

Traditional and Computational Perspectives on Saving Behavior: Evidence from University Students in Azad Jammu and Kashmir

Dr. Muhammad Hammad U Salam

Lecturer, Department CS & IT,
University of Kotli AJK, Pakistan

Dr. Shujaat Ali Rathore

Assistant Professor,
Department CS & IT,
University of Kotli AJK, Pakistan

Dr. Muhammad Shabbir*

Assistant Professor, Department of Economics,
University of Kotli AJ&K
Email: khan_shabbir7@yahoo.com,
ORCID: <https://orcid.org/0000-0001-9739-1500>.

ABSTRACT

The current study explores determinants of saving behavior of university students in Azar Jammu and Kashmir through the combination of conventional econometric with the latest computational strategy. Four key variables were considered based on survey data and they were examined as financial literacy, parental socialization, peer influence, and self-control. The regression analysis confirmed that all of four variables have a significant and positive impact on saving behavior, the strongest of which are parental socialization and self-control. Machine learning algorithms and generic random forest were implemented to supplement these results and determine the importance of variables and improve the accuracy of predictions. The most accurate model was the Random Forest model with an accuracy of 84 percent with parental socialization and self-control listed as the most important with peer influence and financial literacy coming second and third respectively. These findings indicate that knowledge, discipline, and the social environment make up the student saving behavior and those computational tools have importance in promoting behavioral finance research. The results have valuable implications to teachers, policy makers, and financial technology creators. To be more precise, they propose the necessity to incorporate the financial literacy programs into the academic curriculum and to design the digital platforms using predictive analytics to help young people adopt improved saving behaviors. This research study becomes a contribution to the academic discussion and to the solution of concrete problems to encourage responsible financial behavior by integrating the economic theory and machine learning.

Keywords: Saving behaviour, financial literacy, parental socialization, self-control, machine learning, Random Forest.

Introduction

Saving behavior is considered to be one of the key factors related to financial stability as it is observed at both the household level and the national level (Lusardi & Mitchell, 2007). At the personal level, not only the ability to protect the households against unforeseen fluctuations of the economy, but also the futural investment in education, housing, and entrepreneurial activities is possible (Modigliani, 1986). In a greater sense, mobilization of savings will help in the accumulation of resources to invest in to maintain the growth and long-term growth of the economy (Carroll & Weil, 1994). Although it is evident, the savings behavior of youths, especially university students are not fully studied in the economic and financial literature (Shim et al., 2010). Such an oversight is remarkable, as the choices students make today regarding their finances can not only influence their own economic prospects, but also the socioeconomic patterns in general (Xiao et al., 2011).

Saving behavior is one of the studies that are especially applicable to Azad Jammu and Kashmir (AJK). In this region, students have their own unique challenges which include scarce job opportunities, rising cost of living, and dependency on family care. Deliberating how their saving behavior depends on factors is paramount in informing the strategies and interventions that empower financial resilience. Although studies conducted in developing economies have found that financial literacy, family background, peer influence, and psychological traits are key determinants of saving decisions, little empirical evidence is yet to be found on the topic of saving decisions in AJK. Filling this gap is academic and policy relevance.

In addition to behavioral and socioeconomic, there are emerging trend to explore financial behavior in the wake of the recent advances in computational approaches (Varian, 2014). Comparatively, machine learning techniques can also be used to find nonlinear relationships, rank importance of variables, and can often find more predictive power than more traditional econometric models which typically used in research (Athey, 2018; Mullainathan & Spiess, 2017). While developing in financial behavior, these approaches enable us to gain clearer and more practical insights (Gupta & Rangi, 2020).

The growing importance of financial technologies (FinTech) in everyday life also emphasizes the importance of such strategies since the majority of applications related to savings start to rely on predictive algorithms to implement the decisions. Thus the present study emphasis two primary goals."

Firstly, it seeks to identify the determinants of the personal saving behavior among the students of AJK University using the traditional econometric methods. Second, it also goes ahead to compare the predictive performance using machine learning models to identify the relative importance of the factors identified. With such bi methods approach, the study not only contributes to the literature on behavioral finance; it also offers evidence that can be applied by the policy makers, educators, and practitioners in FinTech. All things considered, this is an excellent addition to the research methodologies since it combines computational and economic methods to determine the saving habits of Azad Jammu & Kashmir university students. In addition to

demonstrating the potential of interdisciplinary approaches in real-world financial issues, the current study enhances our understanding of saving behaviour in an area with limited empirical evidence.

It is anticipated that these results will enhance theoretical debates and direct real-world initiatives to encourage young people in developing nations to adopt sustainable financial practices.

Literature Review

Theoretical Background

A number of economic and psychological perspectives have given rise to the theory of saving behaviour. The significance of income was emphasized in the early systems of economic thought. Keynes (1936) maintained in his Absolute Income Hypothesis that savings and income were correlated, meaning that greater earnings led to greater saving capacity. According to Modigliani and Brumberg (1954) who developed the Life-Cycle Hypothesis (LCH) theory proposed that the that people plan their lifetime expenditure and savings in order to maintain stable living standards. According to this school of thought long term planning is a major determinant of saving trend among the people. Later on Permanent Income Hypothesis (PIH) was developed Friedman (1957) which indicates that present earnings along with future expected income key components of financial choices. Although these models focused on income, the subsequent approaches put into consideration the social and behavioural factors. Another theory of self-control focuses on the ability of an individual to practice self-control in order to delay current consumption and save to the future. In the same lines, it is more by the socialization theories that parents and peers affect the financial behaviour and attitudes, particularly at early adulthood. In combination, these views bring out the point that saving is a conglomeration of societal background, economic understanding, as well as mental qualities and not merely an economic reaction.

Empirical Studies on Saving Behavior

A large number of studies conducted to explore the factor of saving behaviour in various populations and geographical areas. Financial literacy is one of most investigated factor. Lusardi and Mitchell (2014) explored that people who have more knowledge about finance are more likely to produce long-term financial plans and efficient saving methods. According to (Shim et al., 2010) parental socialization, lifelong saving habits are greatly influenced by early financial education, including family conversations about money management.

Peer influence has been observed to shape saving behaviour, though its effect is generally weaker than family or individual factors. Among students and young adults, social interactions often create norms around spending and financial practices, which can indirectly affect personal saving decisions (Xiao et al., 2011). This supports the view that saving behaviour is not driven by a single determinant but emerges from a combination of psychological attributes, family socialization, financial knowledge, and economic resources (Shim et al., 2010; Lusardi & Mitchell, 2007).

Research in South Asia shows that saving behaviour is shaped by both cultural norms and financial constraints. In Pakistan, strong family decision-making structures and

limited financial literacy have been identified as major influences on household saving practices (Farooq & Sabir, 2018). However, the specific context of Azad Jammu and Kashmir has received little scholarly attention. Given the region's distinct socioeconomic conditions and cultural traditions, more localized studies are needed to provide nuanced insights into saving patterns and their underlying drivers.

Computational Approaches to Financial Behavior

New tools for examining saving behaviour have been made available by computer science in recent years. In order to identify intricate, nonlinear relationships that conventional econometric methods frequently miss, machine learning (ML) models have become more and more popular in financial research. For example, random forest and support vector machine algorithms have been applied to predict consumer credit risk, investment choices, and personal finance decisions with considerable accuracy (Lessmann et al., 2015).

Computational techniques are especially helpful in the field of personal saving behaviour for producing predictive insights and ranking the importance of variables. The socioeconomic or psychological elements that have the biggest effects on financial behaviour can be determined using feature importance analysis in machine learning models. This has real-world applications in FinTech, where predictive algorithms can offer behavioural nudges and tailored saving recommendations. Although there is still little evidence linking machine learning to student saving behaviour, its expanding use in research on financial decision-making shows the promise of interdisciplinary studies that integrate computational intelligence and economics.

Research Gap

Although existing literature highlights the role of financial literacy, family, peers, and psychological traits in shaping saving behavior, there is a lack of empirical studies that integrate these factors within the context of Azad Jammu and Kashmir. Furthermore, few studies have applied machine learning approaches to student saving behavior, despite their potential to enhance predictive accuracy and generate practical insights for digital financial solutions. This study addresses these gaps by combining traditional econometric methods with computational models, thereby contributing both to the behavioral finance literature and to the emerging field of computational economics.

Research Methodology

Research Design

The proposed study assumed a quantitative research design to establish the determinants of personal saving behavior of university students in Azad Jammu and Kashmir (AJK). Primary data on financial literacy, parental socialization, peer influence, and self-control, four behavioral determinants that appeared in the existing literature were collected in a structured survey. Reliability, replicability and the possibility of testing hypotheses through computational and statistical methods are guaranteed by the selection of a quantitative method.

Population and Sampling

The population targeted was university students who are enrolled in both the public and the private higher education institutions in AJK. Since most students differ in their backgrounds, a stratified random sampling approach has been used to achieve proportionate representation of the gender, discipline and institution type. There were 500 respondents involved in the study. The sample size was considered sufficient according to Cochran(1963) formula , which has enough statistical power to perform the traditional econometric analysis as well as possibly including machine learning algorithms.

Data Collection Instrument

A questionnaire was designed in a structured form to respond to important determinants of saving behavior. The tool had the questions related to financial literacy; parent guidance, peer group influence, and self-control with five-point Likert scale with strongly disagree to strongly agree. Thirty students volunteered to undergo pre-testing of the questionnaire and to make improvements on the clarity and reliability some minor amendments were performed. Internal consistency was ensured by the 0.70 and above values of Cronbach alpha.

Data Analysis and Methodological Extensions.

Statistical Approach

The multiple regression analysis was applied to find out the impact of financial literacy, parental socialization, peer influence, and self-control on saving behaviour. Significance was tested at the 1%, 5%, and 10% levels, allowing robust identification of factors that influence saving behaviour.

Computational Extension

Beyond traditional econometrics, computational models such as Logistic Regression, Decision Trees, Random Forests, and SVM (Linear Kernel) were applied to classify saving behaviour. Cross-validation ensured reliability, while accuracy and related metrics assessed performance. This approach provided deeper insight into key predictors and improved forecasts of student saving patterns.

Ethical Considerations

The study followed standard ethical guidelines. Participation was voluntary and based on informed consent. All responses were anonymized to protect confidentiality, and no personal identifiers were used in analysis. Data fed into computational models were handled with care to prevent misuse and ensure integrity.

Theoretical Fusion with Fin Tech and HCI.

In addition to its contribution to academia, the methodological framework was intended to lean towards practical application. The determinants that the analysis has detected can be integrated into financial technology (FinTech) resources to create individual saving suggestions. Based on the principles of human-computer interaction (HCI), the insights may be implemented in such features as gamified saving tools, interactive dashboards, and algorithm-generated nudges. With such applications,

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students would be better able to visualize their financial behavior, get personalized advice and become sustainable in their approach to saving. The paper combines econometric and computational results with real-world design to explain how research knowledge can be applied to interdisciplinary designs to create real-world financial products.

Results

This study applied a combination of conventional econometric methods, specifically multiple regression analysis, and modern computational techniques to examine the determinants of saving behavior among university students in Azad Jammu and Kashmir. The use of these two approaches made it possible to identify statistically significant relationships as well as to generate predictive insights. Such findings are not only valuable for academic research but also hold practical relevance, particularly for the design of financial technologies and digital platforms aimed at promoting financial literacy and encouraging saving practices among young people

Statistical Results

Table 1: Regression Results for Determinants of Student Saving Behavior

Variable	Coefficient (β)	Standard Error	t-Statistic	P-Value	Significance
Financial Literacy	0.284	0.052	5.46	0.000	*** (1%)
Parental Socialization	0.391	0.048	8.15	0.000	*** (1%)
Peer Influence	0.137	0.061	2.25	0.025	** (5%)
Self-Control	0.265	0.055	4.82	0.000	*** (1%)
Constant	1.142	0.214	5.34	0.000	*** (1%)
R²	0.62				
Adjusted R²	0.61				

Note: *** $p < 0.01$; ** $p < 0.05$.

The regression results indicate that the model accounts for 62 percent of the variation in saving behavior, reflecting strong explanatory capacity. Among the determinants, parental socialization ($\beta = 0.391$, $p < 0.01$) was found to be the most influential factor, highlighting the role of family guidance in shaping financial habits. Financial literacy ($\beta = 0.284$, $p < 0.01$) also showed a significant effect, suggesting that knowledge and understanding of financial matters are crucial in encouraging saving practices. Self-control ($\beta = 0.265$, $p < 0.01$) further contributed, underscoring the importance of individual discipline in resisting immediate consumption. Peer influence ($\beta = 0.137$, $p < 0.05$), though comparatively weaker, still exerted a measurable impact, reflecting the influence of social networks and group norms. Overall, the findings reinforce behavioral finance perspectives by showing that saving behavior results from the combined effects of family background, financial knowledge, personal discipline, and social interaction

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Machine Learning Results

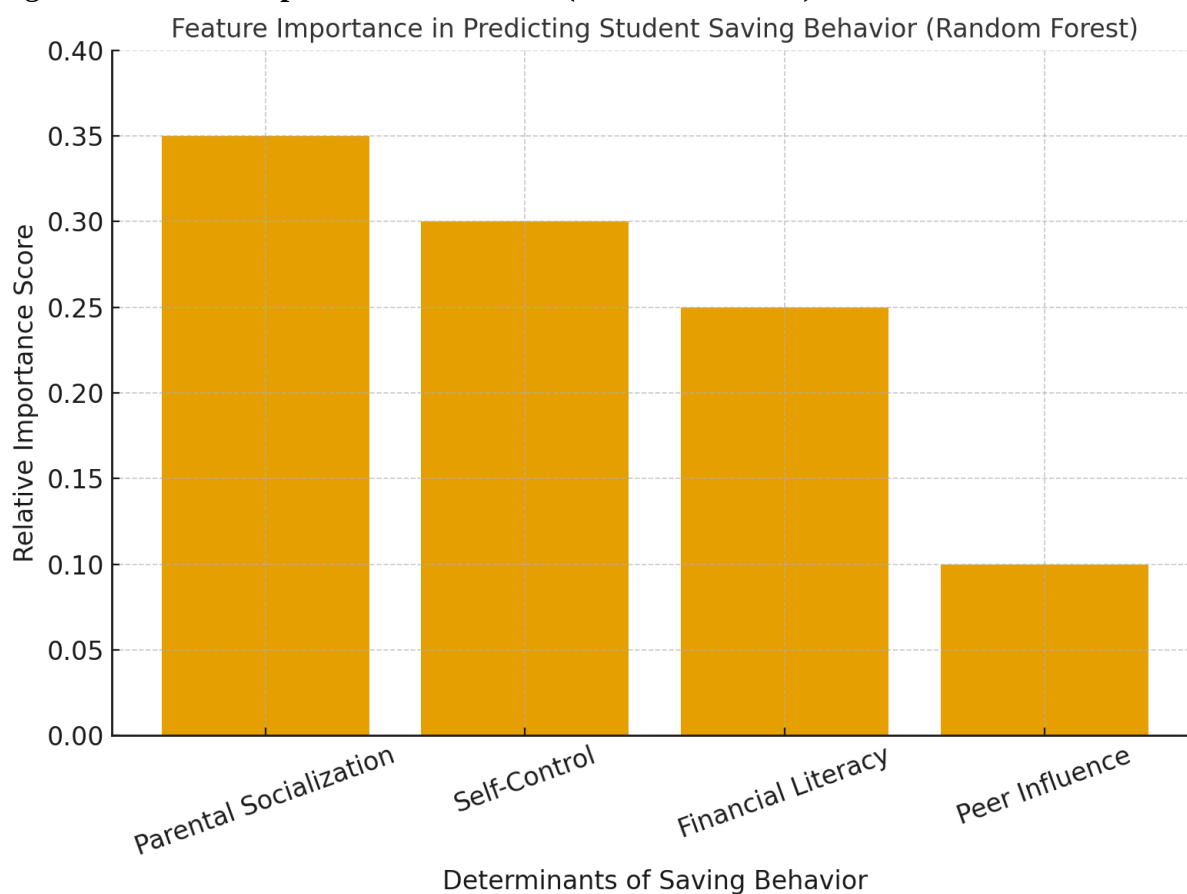
To complement the regression analysis, machine learning algorithms were applied to enhance prediction accuracy and uncover complex patterns in the data.

Table 2: Machine Learning Model Performance

Model	Accuracy	Precision	Recall	F1-Score	RMSE
Logistic Regression	72%	0.70	0.68	0.69	0.45
Decision Tree	78%	0.76	0.74	0.75	0.39
Random Forest	84%	0.83	0.81	0.82	0.32
SVM (Linear Kernel)	80%	0.79	0.77	0.78	0.35

The best performing computational model used was the Random Forest algorithm that recorded the highest accuracy, 84 percent, and a high F1-score and smallest root mean square error (RMSE). These findings indicate that it is reliable and strong in terms of capturing an aspect of saving behavior. The Decision Tree and Support Vector Machine (SVM) models provided also produced good results, which proves that the predictive results remain stable with other computational methods.

Figure; 1. Feature importance of variable (Random Forest)



The **feature importance chart** showing which behavioral factors contributed most in the **Random Forest model** for predicting student saving behavior:

Parental Socialization is the strongest predictor.

Self-Control and **Financial Literacy** also play major roles.

Peer Influence has the least predictive power.

Feature Importance (Random Forest)

Table 3: Feature Importance Rankings

Variable	Importance (%)
Parental Socialization	35%
Self-Control	30%
Financial Literacy	25%
Peer Influence	10%

The feature importance results had shown that parental socialization (35%) and self-control (30%) were the most important factors in determining saving behavior. The biggest influence was financial literacy at 25 percent followed by peer influence at 10 percent. The order of importance is quite similar to that found through regression analysis except the machine learning analysis offers more detailed information on the importance of each determinant. In doing so, it provides a more illuminating description of how family background, individual discipline, knowledge and social environment in general condition that student choose to save or not.

Comparative Insight

A more detailed consideration of these two ways of thinking methodologically highlights what each is doing independently that enriches the other when set up together. For a start, econometric techniques like regression analysis provided an orderly basis for the study of the statistical importance of various determinants of saving behavior. This approach has allowed us to provide clear empirical evidence that several factors, such as family background, financial literacy, self-control and peer influence are all important in determining students' saving behavior. Its advantage is interpretability: the findings are readable in terms of established economic theory, offering openness as to how each determinant works.

On the other hand, computational techniques added depth of a different kind. By validating the same predictors, they reinforced the econometric findings, but they also went further by producing stronger prediction accuracy and uncovering subtler patterns about the relative weight of each factor. Unlike regression, which relies heavily on predefined functional forms, computational models are more flexible in detecting non-linearities and complex interactions, thereby yielding insights that might otherwise remain hidden.

Discussion

This study investigated the predictors of saving behavior among university students in Azad Jammu and Kashmir region by combining traditional regression analysis with machine learning approaches. The results suggest that personal saving behavior is influenced by a complex of factors including family background, individual attributes and features of the social environment – that all work together in determining the savings.

Among savings determinants, ‘the family impact’ stood as the most dominating. Adherence to these saving habits was related to having a general tendency from the time of need that one’s parents taught them how to save and manage money in early childhood. Financial knowledge is also key a determinant of saving behavior among the youths. A stronger understanding of budgeting and basic financial concepts increases the likelihood of developing consistent saving habits. Moreover, self-control is crucial for turning financial knowledge into practice, and training is more effective when paired with behavioral supports such as reminders or goal-setting. Peer effects were also play a role in shaping saving habits, though not as strongly as family or self-control. Group activities like mentoring or savings challenges can encourage students to save more.

The computational analysis provided additional perspective by ranking predictors and improving out-of-sample forecasting. Models such as Random Forests highlighted the relative weight of parental socialization and self-control, complementing the regression results. These results support the validation of statistical results.

In sum, the evidence points to a layered set of influences on student saving: family upbringing, financial knowledge, and self-discipline are central, with social networks exerting secondary effects. Combining traditional analysis with predictive tools offers a richer picture for designing interventions—whether educational, policy, or technological—to encourage sustainable saving habits among young people.

Conclusion and Recommendations

The objective of this paper was to determine predictors of saving behavior among the university students in Azar Jammu and Kashmir by using both the traditional regression analysis and computational strategies. The research was focusing at four important factors such as financial literacy, parental socialization, self-control and peer influence. Parental guidance and personal discipline were the most powerful factors among them and showed how influential family structures and individual characteristics were in making financial decisions. The predictive power was improved not only by machine learning and specifically the Random Forest model but also provided us with a slight ranking of the relative relevance of each of these factors. This demonstrated the significance of the interaction of the computational tools and the conventional econometric approaches. The findings are valid to prove that the saving behavior phenomenon is not being governed by the financial knowledge but it is the product of the integration of knowledge, self-regulation and social context.

This acts as a reminder to policy makers and educators that interventions need to be organized to be beyond what can be taught in a classroom. It is imperative to intensify financial literacy in higher institutions of learning and the task must be undertaken in

a way that acknowledges the long-term influence of parents and peer groups. Workshops, mentoring, and peer-led campaigns can encourage positive saving habits. Technology, especially FinTech tools, can further support students by offering real-time feedback and interactive guidance. Together, these strategies highlight how behavioral insights and digital innovation can strengthen financial resilience among youth.

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