-if scenario simulation, OCR-based receipt capture, and a conversational AI assistant simultaneously. Indian-market competitors ET Money and Walnut provide partial investment and tracking features respectively but lack intelligent automation and simulation capabilities. Western tools such as Mint and

YNAB, while more feature-complete, are not designed for the Indian financial product ecosystem, regulatory environment, or the low-income student demographic that constitutes Fiinora's primary user base.

The comparative analysis also highlights that no existing tool combines all five survey-demanded features (auto budgeting, smart alerts, investment advice, what-if simulation, AI chat) in a single, cohesive product. Fiinora's design specifically addresses this integration gap, positioning it as a category-defining rather than merely competitive offering in the Indian fintech landscape.

## IX. FUTURE SCOPE

The current prototype, while functionally comprehensive, represents a foundational implementation upon which several high-impact extensions are planned. First, AI-driven financial risk scoring will be developed to provide users with a dynamic, personalized financial health index incorporating debt ratios, savings rates, and investment diversification metrics. This score will serve as a gamification anchor to drive sustained engagement and behavioral change.

Second, bank account integration via Open Banking APIs (leveraging the Account Aggregator framework mandated by the Reserve Bank of India) will enable automated, consent-based transaction ingestion, eliminating the reliance on manual entry or OCR-based capture for users who prefer seamless synchronization with their existing financial accounts.

Third, real-time portfolio tracking will extend the Investment Mentor module to provide live net asset value (NAV) updates for mutual fund holdings, equity portfolio performance monitoring, and rebalancing recommendations aligned with the user's evolving risk profile.

Fourth, a voice-based financial assistant interface will be implemented to serve users who prefer spoken interaction, expanding accessibility for users with limited typing proficiency or visual impairments. Voice-to-intent parsing via a fine-tuned speech recognition model will route audio commands to the appropriate agent module.

Finally, predictive financial planning capabilities will be introduced, employing time-series forecasting models to project income trajectories, expense evolution, and goal achievement probability over multi-year horizons. These projections will enable users to make strategically informed decisions about major financial commitments with quantified confidence intervals.

## X. CONCLUSION

This paper has presented Fiinora, a prototype AI-driven financial assistant specifically designed to address the financial management deficiencies prevalent among young Indian users. Through a rigorously conducted primary survey of 91 respondents, the research demonstrates that the failure of existing financial tools is not attributable to inadequate feature sets, but to a fundamental absence of personalization, intelligence, and usability alignment with the target demographic's behavioral and economic realities.

The proposed agent-based modular architecture—comprising a Budget Agent, Smart OCR Agent, Insight Engine, Investment Mentor, Financial Simulation Module, and AI Chat Assistant—provides a technically sound and empirically grounded response to the five principal financial challenge categories identified in the survey: budgeting deficiency, memory-based management, investment confusion, income-expense imbalance, and application usability barriers.

Survey findings validate strong market demand for Fiinora's capabilities: 63.7% AI adoption readiness, 50.5% demand for automated budgeting, and 57.1% conditional payment willingness collectively represent a compelling commercial and social use case. Comparative analysis against Mint, YNAB, ET Money, Walnut, and spreadsheet tools confirms that Fiinora occupies a unique, unaddressed market position in the Indian fintech ecosystem.

As a prototype and feasibility study, Fiinora establishes a robust foundation for continued development. Future work will focus on longitudinal deployment studies to quantify actual behavioral and financial outcomes, bank integration for frictionless data capture, and advanced predictive modeling capabilities. Fiinora has the demonstrable potential to meaningfully improve financial literacy, decision-making quality, and long-term financial stability for millions of young Indians navigating the complexities of personal finance for the first time.

## Acknowledgment

- [1] The author expresses sincere gratitude to Prof. Shahjahan Shaikh, Rizvi College of Engineering, Mumbai, [shahjahanshaikh@eng.rizvi.edu.in](mailto:shahjahanshaikh@eng.rizvi.edu.in) for academic guidance and support during the development of this project.
- [2] The primary system design, research conceptualization, implementation, and data analysis were carried out by the first author. Other authors contributed to preliminary discussions and academic coordination.

## References

- [3] A. Lusardi and O. S. Mitchell, "The Economic Importance of Financial Literacy: Theory and Evidence," *Journal of Economic Literature*, vol. 52, no. 1, pp. 5–44, 2014.
- [4] R. H. Thaler and S. Benartzi, "Save More Tomorrow: Using Behavioral Economics to Increase Employee Saving," *Journal of Political Economy*, vol. 112, no. S1, pp. S164–S187, 2004.
- [5] S. Bhattacharjee and P. Premkumar, "Understanding Changes in Belief and Attitude Toward Information Technology Usage: A Theoretical Model and Longitudinal Test," *MIS Quarterly*, vol. 28, no. 2, pp. 229–254, 2004.
- [6] V. Dhar and R. Stein, "FinTech Platforms and Strategy," *Communications of the ACM*, vol. 60, no. 10, pp. 32–35, 2017.
- [7] Reserve Bank of India, "Account Aggregator Framework: Enabling Consent-Based Data Sharing," *RBI Reports*, 2021.
- [8] P. Philippon, "On Fintech and Financial Inclusion," NBER Working Paper No. 26330, National Bureau of Economic Research, 2019.
- [9] M. Baker and J. Ricciardi, "How Biases Affect Investor Behaviour," *The European Financial Review*, pp. 7–10, 2014.
- [10] C. R. Harvey, Y. Liu, and H. Zhu, "... and the Cross-Section of Expected Returns," *Review of Financial Studies*, vol. 29, no. 1, pp. 5–68, 2016.
- [11] S. Agarwal, J. C. Driscoll, X. Gabaix, and D. Laibson, "The Age of Reason: Financial Decisions Over the Life Cycle," *Brookings Papers on Economic Activity*, pp. 51–117, 2009.
- [12] A. Seetharaman, J. R. Niranjana, N. Saravanan, and A. Balaji, "A Study of the Factors Affecting the Choice of Investment Instruments by Individual Investors," *IOSR Journal of Business and Management*, vol. 18, no. 4, pp. 36–42, 2016.