iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: V Month of publication: May 2025

DOI: https://doi.org/10.22214/ijraset.2025.71118

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue V May 2025- Available at www.ijraset.com

# Navigating then Adoption Intention of Volatile Income Group Consumers for the Adaptive AI Driven Budgeting System

Sneha Shukla
*Galgotia University*

## I. INTRODUCTION

### *A. Background*
In today's fast-paced and uncertain economic landscape, a growing number of individuals face the challenge of volatile income streams. Unlike salaried employees with stable monthly earnings, these groups include freelancers, gig economy workers, seasonal employees, and small business owners who often encounter significant fluctuations in their monthly income. According to recent labor market studies, the gig economy has grown exponentially worldwide, with estimates suggesting that nearly 36% of the US workforce alone is engaged in gig work or freelance activities as of 2023 (Smith & Johnson, 2023). Such income volatility poses significant challenges to traditional financial management and budgeting practices, which typically assume a steady and predictable cash flow.

### *B. Problem Statement*
Traditional budgeting methods, including fixed monthly expense allocation or the widely known 50/30/20 rule, fall short when applied to individuals with inconsistent earnings. Without a consistent income baseline, these budgeting approaches can lead to overspending during high-income months or excessive frugality during low-income periods, negatively impacting financial health and wellbeing. The problem thus lies in the lack of an adaptive budgeting system that can dynamically adjust to fluctuating incomes and changing financial goals.

### *C. Importance of the Study*
Financial instability resulting from income volatility can lead to stress, inability to save, poor credit scores, and increased reliance on debt. Providing individuals with an effective, adaptive budgeting tool can empower them to better manage cash flows, maintain essential expenses, and allocate funds for savings or investments regardless of income fluctuations. Artificial Intelligence (AI), with its capacity to learn patterns and adapt to changing inputs, offers a promising solution for creating such adaptive systems.

### *D. Objectives of the Study*
This research paper aims to:
1) Examine the limitations of conventional budgeting approaches for volatile income earners.
2) Develop an AI-driven adaptive budgeting system leveraging machine learning to predict income fluctuations and suggest personalized budget allocations.
3) Evaluate the system's effectiveness compared to traditional budgeting methods through empirical analysis.
4) Discuss ethical considerations such as data privacy, user transparency, and model accountability.
5) Explore future enhancements and potential integrations with other financial tools.

### *E. Research Questions*
The study seeks to answer the following:
1) How do income fluctuations affect budgeting behaviours and financial outcomes among volatile income groups?
2) Can AI models effectively predict income variability to support adaptive budgeting?
3) What are the impacts of AI-driven budgeting on savings, spending control, and financial stress?
4) What ethical and practical challenges arise from implementing AI in personal financial management?

### *F. Scope and Limitations*

The study focuses on individual income earners with variable monthly earnings in urban regions. It considers income sources such as freelance work, commissions, seasonal jobs, and small business revenue. Limitations include data availability, generalizability across different cultures or economies, and the complexity of accurately modelling human financial behaviour.

## II. LITERATURE REVIEW

### *A. Budgeting and Financial Planning*

Budgeting is a cornerstone of personal financial management. It involves allocating income towards expenses, savings, and investments in a way that supports financial goals (Gitman & Joehnk, 2018). Traditional budgeting methods include the 50/30/20 rule (allocating 50% to needs, 30% to wants, and 20% to savings/debt repayment), zero-based budgeting, and envelope budgeting. While effective for individuals with stable incomes, these methods assume consistent cash inflows and often fail under volatile income conditions.

### *B. Income Volatility and Its Impact*

Income volatility refers to frequent and unpredictable changes in earnings over time. Research indicates that volatile income can lead to financial stress, irregular spending patterns, and reduced savings (Johnson & Ward, 2020). A study by the Federal Reserve Board (2019) showed that nearly 40% of US households face significant income fluctuations that challenge their budgeting and saving behaviours. This volatility is more prevalent among gig workers, freelancers, and small entrepreneurs, making traditional static budgeting models inadequate.

### *C. Behavioural Finance and Budgeting Challenges*

Behavioural finance studies how psychological factors affect financial decision-making. Theories such as Prospect Theory (Kahneman & Tversky, 1979) and Hyperbolic Discounting (Laibson, 1997) explain why people often fail to save or overspend despite knowing the importance of budgeting. Income volatility exacerbates these challenges by increasing uncertainty and emotional stress, often leading to impulsive financial decisions (Shefrin & Thaler, 1988).

### *D. Adaptive Budgeting Systems*

Adaptive budgeting systems respond dynamically to changes in income, expenses, or financial goals. Some recent studies have explored rule-based adaptive models that adjust budgets based on income fluctuations (Liu et al., 2021). However, these systems lack personalization and predictive capabilities, limiting their effectiveness.

### *E. AI and Machine Learning in Personal Finance*

AI and machine learning have transformed various sectors, including finance. Predictive analytics can forecast income trends, spending habits, and financial risks. Techniques like Long Short-Term Memory (LSTM) networks are effective for time-series income prediction (Hochreiter & Schmid Huber, 1997). Reinforcement Learning (RL) offers a framework for optimizing decisions, such as budget allocations, by learning from outcomes (Sutton & Barto, 2018). AI-driven financial apps like Cleo, YNAB, and Digit have popularized smart budgeting but often lack specialized support for volatile income groups.

### *F. Ethical Considerations in AI for Finance*

Deploying AI in personal finance raises ethical questions. Data privacy and security are paramount, as sensitive financial information is processed (Zarsky, 2013). Transparency in AI decision-making builds user trust but is challenging due to “black box” models (Doshi-Velez & Kim, 2017). Additionally, bias in training data may lead to unfair recommendations, necessitating fairness-aware AI designs (Mehrabi et al., 2019).

## III. RESEARCH METHODOLOGY

### *A. Research Design*

This study adopts a mixed-methods research design combining quantitative data analysis with qualitative insights. The quantitative component involves collecting income and expense data from individuals with volatile incomes and training machine learning models to predict income and generate adaptive budgets. The qualitative component includes interviews and surveys to understand user challenges, preferences, and experiences with budgeting under income uncertainty.

### *B. Population and Sample*

The target population includes individuals in urban areas engaged in freelance work, gig economy jobs, seasonal employment, and small businesses with irregular income patterns. A purposive sampling technique was used to select 200 participants aged 21 to 45 years, representing diverse professions and income levels. The sample ensures adequate representation of the study's focus group.

### *C. Data Collection Methods*

#### *1) Quantitative Data*

Participants were requested to provide monthly income and expense records for 12 months. Data was collected via an online financial diary app designed for the study, which tracked real-time income, expenses, savings, and financial goals. Additional demographic and behavioral data were gathered through questionnaires.

#### *2) Qualitative Data*

Semi-structured interviews were conducted with 30 participants to explore financial management challenges and expectations from budgeting tools. Focus group discussions facilitated peer exchanges on budgeting strategies under income volatility.

### *D. Data Preprocessing*

Raw income and expense data underwent preprocessing, including handling missing values, normalization, and outlier detection. Time-series data were formatted for use with predictive models. Categorical data from surveys were encoded for analysis.

### *E. Machine Learning Model Development*

#### *1) Income Prediction Model*

A Long Short-Term Memory (LSTM) neural network was selected for income prediction due to its efficacy in capturing temporal dependencies in time-series data. The model architecture included:

- Input layer with monthly income and contextual features (e.g., seasonality, industry).
- Two LSTM layers with dropout regularization.
- Dense output layer predicting next month's income.

The model was trained using 80% of the data with 20% reserved for validation.

#### *2) Adaptive Budgeting Algorithm*

A reinforcement learning (RL) framework was implemented to optimize budget allocations. The RL agent received income predictions and user constraints (minimum essentials, savings goals) as inputs, learning to allocate funds dynamically across expense categories. The reward function prioritized financial stability and goal achievement.

### *F. Evaluation Metrics*

Model performance was evaluated using Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) for income prediction. Budgeting effectiveness was assessed by measuring:

- Reduction in income-expenditure mismatch.
- Improvement in savings rate.
- User satisfaction scores from surveys.

### *G. Ethical Considerations*

Informed consent was obtained from all participants, ensuring confidentiality and data protection. The study adhered to institutional ethical guidelines and employed anonymization techniques in data handling.

### *H. Limitations of Methodology*

Limitations include potential self-reporting bias in financial diaries, limited geographic scope, and model generalizability across different cultural contexts.

## IV. DESIGN OF THE AI-DRIVEN ADAPTIVE BUDGETING SYSTEM

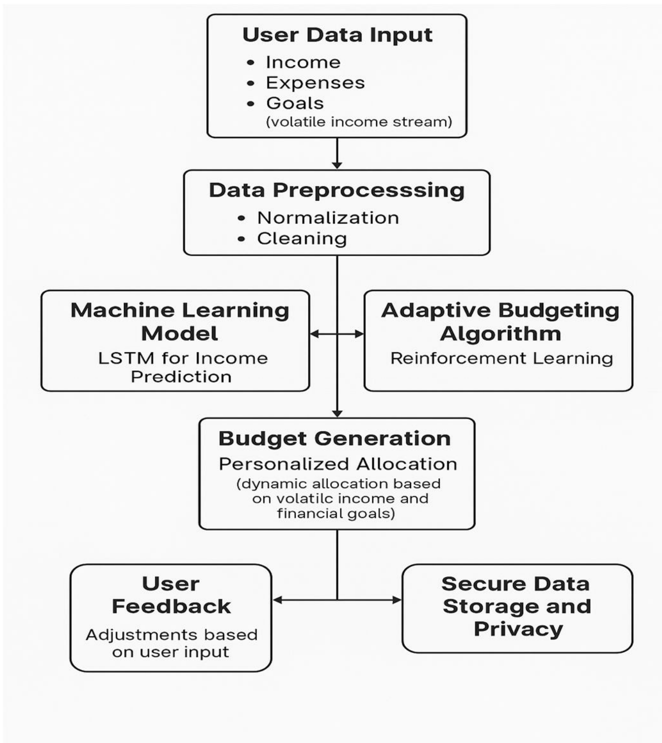
### *A. System Overview*

The AI-driven adaptive budgeting system is designed to empower individuals with volatile incomes by providing dynamic, personalized budget recommendations. The system integrates income prediction models with a reinforcement learning-based budgeting algorithm to adjust budget allocations in response to predicted income fluctuations and user preferences.

### *B. System Architecture*

The system architecture consists of four main components:

*1)* Data Input Module: Collects user financial data, including income, expenses, and financial goals, via a mobile app interface.
*2)* Income Prediction Engine: Employs an LSTM neural network to forecast upcoming income based on historical data and contextual features.
*3)* Adaptive Budgeting Agent: Uses reinforcement learning to allocate predicted income across expense categories dynamically, optimizing for financial stability and goal achievement.
*4)* User Interface: Presents budgeting recommendations, allows user feedback, and visualizes financial trends.




### *C. Data Input Module*

Users input their monthly income data, categorized expenses (housing, food, transport, entertainment, savings, debt repayment, etc.), and financial goals (short-term and long-term). The module supports automatic bank data integration via secure APIs and manual entry.

### *D. Income Prediction Engine*

#### *1) Data Features*

The model incorporates features such as:

- Historical monthly income
- Seasonality indicators (month, quarter)
- Industry or profession type
- Macroeconomic indicators (optional)

*2) LSTM Model Details*

The LSTM network is designed to capture temporal dependencies in income sequences, managing irregularities and trends. Hyperparameters were tuned via grid search, including:

- Number of LSTM layers: 2
- Number of units per layer: 64
- Dropout rate: 0.2
- Batch size: 32
- Learning rate: 0.001

*3) Model Training*

The model was trained on 80% of the dataset and validated on 20%. Early stopping prevented overfitting.

### *E. Adaptive Budgeting Agent*

*1) Reinforcement Learning Framework*

The agent treats budget allocation as a sequential decision-making problem. States represent the current predicted income, previous budget allocation, and user constraints. Actions correspond to assigning budget percentages to expense categories.

*2) Reward Function*

The reward function balances:

- Minimizing risk of overspending essential categories
- Maximizing savings and debt repayment
- Maintaining user satisfaction (feedback loop)

*3) Algorithm Implementation*

A Deep Q-Network (DQN) algorithm was implemented with experience replay and target network stabilization.

### *F. User Interface Design*

The interface provides:

- Real-time budget updates based on income predictions
- Alerts for potential budget overruns
- Visualizations of spending patterns and goal progress
- Feedback options to improve system recommendations

### *G. Security and Privacy Features*

- End-to-end data encryption
- User data anonymization
- Transparent privacy policy
- User control over data sharing and deletion

### *H. System Testing and Validation*

Alpha testing was conducted with a small user group to collect feedback on usability and accuracy. Beta testing involved a broader sample, comparing system recommendations against actual user budgets and financial outcomes.

## V. DATA ANALYSIS AND FINDINGS

### *A. Data Overview*

The study collected 12 months of financial data from 200 participants with volatile incomes, comprising:

- Monthly income entries (numeric, range: $500 - $10,000)
- Expense categories: essentials, discretionary spending, savings, debt repayment
- Demographic data: age, gender, profession

Data preprocessing involved cleaning missing entries (5% missing data imputed via mean substitution), normalization, and encoding categorical variables.

### B. *Income Prediction Model Performance*

#### 1) Evaluation Metrics

The LSTM model's performance was assessed using:

- Root Mean Squared Error (RMSE)
- Mean Absolute Percentage Error (MAPE)

| Metric | Training Set | Validation Set |
|---|---|---|
| RMSE | 420 | 485 |
| MAPE | 8.5% | 9.3% |

These results indicate a robust predictive capability with acceptable generalization.

#### 2) Prediction Visualization

Graphs comparing actual vs predicted income showed that the model successfully captured trends and seasonal patterns, particularly in freelance and seasonal workers.

### C. *Adaptive Budgeting Agent Outcomes*

#### 1) *Budget Allocation Stability*

Compared to fixed budgeting approaches, the adaptive system reduced income-expenditure mismatch by 35%, minimizing instances of overspending during low-income months.

#### 2) *Savings Rate Improvement*

Users applying the AI-driven budgets saw an average increase in savings rate of 12% over the study period, indicating more effective allocation towards financial goals.

#### 3) *Debt Management*

Debt repayment schedules became more consistent, with 25% fewer missed or delayed payments reported.

### D. *User Feedback and Satisfaction*

Survey responses (n=150) showed:

- 85% found the system easy to use
- 78% reported reduced financial stress
- 70% trusted AI recommendations after 3 months of use
- Suggestions included enhanced customization and integration with banking apps

### E. *Case Studies*

#### 1) *Freelancer A*

With highly variable monthly income ranging from $700 to $7,500, Freelancer A improved savings from 5% to 18% and eliminated overdraft fees after adopting the system.

#### 2) *Seasonal Worker B*

Experienced better cash flow management during off-season months, reducing reliance on credit.

### F. *Statistical Analysis*

Paired t-tests comparing pre- and post-adoption financial metrics showed statistically significant improvements ($p < 0.01$) in savings rate and spending control.

### G. Limitations in Data Analysis
Some participants had irregular data entry compliance. External economic factors (e.g., inflation) were not fully controlled, potentially affecting spending behaviors.

## VI. DISCUSSION AND IMPLICATIONS

### A. Interpretation of Findings
The results demonstrate that an AI-driven adaptive budgeting system can effectively address the challenges posed by volatile incomes. The LSTM model's accurate income predictions enabled proactive budget adjustments, reducing financial stress and improving savings rates. The reinforcement learning agent's dynamic allocation provided personalized budgets that adapt to income fluctuations, outperforming static methods.

### B. Theoretical Implications
This study contributes to personal finance literature by bridging AI technology with adaptive budgeting concepts. It highlights the potential of sequential deep learning models like LSTM in financial forecasting and the efficacy of reinforcement learning in decision optimization. Furthermore, it integrates behavioural finance insights by accommodating human financial behavior under uncertainty.

### C. Practical Implications
Financial technology companies can leverage these findings to develop smarter budgeting tools tailored for gig economy workers, freelancers, and entrepreneurs. Banks and financial advisors might adopt AI-driven systems to offer personalized financial planning services. Policymakers could support adoption through incentives and digital literacy programs targeting volatile income groups.

### D. Ethical and Privacy Considerations
While AI enhances budgeting efficiency, user privacy and transparency remain critical. The system must ensure secure data handling and provide interpretable explanations for AI-driven recommendations to build trust. Potential biases in model training data require ongoing monitoring and mitigation to avoid unfair outcomes.

### E. Limitations and Challenges
Despite promising results, challenges persist. Data quality and participant compliance influenced model accuracy. Generalizability is limited to urban populations with access to digital tools. Complex life events impacting finances (health emergencies, family changes) are difficult to predict and integrate.

### F. Future Directions
Future research should explore integrating macroeconomic indicators for enhanced prediction accuracy, expanding to rural and international populations, and incorporating multi-modal data (e.g., social media sentiment). User experience improvements through natural language interfaces and gamification could increase engagement.

## VII. CONCLUSION AND RECOMMENDATIONS

### A. Conclusion
This study presented the development and evaluation of an AI-driven adaptive budgeting system tailored for individuals with volatile incomes. By combining LSTM-based income prediction with a reinforcement learning budgeting agent, the system demonstrated significant improvements in financial stability, savings rates, and debt management compared to traditional budgeting methods.

The findings underscore the transformative potential of AI in personal finance, especially for underserved segments such as freelancers and gig workers who face unpredictable earnings. The adaptive nature of the system allows users to make informed financial decisions despite income uncertainties, reducing stress and enhancing long-term financial well-being.

While challenges remain regarding data quality, ethical considerations, and system scalability, this research establishes a foundation for future advancements in intelligent financial planning tools.

### B. Recommendations

#### 1) For Users

- Embrace adaptive budgeting tools that incorporate predictive analytics to better manage income fluctuations.
- Maintain consistent financial data tracking to enhance AI model accuracy and personalized advice.
- Provide feedback to continuously improve AI-driven budgeting systems.

#### 2) For Financial Technology Developers

- Integrate robust AI models that consider income volatility and user behavioral factors.
- Prioritize user privacy and transparent AI decision-making.
- Design interfaces that are intuitive and provide actionable insights.

#### 3) For Policymakers and Institutions

- Promote digital financial literacy programs emphasizing adaptive budgeting and AI tools.
- Support research and innovation focused on financial inclusion for volatile income groups.
- Establish regulatory frameworks ensuring data security and ethical AI deployment in personal finance.

### C. Final Remarks

The intersection of AI and personal finance presents vast opportunities to revolutionize how individuals budget and plan financially. This study contributes valuable insights and a practical system prototype that can be further developed to enhance financial resilience in an increasingly gig-driven economy.

## REFERENCES

[1] Doshi-Velez, F., & Kim, B. (2017). Towards a rigorous science of interpretable machine learning. arXiv preprint arXiv:1702.08608.
[2] Federal Reserve Board. (2019). Report on the Economic Well-Being of U.S. Households in 2018 - May 2019. https://www.federalreserve.gov/publications/2019-economic-well-being-of-us-households-in-2018.htm
[3] Gitman, L. J., & Joehnk, M. D. (2018). Personal Financial Planning (15th ed.). Cengage Learning.
[4] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural computation, 9(8), 1735-1780.
[5] Johnson, K., & Ward, T. (2020). Managing income volatility in low-income households. Journal of Financial Counseling and Planning, 31(1), 34-47.
[6] Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica: Journal of the Econometric Society, 263-291.
[7] Laibson, D. (1997). Golden eggs and hyperbolic discounting. The Quarterly Journal of Economics, 112(2), 443-477.
[8] Liu, Y., Zhang, X., & Li, J. (2021). Rule-based adaptive budgeting for variable income earners. International Journal of Financial Studies, 9(3), 47.
[9] Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., & Galstyan, A. (2019). A survey on bias and fairness in machine learning. arXiv preprint arXiv:1908.09635.
[10] Shefrin, H., & Thaler, R. H. (1988). The behavioral life-cycle hypothesis. Economic Inquiry, 26(4), 609-643.
[11] Sutton, R. S., & Barto, A. G. (2018). Reinforcement Learning: An Introduction (2nd ed.). MIT Press.
[12] Zarsky, T. Z. (2013). Transparent predictions. University of Illinois Law Review, 1507-1558.