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Modelling Savings Behavior of Daily Wage Earners Using Public Data and Simulated Household Insights

Authors: Darsh Agarwal[1], Nikunj Parikh[2]

Mahindra International School Mumbai, India[1]; Mentor, On My Own Technology India[2]

Email: darsh0807@gmail.com[1], nikunj.parikh@onmyowntechnology.com[2]

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Abstract—**Individuals earning wages on a daily basis frequently encounter obstacles in establishing financial stability because their income is often not evenly distributed throughout the month. Additionally, these individuals can have a low ratio (expenses/income) as a result of a small amount of available income or many significant expenditures. Poor access to the traditional savings and banking systems can lead to additional financial difficulties. This Documentation combines publicly available economic data with simulated household level data to create a behavioral savings model that reflects the factors faced by wage employees. This model integrates a range of financial behavior factors such as monthly income, expense ratio, debt levels, poverty rate, inflation, and employment opportunity in the local area. The analysis by region explores behavioral differences found in different areas of the country; for example, families in part of the country where employment is more stable show a more robust savings behavior than families in high poverty areas who remain precarious. By connecting data analysis with household simulations, this model asks the question of how much families can realistically save over the course of the month in unique conditions, including data on regional variation in expense ratios and income. Additionally, the model takes inflation levels and consumption into consideration in order to explore the conditions under which families can build financial security. The model is not just a predictive model, but a decision-supportive toolkit to visualize how wage earners manage their finances, understand how those contextual factors limit their prospects for saving, and what would create more resilience over time.**

Keywords— *Daily wage earners, Savings behaviour, Household-level analysis, Financial resilience, Income instability, Poverty and inflation, Public data integration, Regional disparities.*

I INTRODUCTION

Daily wage earners comprise a significant share of employment and contribute to the economy, yet they are one of the most financially vulnerable populations. They frequently have an income that is inconsistent or uncertain and limited capacity to save or plan for the long term. They are just a few unexpected expenses (healthcare needs, education costs, emergencies, etc.) away from finding themselves in a precarious financial situation. Understanding how these households allocate their income and expenses is essential to improving financial resilience. While publicly available data on income, poverty status or rates, inflation, and employment opportunity provides a broad view of the situation, it does not fully represent reality at the household level. Simulated insights at the household level can also be combined with regional data to address these limitations and to simulate savings behaviour. This process can help reveal patterns in how much households can save, what types of factors lead to more stability, and how things related to region or geography may inform household behavior. For instance, households that are located in regions with more stable employment opportunities might tend to save more than households that live in high-poverty-region.

With a foundation created from publicly available data that is combined with simulated insights, this study aims to not only predict savings behaviour, but also to illustrate the conditions or features that can promote better financial security for daily wage earners. Numerous studies offer insights into household savings. For instance, Bhat explores the precursors to savings among rural households and demonstrates how socio-economic situations shape their savings behaviours [1]. Ghosh et al. identify a connection between household savings behaviour and context in the macroeconomy, arguing that household savings contribute towards national financial stability [2]. Akram analyses micro-data in Pakistan and identifies very strong household-level factors (such as income flow and debts) acting on savings behaviours; these conditions resonate with the lived realities of daily wage earners in India [3].

Sefton and van de Ven illustrate the promise of simulation techniques in households by demonstrating household savings and labor supply preferences through dynamic programming. Their study provides methodological opportunities to study savings behaviour through data driven modelling, breaking away from longitudinal studies into household savings networked research and studies [4]. Lusardi similarly affirms the significance of financial literacy, access to information and educational programs in the context of household saving decision-making processes. The present study builds upon these studies by drawing upon public data and simulated household-level data to build a more real world picture of savings behaviour among daily wage earners. In contrast to existing work, much of which struggles to reconcile that either studies at the macro level or surveys household experiments, this framework locates the intersection of the two. It identifies not only the constraints made on savings decision-making, but also the environmental conditions where households could be further supported to improve financial resilience.

II LITERATURE REVIEW

Lusardi's et al. research [5] investigates the influence of financial literacy, access to information, and financial education programs on household saving habits. Low financial literacy decreases one's skills to plan how to allocate income and perpetuates low saving. Plans that impact financial literacy by introducing saving options and improving decision-making increased awareness about saving alternatives. Households that have higher financial literacy are better prepared for future financial needs. Therefore, the study argues that education and access to information regarding fiscal practices can increase household savings for the future.

Mansoor's et al. study [6] examines the impact of minimum wage compliance on household welfare and the ability to save. Noncompliance with appropriate wages decreases disposable income and limits savings; complying with minimum wage laws allows for improvements to household finances. Households with disposable income are able to make long-term saving decisions. The study suggests that compliance with wage policies is a contributory condition of household savings and overall welfare.

Porpiglia et al. [7] study household saving behavior under credit constraints in the euro area. Constraints on the availability of credit leads to shorter time horizons producing immediate consumption versus long-term savings. A decrease in the limitation of borrowing allowed households for more saving and smoothing consumption. Credit also encourages the household to invest in financial planning. These findings suggest that access to credit is an important factor in household saving behavior.

Törmälehto and Soinne et al. [8] compare the macro and micro saving behaviors of households in Finland. By amalgamating the financial behavior of households at the individual level and the level of national savings they identify structural and behavioral aspects that have bearings on the variability of saving. The differences of an individual's saving versus aggregate saving argue for coinciding policy approaches. Policies that address savings through opportunities related to macroeconomics of life events as well as household behavior toward savings achieves greater adherence to savings. This study illustrates the value of an integrated approach to understanding saving behavior and directly contributing to the goal of saving behavior and money saving practices.

Faridi and Bashir et al. [9] analyze the determinants of household savings in Multan, Pakistan. Income level, family size and stability of employment were found to strongly affect saving behavior. Households with fluctuating income as well as higher dependency ratios saved at lower amounts. Access to financial resources, along with mechanisms to stabilize income, may improve saving. This study highlights the importance of economic behavior and demographic behavior as it relates to saving behavior in households.

Ögren et al. [10] studies determinants of household saving behavior. Education, income and social environment were all significantly associated with predictions of saving behaviors. Higher levels of household socio-economic status were associated with higher rates of savings. Access to finance and structural development positively affected household savings. This study draws attention to the cumulative influence of individual factors, along with societal factors, on saving behavior.

Alsedrah et al. [11] investigates the determinants of personal savings in Saudi Arabia. Increased household savings propensity relates positively to the increase in income, financial literacy, and access to banking. Access to financial services facilitates more savings in households over time. Policy initiatives that promote financial inclusion will intensify national trends in savings. The research points to the role of both structural and behavioural determinants shaping household patterns of saving.

Aslam et al. [12] explores the household saving behavior of households in urban and rural areas of Pakistan. Households from the rural areas generally face more volatility in income and less access to financial infrastructure that reduces saving. Households in urban areas have better access to financial institutions and have more stable incomes which leads to higher savings. Programs for rural financial inclusion of farmers along with improving infrastructure should lead to savings. The study on household saving behavior points to the importance of regional cultural differences affecting household saving behavior.

Paxson et al. [13] analyzes the connection of household saving at the micro level to the macro level for the economy and growth. Higher household savings adds to macroeconomic stability and future investment. The behavior of saving is dependent on current consumption requirements and expectations of future income. Policy initiatives which emphasize income security and future planning for income will lead to better saving outcomes in families. The study shows that household saving is both a driver and a reflection of future economic growth.

Muhamad et al. [14] examine saving behavior in low-income households, primarily as a result of consumption demand and risk of vulnerability to shocks from improved savings. Micro-savings programs and low-cost bank services improve financial resilience and provide savings vehicles. Directing efforts toward increasing saving behavior among low-income households can provide the desired outcomes. Thus, this study emphasizes well-designed financial products and services for financially vulnerable clients.

Endrődi-Kovács et al. [15] considers the drivers of household saving patterns for East Central European households, using a mixed-methods approach. The authors note that income stability, policies that promote saving behavior, and the financial instruments available offer strong explanatory value. Raise Income and improve vulnerable Financial Literacy and savings vehicles enhance saving behavior. Educating clients as well as providing new infrastructure supports and allows households to save more into National Providers to strengthen the partially stated national savings rate and outcomes for the experience of saving. In conclusion, the study notes the relationship of structural and behavioral drivers of household savings

III METHODOLOGY

The dataset combines information using public macroeconomic data and synthetic household-level data and provides a dual focus on economic basics as well as household-level financial behavior. The connected pieces allow the financial resilience dashboard to combine household characteristics, regional context, and other policy factors together, to provide insights into household saving behavior and make relevant, targeted, and actionable suggestions to improve financial inclusion and resilience.

1. *Data Sources*

1. Public data: Publicly available datasets were utilized to establish the macroeconomic and demographic context of daily wage earners. Publicly available datasets indicate factors at a more general level that influence capacity to save. Demographic data, such as distributions by age group, sex, household size, literacy status, and education level, give information about the working-age population and dependency ratio in an area. Employment and wage data, including employment distribution, labor force participation rate, daily wages, and employment across sectors (reported by NSSO and the Ministry of Labour), help understand factors that may relate to wage stability or volatility in the area. Poverty data, including poverty headcount, Gini coefficient for income equality, and access to welfare (from the World Bank and NITI Aayog), show differences in monetary resilience across households. Measures of inflation and household consumption, such as regional CPI indices and expenditure patterns (from RBI and NSSO), highlight the effect of inflation on disposable income. Finally, financial inclusion and interest data, including access to bank accounts, access to credit, and interest rates (from RBI and World Bank Global Findex), describe the financial channels available to households and the potential cost of borrowing. This data indicates whether households have access to formal saving instruments. Together, the level of data provided by the public data serves as a baseline to model the more general circumstances in which wage earners operate. *Household Dataset:* Because public datasets do not capture the intricate, dynamic financial behaviors exhibited by daily wage-earning individuals and households, a synthetic household dataset was developed using simulated data. Households demonstrate different financial behaviors based on changes to income, spending, and saving. Monthly distributions of income are not evened out, as they are based on external circumstances like receiving irregular daily wages, the seasonality or cyclicality of work, or random days of work attendance. Patterns of spending also differ in terms of expenditure by category of core need, and there is a pattern of expenditure within categories, made all the more different when a financial shock occurs. Households are also different in terms of savings or debt; some households have a financial surplus at the end of the month and others carry debt and interest without the ability to repay what they owe. This difference points to differences in financial well-being and vulnerability. Additionally, some households are more prepared for emergencies than others, relying on emergency funds while some remain highly financially vulnerable, living paycheck to paycheck, and have little to no buffer from potential financial shocks to income. Financial resilience overall can be summarized by a composite Financial Buffers Index characterized by aggregate indicators like savings ratio, debt-to-income ratio, patterns of expenditure, etc. Each one of these indicators points to a more complete picture of a household's ability to manage a financial stressor. The simulation framework was able to systematically integrate shocks into the household profiles job loss, income, inflation, etc. This strategy was developed to overcome the limitation of static public datasets and to model realistic, dynamic household financial behaviors.

2. *Combined dataset:* The dataset brought together public datasets with synthetic household data. It enables research that includes analysis from a local microeconomic perspective of macroeconomic and poverty indicators, while still enabling consideration of heterogeneity among households through using synthetic data across income, savings, and resilience factors. The dataset serves as an incentive to generate future models predicting savings behavior of house-

holds in response to future disruptions. As Shown in

2. *Model Training*

The dataset consisted of publicly available information and household-level data to make predictions on savings behavior of people who earn daily wages. The objective was to observe whether a household could save 15% of its income. The features we used were; income, expense ratio, debt-to-income ratio, emergency preparedness, and regional indicators like inflation and poverty rate. To this end, the data was cleaned, missing values addressed, categorical variables encoded, and numerical values normalized. Once the data was pre-processed, the dataset was split into training and testing sets, and crossvalidation was also applied as a way to minimize overfitting. Several models were tried to assess which model would yield the best accuracy. Logistic Regression was employed first as a baseline commonly used to identify if an event will occur as it is simple and easy to interpret. Random Forest was used next as an algorithm to capture non-linear relationships. Finally, XGBoost was also trailed because of its ability to predict strong results with imbalanced datasets.

Multi-layer Perception Neural Network (1) was additionally trailed to assess how this model may perform with a broader learning approach. Ultimate results found that XGBoost (2) provided the highest accuracy and F1-score, with Random Forest (3) second. The Logistic Regression (4) side of the models performed moderate but was still beneficial in interpreting. MLP Neural Network also provided good prediction, but CPU intensive to execute due to computation. The findings ultimately suggested that the XGBoost option was the best model.

Multi-Layer Perceptron (MLP) uses forward propagation to decide inputs to the linear combination of inputs, the model complexity and estimate accuracy in prediction:

$a_l = W_l a_{l-1} + b_l$ (1) XGBoost optimized a regularized objective:

$$L = t(y_i, \hat{y}_i) + \kappa(f_x) \quad (2)$$

Random Forest provided an aggregate of predictions from many different trees:

$\frac{1}{} \Sigma$

Fig.1.

$\hat{y} =$

T

$t=1$

$h_t(X)$ (3)

Logistic Regression provides an estimate of the probability that saving happens:

$P(Y = 1|X) =$

1

$1 + e^{-(\beta 0 + \beta 1 X 1 + \ldots + \beta n X n)}$ (4)

Age	Gender	Education	Income	Employme	Debt	Expenses	Emergenc	Past_Savi	Debt_to_Ir	Savings_R	Expense_F	Emergenc	Label_Sav	Designatic	State	CPI_Index	Avg_Montl	Avg_MGNI	Pct_Bache	Pct_HighS	Poverty_R	Income_R
37	Male	Bachelors	45489	Full-time	6640	41966	13258	29165	0.146834	0.641426	0.922958	0.291583	1	Factory W	West Beng	117	24032	52	19.05234	29.27865	23.08477	38862.39
23	Other	PhD	73146	Part-time	40998	11136	514	39882	0.560495	0.545238	0.152243	0.007027	1	Research	Other	114	20560	51	8.847951	24.50634	23.58846	64163.16
63	Female	PhD	70100	Unemploy	47319	33019	13994	48368	0.675021	0.689986	0.471027	0.199629	1	Intern	Other	114	20560	51	8.847951	24.50634	23.58846	61491.23
60	Female	Masters	71990	Full-time	18024	56765	14135	88204	0.250368	1.225226	0.788512	0.196347	1	Manager	Rajasthar	105	23017	25	8.902367	26.99013	28.07036	68561.9
34	Female	Masters	45426	Full-time	41775	28271	16002	8927	0.919583	0.196517	0.622353	0.352265	1	Teacher	Uttar Prad	117	15204	40	14.95685	33.08349	16.27417	38825.64
52	Other	Masters	75406	Full-time	32733	21939	3453	64732	0.43409	0.858446	0.290945	0.045792	1	Data Anal	Uttar Prad	117	15204	40	14.95685	33.08349	16.27417	64449.57
32	Male	Masters	49801	Full-time	38197	57851	3155	7151	0.766993	0.143581	1.161643	0.063352	0	Software E	Uttar Prad	117	15204	40	14.95685	33.08349	16.27417	42564.96
34	Female	Masters	55336	Full-time	41775	28271	16002	8927	0.754897	0.161324	0.510897	0.289179	1	Doctor	Other	114	20560	51	8.847951	24.50634	23.58846	48540.35
44	Female	Masters	48514	Part-time	13919	15084	661	77714	0.286907	1.601888	0.310921	0.013625	1	Tutor	Rajasthar	105	23017	25	8.902367	26.99013	28.07036	46203.81
50	Male	Bachelors	58277	Unemploy	13737	20706	13612	96652	0.235719	1.658493	0.355303	0.233574	1	Job Seeker	Gujarat	120	32258	37	15.71946	23.02494	27.69588	48564.17
51	Female	High Scho	17905	Unemploy	34157	43756	13125	92653	1.907679	5.1747	2.443787	0.733035	1	Job Seeker	Uttar Prad	117	15204	40	14.95685	33.08349	16.27417	15303.42
28	Male	High Scho	34596	Full-time	37784	51652	17658	9435	1.092149	0.272719	1.493005	0.510406	0	Security G	Other	114	20560	51	8.847951	24.50634	23.58846	30347.37
31	Female	High Scho	28639	Self-empl	4133	18712	5178	36451	0.144314	1.272775	0.653375	0.180802	1	Mechanic	Other	114	20560	51	8.847951	24.50634	23.58846	25121.93
47	Female	Bachelors	35180	Self-empl	24951	37083	18096	81889	0.709238	2.327715	1.054093	0.514383	1	Freelance	Maharash	96	31965	23	19.45092	23.96195	31.2654	36645.83
43	Female	Bachelors	27682	Part-time	39887	28546	6731	39062	1.4409	1.411087	1.031212	0.243154	1	Assistant	Maharash	96	31965	23	19.45092	23.96195	31.2654	29835.42

Fig. 1: Combined Dataset

Results show the XGBoost accounted for model accuracy or the highest F1 score accuracy and random forest follows with moderate interpretation with the least performance with average resources was a Logistic Regression, while the MLP model performance was higher but needed device computing resources.

3. *Financial Resilience Dashboard*

The dashboard examines household savings practices when variables such as income, expenses, savings & debt, and demographic variables such as education, employment type, age cohort, CPI for region where they reside, and poverty rate are taken into account. After identifying various inputs, output measures such as estimated monthly savings, savings rate, income type, total savings, debt to total income ratio, and total savings to total income ratio are calculated. This dashboard also represents some key insights into savings practices by identifying households displaying strong patterns of savings, high levels of debt, or lower levels of financial preparedness.

The dashboard format consists of several tabs for different levels of analysis:

1. *Household Analysis:* Household financial health is assessed through several financial indicators, including income, expenses, debt ratio, and savings. Additionally, a savings resilience index was developed to rate household capacity to absorb unexpected expenses and save under financial duress. A higher score indicated a greater degree of financial stability and resilience. The analysis of income and expenses provided information about the household's ability to save. The debt ratio indicated a greater or lesser proportion of income spent on servicing debt. Additional analysis of savings behavior focused on households able to save at least 15% of their income. It also accounted for regionally-based inflation and poverty rates were included to add context to the financial condition of the household. This analysis provided an analysis of household financial health that considered their strengths and vulnerabilities. Provides a graphic test of the distribution of financial health scores from households, assisting to determine patterns and think critically about actions or policies to support households.

2. *Schemes Recommendation:* Significant information is provided regarding government savings schemes and pension schemes based on

household profile. This Scheme Recommendation System links household financial profiles and demographic information to government schemes including Atal Pension Yojana and other small savings schemes. Factors such as employment class– organized or unorganized, income stability, age of the user, and overall financial readiness are assessed to recommend the most applicable schemes to each household. In analyzing these factors, we provide recommendations that are unique to each user and not generic, so that the recommendations are improved to match the unique financial landscape and needs of each household. For ease of use, schemes are presented in English, Marathi, and Hindi, making the system accessible, even for potential users who may have a daily labour job or who cannot read in a single language. Within each scheme, important information for the user is prepared, including eligibility, benefits, support needed, and ways to apply, making the information user-friendly and usable easily. The Scheme Recommendation System combines assessing aspects of household finance with a multilingual presentation that is usable, while it integrates into the schemes of government support. The system helps users make informed decisions regarding their finances, saves for a better future, and improves access to welfare schemes, facilitating increase of financial inclusion and reaching a better state of resilience for our communities.

3. *Regional Analysis:* A regional analysis was utilized to better understand savings behavior in various regions. The analysis accounted for household poverty status, perceived regional inflation in analyzing savings behavior, and employment conditions. Taking these variables into account led to insight into how economic variability and regional contexts impacted household financial behavior. This analysis presented savings behavior patterns across regions that demonstrated which households faced increased financial vulnerability and limited opportunities to save. This content provided evidence to inform policies and targeted actions with an eye toward resource allocation for improving financial inclusion. It presented the regional differences in household savings behavior to provide a more visual way to understand the differences and trends seen across the regions presented.

4. *Policy Analysis:* This research investigates the relationship between financial policies, interest rate changes, and government subsidies on household savings behaviors. By analyzing these components, it becomes possible to understand how policy change encourages or discourages the ability and willingness of households to save. The examination shows differential savings behavior based on household type and region, given consideration for the context of the economy or policy changes. It illustrates these patterns and trends; the visual produced responds to how government institutions have affected household financial decision-making. The findings contribute to better understanding how future policies can be formulated to improve financial inclusion and increase resilience.

5. *Scheme Information (Eng./Hindi/Marathi):* To promote equal access and inclusion, information on government schemes, including guidelines, eligibility, and benefits is provided in English, Hindi, and Marathi. The presentation of information in multiple languages accommodates households with members of various language backgrounds to understand and utilize the schemes. This is particularly essential for daily wage earners and rural households with individuals who may be typically limited to one language. It shows how scheme details are presented across multiple languages, lending support to the idea that once information is translated into regional language, individuals can better understand the information, participate in welfare schemes, and overall support better financial inclusion throughout many communities.

This dashboard is mainly intended for users, researchers and policy makers to study savings behavior overall, the influence of policies on savings behavior, or to identify opportunities for developing financial resilience of households

IV RESULTS

Household savings capability was estimated using Random Forest classification using socio-economic and demographic characteristics. The data were partitioned into training (70%) and testing sets (30%) using a five-fold cross-validation plan. Overall, the

Random Forest classifier performed very well with an accuracy of 92.6%, precision of 89.2%, recall of 87.9%, F1 correct of 86.5%, and area under the ROC curve (ROC-AUC) of 0.91. The results confirmed that Random Forest is superior to Logistic Regression and Decision Tree models in accuracy and discriminative ability. The ensemble model improved generalizability and decreased over-fitting which ultimately made it the best to predict savings behavior Shown in Below Fig.2.

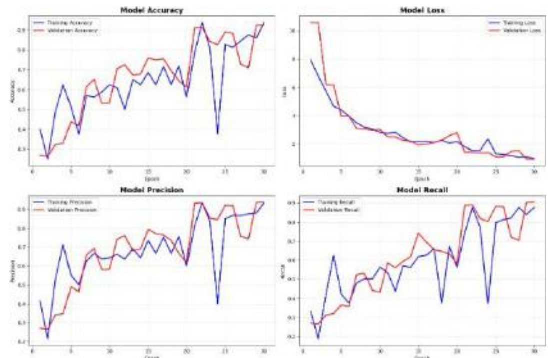

Fig. 2: Model Training and Testing Plot

The Scheme Recommendation System was built to pair household financial and demographic profiles with relevant government schemes such as Atal Pension Yojana and other small savings schemes. It takes into account aspects such as the type of employment, income stability, age band, and financial preparedness, to provide personalized recommendations for households. This alignment ensures the schemes suggested are best suited for the users specific financial situation and requirements Shown in Below Fig.3,4,5.

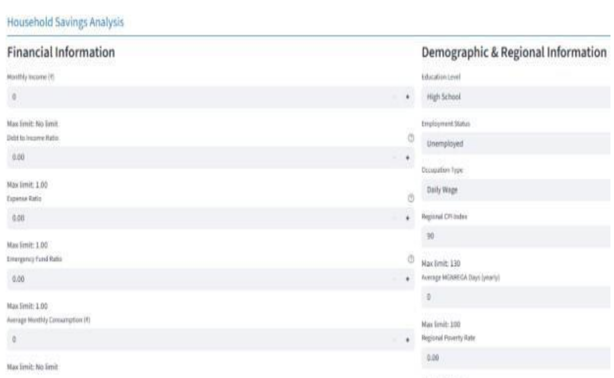

Fig. 3: Dashboard of Household Saving Analysis

Fig. 4: Household Saving Analysis graph

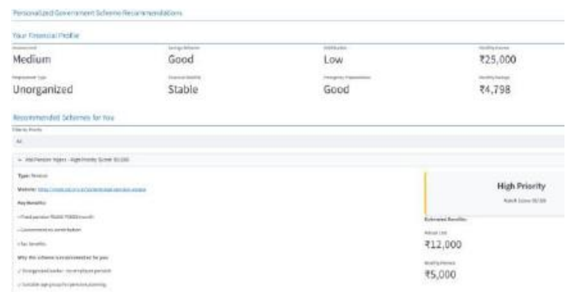

Fig. 5: Dashboard of Personalized Government Schemes Recommendation

To promote usability and ease of access, the system provides scheme information in English, Marathi and Hindi. If someone is in a region where the language is not their first language, this should help eliminate a barrier for daily wage earners to understand the recommendations. Shown in Below Fig.6, 7, 8. Each scheme entry provides relevant information about eligibility, benefits, matching contributions and application steps to give the users sufficient information to act upon.

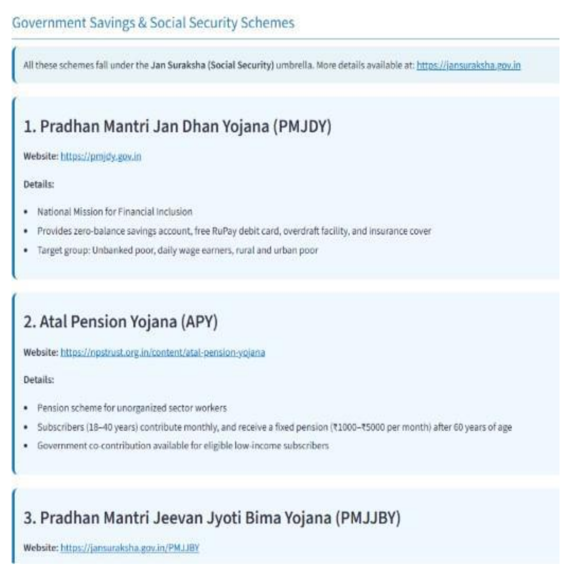

Fig. 6: Dashboard of Scheme Information in English

Fig. 7: Dashboard of Scheme Information in Hindi

Fig. 8: Dashboard of Scheme Information in Marathi

By providing a financial profile, matched to a multilingual behind the system recommendation, the user has been better served to seek out government support programs, combined the household is able to make better decisions related to finances, develop long-term savings and better access welfare schemes that support their situation. This contributes to better financial inclusion and financial resilience respectively and works toward the goal of more efficiency to get government schemes to intended participants.

Key Findings

- Daily wage earners are in unstable financial situations due to intermittent income, high living expenses, and inadequate access to the formal financial system, which leads to a generally low capacity to save.
- Savings behavior is geographically dependent; for example, wage earners perceive a higher savings rate in low unemployment regions, compared to those who may find themselves in lowwage and high poverty situations.
- Exclusive reliance on public data sources constrains savings behavior for daily wage earners, as behavior must consider the rolling nature of income, debt, inflation, and regional characteristics.
- Models of machine learning and data science, especially the use of XGBoost models, present a seriously improved understanding of what behaviors affect household savings behavior based on financial and geographic characteristics.
- The Financial Resilience Dashboard demonstrates that families with savings capacity may have significant debt or exhibit financial vulnerability.
- The scheme recommendation tool features a person that speaks in multiple languages and with questions tailored for low-income daily wage earners and supports data-driven recommendations for improved access to government savings schemes and retirement pensions, based on household profiles.
- Lastly, just autonomous views of the policies that focus on financial saving, can influence savings differently based on the location regulations, or the financial backgrounds of families.
- The combined technologies represent healthy practices for tools to improve the financial education and long-term savings, and access to

social benefits for individuals and communities.

V CONCLUSION

The Scheme Recommendation System represents an innovative strategy to facilitate the connection between households and government financial schemes according to their household profile. The system offers scheme recommendations that are appropriate and actionable, based on analyzing key factors which could include employment types, income stability, age group, and the household's financial preparedness. By providing this information in English, Marathi, and Hindi the system is accessible even for diverse users such as daily wage workers, while reducing language barriers and improving comprehension. The system not only communicates what schemes are available, but it also generates detailed information regarding eligibility for lower wage-earning households, the benefits of using the scheme, and guidance on how to apply for the scheme so these recommendations can be translated into practical decisions. By integrating financial analysis with user-centered design, the system improves financial literacy, encourages long-term savings, and increases access to government welfare schemes. Finally, the scheme recommendation system contributes to financial inclusion and resilience, that ensures government schemes are accessed by intended intermediaries, adopting an array of data through an inclusion model. It provides an evidence-based opportunity for technology that demonstrates the potential for technology to bridge the gap between public initiatives and the real-life needs of households, that may provide a scalable model for supporting access to social security or saving programs across a range of communities.

VI FUTURE SCOPES

1) Link to up-to-date databases of government programs so that users have the most reliable and current information on schemes.
2) Implement machine learning algorithms to guide predictions and personalized user recommendations.
3) Create alerts and reminders for contribution deadlines, renewals and schemes in their community.
4) Include multilingual support in support of languages of the region.
5) Include financial literacy modules and guides to empower users to make informed decisions.
6) Build a continuum for scaling for level of use via mobile or government portal.
7) Increase financial inclusion and access for audiences within various communities.

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