A Comprehensive Review on Family Budget Management

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Abstract. In the modern economic era, households have become one of the most significant corporate entities, and personal finances are essential management-related topics. Effective management of personal finances at a family level is really important to address all the financial related issues in an organized way. Any automated budget management system can help a family to utilize their incoming income in an efficient way. In this paper, we try to address the potential researches that were carried out considering the budget management related issues with a strong focus on family budget management.

Keywords: Budget management · Household expenditures · Machine learning · Savings · Income · Expense · Family finance

1 Introduction

Researchers have focused on the issue of analyzing household spending and poverty measurements in recent decades. Income, spending, or consumption data can reflect household wealth indicators. Budget planning has the opportunity to produce more and better insights at a faster rate, adding more value to the sector, thanks to the expanding availability of big data and innovative research methodologies [16]. However, collecting precise income and consumption data for household surveys necessitates a significant investment. Numerous studies have shown substantial regional differences in spending habits and living standards. In reality, expenditure information is a helpful tool for estimating poverty in emerging nations. In general, the GDP is a suitable metric for comparing national wealth.

A fundamental statistical study that is mainly seen used in the majority of countries to accomplish various economic and social objectives is the household budget survey. The tendency of household spending and income, their pattern, and relevant briefing

P. Vasant et al. (Eds.): ICO 2023, LNNS 729, pp. 1433–1445, 2023.
https://doi.org/10.1007/978-3-031-36246-0_137

will be obtained through this study. It is possible to consider creating a prediction model for the consumers' demand because order might significantly influence many different problems.

Budget management is crucial not only at the macroeconomic level, such as in states, but also in families where the needs are often more significant than the income. In addition to managing their spending to compensate for a future income reduction, such as during retirement, households often apply budget management to insure against various types of income risks, including the risk of an unanticipated income decline [19]. Traditionally household budgeting is done by an earning member of the family. Instead of focusing on long-term optimization, short-term management takes over to address the immediate concerns in expenditure patterns. While this approach may be outstanding in making ends meet, long-term calculations and optimizations can improve the family's financial situation by a marginal amount.

Income can be defined as the opportunity for consumption and savings that an entity acquires within a given period and is typically stated in monetary terms. Household income, on the other hand, is defined as the sum of the salaries that are earned by all household members, profits earned due to business or investment, rents and interests, and many other forms of revenues collected over a specific period for all of the members of the household.

Household expenditures habitually rely upon household income, and differences in expenditure patterns highlight the difference in income range between the families. There is also the preferred aspect, as the expenditure is mainly based on preferences. However, expenditure patterns become harder to distinguish from each other when controlling for income.

Expenditure can have a biased effect by the spender that will result in an uneven distribution of income. Other factors like change of lifestyle or change of income may also affect the way money is spent. For this purpose, automation of money management can have a vital role to make life in general more comfortable.

2 Methodology

A systematic review is a survey of the evidence regarding a figured investigation that makes use of purposeful and explicit approaches to identify, choose, and fundamentally evaluate the significant critical analysis. It can be a review of specifics from earlier studies. The following systematic review provides instructions on conducting the survey and adequately analyzing the results.

2.1 Phase 1 - Planning

This section details the procedures used to choose the pertinent publications (such as the search terms and inclusion/exclusion criteria). Prestigious sources for the writing analysis included Springer, ResearchGate, MDPI, Elsevier, IEEE Access, ScienceDirect, and MDPI. The following search phrases were utilized in this audit:

family <OR> financial <AND> income <OR> saving <OR> budget management income <OR> expenditure <OR> expense <OR> budget <OR> saving <OR> financial planning

budget <OR> allocation <AND> machine learning <OR> model

expense <OR> expenditure <OR> budget <OR> income <OR> saving <OR> budget management

(household <OR> (income <OR> expense <OR> expenditure) [AND] (budget <OR> management) [AND] (model <OR> system))

2.2 Phase 2 - Conducting

This section concentrates on the method used to examine the articles.

The papers were rigorously examined for their validity and dependability before being used as the final sample papers for the review. The selected papers were thoroughly inspected to ensure they fulfilled the research's objective.

A few exclusion criteria were used in the literature review on family financial management to limit the selection of final papers for review. First, because the focus of this research is on family budget management, studies that only examined individual budgeting or personal finance were eliminated. In order to make sure the review reflects contemporary trends and practices in family budget management, studies that were conducted more than fifteen years ago were disregarded. Furthermore, due to limited resources for translation, studies that were not published in English were disregarded.

2.3 Phase 3 - Reporting

A total amount of 31 good research papers were picked for review after thorough observation. The research articles are divided into three categories for a systematic evaluation: concept-based, framework-based, and data analysis-based studies. The review is classified to show contributions, work processes, and research errors.

3 Paper Collection

3.1 Identification of Studies

A significant stage was identifying the primary data sources. For the selection of preliminary studies, Google Scholar served as our main search engine. To locate pertinent publications, we also considered several notable academic publishers, including Scopus, IEEE, ScienceDirect, ACM Digital Library, and ResearchGate.

3.2 Study Selection

The process of choosing studies is done in two stages: the first is primary selection, and the second is the final selection.

3.3 Primary Selection

The titles, keywords, and abstracts of the primary sources were first used to choose them; however, when these three criteria proved insufficient, we included the conclusions section to evaluate the process. This phase curated 31 publications, including journals, books, conference papers, and other literature.

3.4 Final Selection

The potential of a research article was assessed based on various criteria, including the scope of the research, methodology, dataset evaluation, key contributions, and future research impact.

3.5 Publication Distribution

A crucial step in preparing a survey report is choosing reliable research articles. Only some research articles published in a particular field are of a high caliber. For our survey to encompass the most recent research and earlier research efforts in seeds categorization, DNN, CNN, and image processing, we chose 5 important research pieces from reputable journals published in five different time frames. Table 1 provides a chronological overview of the projects carried out across various periods for the readers' perusal.

Table 1. Considered papers for review according to time distribution format.

	2008–2016	2017–2018	2019–2020	2021–2022
Conceptual research	Sri et al. [14]			Wasserbacher et al. [16]
	Ha et al. [15]			
Framework based	Adhitama et al. [17]		Rivera et al. [11]	Ismail et al. [13]
	Yadav et al. [21]		Luo et al. [12]	
	Alves et al. [28]		Milewski et al. [10]	
Data analysis	Azadeh et al. [6]	Haque et al. [8]	Antonin et al. [19]	Nigus et al. [4]
	Van Rooij et al. [27]		Lara de Paz et al. [29]	Haque et al. [8]
	Barigozzi et al. [18]	Mohd et al. [30]	Toko et al. [7]	Konşuk Ünlü et al. [20]
	Ahmad et al. [23]		Othman et al. [9]	Zhou et al. [5]
			Jang et al. [1]	Chand et al. [2]

We selected 3 papers on cost prediction, 4 papers on budget allocation and funding and 1 papers on evaluation of models from various publishers, ResearchGate, IEEE, MDPI, ScienceDirect and several others Including ACM.

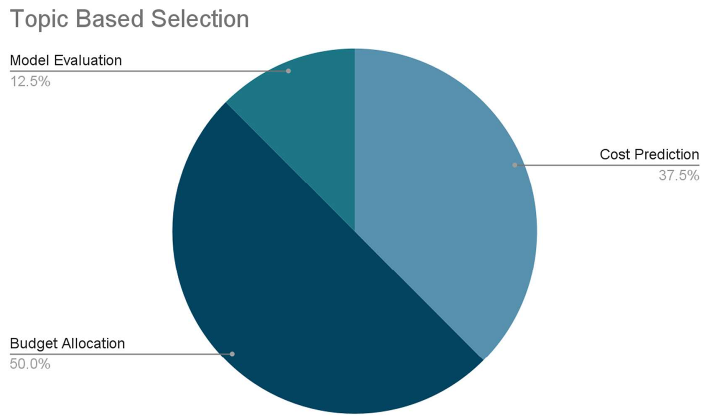

Fig. 1. Topic distribution among selected papers

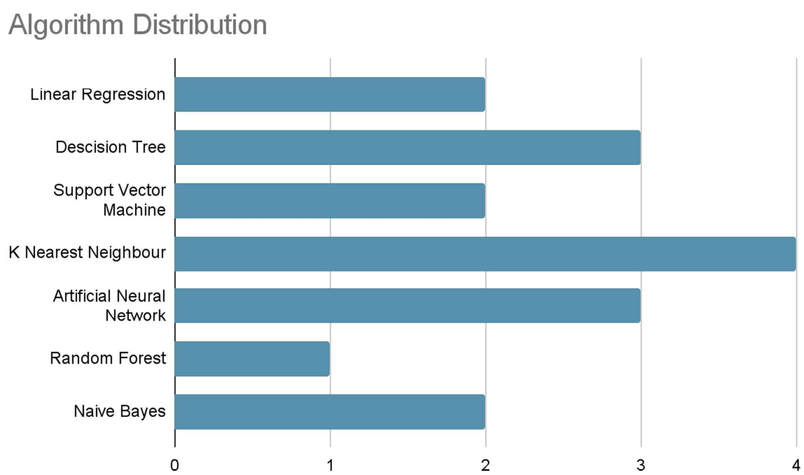

Fig. 2. Algorithm distribution among selected papers

The distribution of topics is shown in Fig. 1.

The distribution of algorithms in the 11 chosen articles, finally, is shown in Fig. 2.

The distribution of publications of the selected documents, according to data sources, is shown in Fig. 3.

4 Analysis Review

In [1], The authors of the study aimed to provide insight into proper management of allocated budgets and their full utilization with the help of machine learning models and various data analysis techniques. They worked on improving the already implemented models that were relevant at that time for the NDIS data. Their analysis aimed to explore the potential of machine learning in the context of NDIS data. There was a demonstration

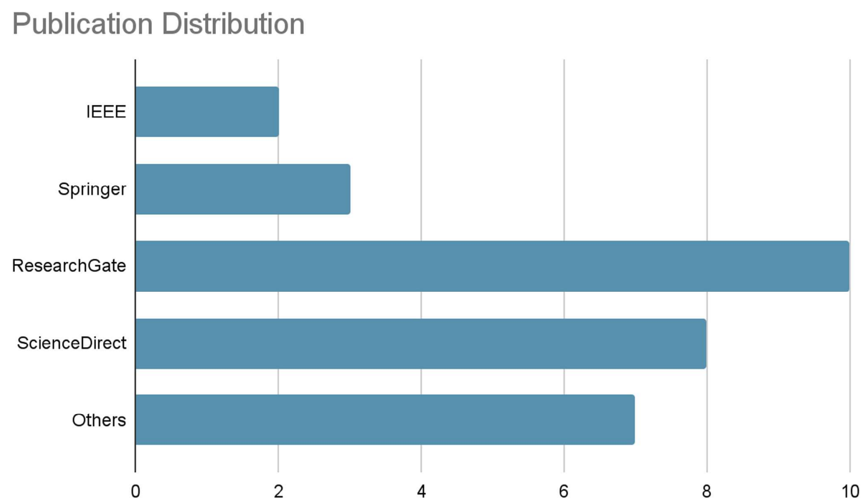

Fig. 3. Publication distribution among selected papers according to data sources

of the overall research framework for this study. Models used for analysis were linear regression, decision trees, support vector machines, and ANNs. The comment was formatted to optimize decision-making tasks using machine learning models or analytic data techniques. There was also a consideration for some improvement in future work that would focus on using the data in a way where the actual expenditure will always be within the limit of the budget allocated (Table 2).

Several recent studies have explored the various combinations of machine learning and analysis to implement in the healthcare management sectors, such as medical information systems, medical technology, and the health insurance sector, with great success. In [2], the study's authors used various machine learning models to improve the budget and resource management for their target sector, the Australian National Disability Insurance Scheme.

The objective was to quantify the budget allocation for each participant to minimize the number of unused funds across NDIS. Specifically, they used NDIS data to examine the ability of Machine Learning Models to predict their fund allocation and the total expenditure of each participant. The analysis includes SVM, ANN, and decision trees. The data show that many NDIS participants left large amounts of unspent funds, but the funds were awarded based on applications reviewed and approved by policymakers. This indicates imbalanced and poor allocation or distribution of funds to the natural and proper needs of single participants and poor choice of the decision by her NDIS regarding the use of funds. Percentage of spending at the individual participant level and b minimizing the number of unused funds across the NDIS.

Using feature selection from the dataset, [4] selected the best features. After that, they divide the data set into parts for training and testing split using the ten-fold cross-validation. Then, using a particular machine learning technique, they applied it to learn about it and tested it. They also evaluated its performance using performance metrics for each machine learning classifier. Naive Bayes (NB), Support Vector Machine

Table 2. Data analysis based

Paper title	Contribution	Dataset	Evaluation
Households income-expenses network simulation [29]	Economic system analyzer with the help of complex network	Mexico's official survey	Interpret a complex system state
Netherlands financial literacy and retirement planning [27]	A suggested strategy for adequately saving and investing for retirement	From questionnaire	Developed a module on financial literacy and plan for it
Household expenditure consumption budget share distributions [18]	Statistical properties of budgeting	Household income and wealth survey obtained from the bank of Italy	Unconditional budgeting as a problem to be solved
Household expenditure prediction [23]	A method for forecasting costs	Household economic integration survey	ANN performed better
Living arrangements of elderly [30]	An analytical study on living agreement of senior citizens	Household income expenditure of Malaysia in 2009	Family tie with the elder members with the effect of income and modernization
Household budget analysis [20]	Huge data was tackled with the help of a regression model	National household budget survey from Turkstat	Demonstrates applicability, monthly consumption expenditure
Links between saving rates, income, and uncertainty [19]	The relationships between French household income and saving rates	Insee household budget survey from 2010 to 11	Extreme income quintiles

(SVM), Gradient Boosting (GB), Extra Tree (ET), Decision Tree (DT), K-Nearest Neighbor (KNN), Random Forest (RF), Logistic Regression (LR) and Ada-Boost (AB) are the algorithms implemented in this case. Except for Gaussian-NB, Linear SVC, and Bernoulli NB, Passive Aggressive Classifier (PAC), the efficiency of the proposed or targeted approach for the accuracy of the training value reaches a higher milestone than 0.80%. Recall, F1-score, and other performance metrics like AUC were also excellent. With a training accuracy of 1.00, the extra tree, decision tree, random forest, and bagging classifiers produce the greatest results. Gradient-Boosting, Ada-Boost, K Neighbors, and Logistic Regression receive scores of 0.9999, 0.9575, 0.9995, and 0.8886, respectively.

In [5], the author used machine learning to more precisely anticipate an OPEX using MLR analysis. Artificial Neural Networks (ANN), k Nearest Neighbors (kNN), Random Forests (RF), and Support Vector Regression are the machine learning approaches used here. The research was divided into two major sections: (1) identifying a relevant component; and (2) assessing the accuracy of the prediction. The primary tool used for the MLR analysis was Minitab. Machine learning analysis was conducted using WEKA, often known as the Waikato Environment for Knowledge Analysis tool. By rescaling the input data from 0 to 1, WEKA automatically sorted and normalized it for all machine learning-based methods. The corresponding prediction MAPE's for the independent test set for the kNN, ANN, RF, and SVR were 11.9%, 8.2%, 9.5%, and 8.5%. Based on the results, kNN had the greatest R2 performance, making it the most accurate method.

In [6], they looked at the relationship between household consumption, income, and LSM. A model for family income spending is also developed. A novel neural network was developed to anticipate and estimate family spending. Four different models have been developed to predict LSM: linear regression, quadratic regression, cubic regression, and GA. In this research, five different forecasting models for household expenditure have been developed. The models were used to assess the utility of the predicted data from the census that was previously incorporated into the model. They used the approach on 18 attributes that are represented by the mean in the dataset. These models are compared using R-square. According to the results, ANN outperformed all other models, with an R2 value of 99.85%. The linear regression model, which had a 99.8% accuracy rate, came in second. The cubic regression's R-square value was 99.6%, while the quadratic's accuracy was 99.6%. The R-square for the GA model is 99.64%.

In [7], coding entails assigning a specific code to each object (or class) type. In the realm of official statistics, this is frequently necessary for the processing of survey data. In this study, they demonstrate how the suggested methodology was applied to the Income and Expenditure of families in Japan. It is simple to process survey items that ask respondents to choose between two or more options while processing survey data. It is challenging to condense general descriptions like profession, industry, and numerous factors affecting family income and expenses. The field of official statistics has seen the development of auto-coding systems. Nearly half of the sectors were covered by the suggested auto-coding method with less than 50% accuracy in most other sectors. In contrast, the rule-based Autocoding System had different coverage for each sector, yet each was reliable and accurate. Both rule-based auto coding and auto coding that uses machine learning offer distinct advantages. A machine learning-based system can classify a sizable amount of the dataset. Although it might be beneficial to design a hybrid system, the precision does not equal the accuracy of a manual coding system.

In [8], they looked into how microfinance affected household income, spending, and savings. They show that when microfinance was used for its intended purpose, ASA clients' income, expenses, and savings considerably rose. As a result, this study concluded that the ASA microcredit program helps rural and urban-disadvantaged houses improve their standard and quality of life through increased income, spending, and savings. Here an empirical model was utilized. They separate it into three halves. In Model 1, the age of the head of the household is found to affect the income of the overall house or family negatively, but this effect is not statistically vital. On the other hand, age is to have a positive, statistically strong, and significant impact, leading to the fact that as the household head becomes older, the effect of it on the household income is impacted more significantly. Household income is positively impacted by the education quality and level of the head and the borrower, a woman, and these effects are statistically significant. In Model 2, The household head's age and the square of that age are not statistically significant and vital. However, it is discovered that the length of ASA participation has a clear relevance and is statistically significant. This shows that household spending rises by 1.13% for every year of participation in ASA. Household heads and the female (borrowers) education levels have a significant and vital correlation. The head of the household's age has a statistically detrimental effect on household savings, according to model 3. Additionally, it is discovered that household savings are positively impacted by the head of the home's age square, and this effect is statistically significant. According to the findings, household savings rise as the head of the household becomes older.

They showed in [9] how data analysis helps figure out what factors contribute to making up the poor category. In this case, less than a quarter of the surveys are used to apply the three models. Since they work with little information, their findings might be off. They invest time and energy into data mining to learn more than is already known. The overall outcomes, driven by the data resource, and the application of those 3 models, provided a clear picture of the analytical potential to manage decision-making to revenue and spending. The results showed that home parameters were the most important determinants of the Family Wellbeing Index. This article did not help determine a lifestyle since it focused on demographic data. More study is needed to build overspending models based on several costs associated with this way of living. The category of costs that generates the most receipts may then be investigated further. As a result, this may inspire communities to be frugal from the get-go rather than waste money because they fear they'll end up in the "overspending" category (Table 3).

There is a model in [12] that users may use to track their finances better. An extensively used supervised learning approach in machine learning is linear regression. The attribute MSE (L2) is utilized as the value. Mean Squared Error (MSE) is the square root of the squared difference between an observation's actual value and its predicted value. The research [10] aims to provide a complete picture of how Philippine income and poverty have changed over time. It also indirectly attempts to clarify the efficacy of anti-poverty policies and initiatives related to income distribution. The model provided in [21] is adaptable, so it may be used with other technologies to improve the model and get us closer to the goal of developing user-specific tools. In this paper, we describe a model that only analyzes user-provided data. When a system that can connect to the internet is installed, it may provide the resident with a wealth of additional financial data, such as the difference in energy consumption between the resident's appliances and those on the market that meet the same criteria. For similar savings and resource preservation, the system may also monitor water and phone use (Table 4).

Using data from 30 semi-structured interviews with males and 122 questionnaires, the authors of [15] set out to better the judgment and budget management procedures. They discovered significant outcomes in managing family finances and making important choices.

Table 3. Framework-based research

Paper title	Contribution	Dataset	Evaluation
Model of performance-based budget planning in public sector entities [11]	To solve the personal financial planning problem and produce better results than those produced by more conventional approaches, this study developed a decision model and used fuzzy goal programming to solve the problem	Private dataset	To demonstrate the efficiency of the strategy, numerical exaASA clients are given. The proposed model is quite effective since it can quickly handle a common problem
Account charting and financial reporting at accounting module on enterprise resource planning using tree traversal algorithm [17]	Adding a sub-module that is a combination of accounts or manually checking the parent and non-parent checkboxes	Private dataset	Unconditional budgeting as a problem to be solved
The impact of education on household income and expenditure inequality [28]	Schooling increases within-level income inequality but not expenditure inequality	The most recent survey on household expenditure from statistics Portugal in 206 is used for the analysis	Using quantile regressions, they have found the importance of education level's impact on within-level driving income disparity

Table 4. Conceptual research

Paper title	Contribution	Evaluation
Budgeting as a methodological basis [14]	Methods for handling one's money and maintaining a household budget	
Machine learning for financial forecasting [16]	An introduction to financial planning and analysis and machine learning	A clear delineation between the responsibilities of forecasting and those of planning

5 Discussion

The rapid increase of prices or inflation has changed and reshaped the lifestyle. Proper family budget management will lead to a more stable and affordable life. The budget section of a family includes both necessary and recreational interests. A balance of both is required to ensure the stability of the family economy. Manual budget management may lead to overspending or underspending in several cases. The primary earner or spender of the family overlooks some instances. Machine learning can significantly help get an unbiased overview of the spending situation. Input for the machine learning algorithm is a detailed dataset that includes comprehensive income to every spending sector. Frequently used prediction algorithms can be used to analyze the dataset. Several relevant works on this have featured algorithms Like ANN, Random Forest, Decision tree, Logistic Regression, and a few others. With the help of those algorithms, an overall prediction of a realistic and doable budget outcome is possible.

This study shows that an effective solution aided by machine learning is yet to be introduced. Most of the existing solutions do not have enough relevancy to be able to help manage the budget of a family. A regression or classification model is simply not enough to be able to perform and generate financial reports that will help maintain a healthy budget distribution for all expenditure sectors. A large amount of training data is needed to train a model that will be able to understand, split, calculate and overview the budget in each spending sector of a family income. There are already such models available at large scale for example openAI and LaMD. A similar but smaller model can be assembled for budget management purposes that may take several inputs and will generate purposeful and intelligent outcomes. Researchers may also examine a wide range of topics in this field in the future. As an example, how social and cultural factors affect family budget management, impact of government policies on family budget management etc.

6 Conclusion

The studies analyzed in this research have shed light on a variety of family budget management issues, such as the value of financial literacy, variables affecting budget management, and techniques for efficient budgeting. The assessment emphasizes that effective budget management depends heavily on financial literacy. According to several studies, families need financial education to improve money management skills, make wise choices, and reach their financial objectives. The studies also emphasize how socioeconomic elements like income, work situation, and educational attainment have an impact on budget management strategies. Budget management is more difficult for low-income families, and they need more assistance to get ahead financially. The analysis also shows that families may manage their finances more effectively by using good budgeting techniques including monitoring costs, establishing financial objectives, and prioritizing spending. The review study emphasizes the value of family budget management in attaining financial success and stability. The research offers insightful information on a range of variables impacting budget management, budgeting techniques, and the significance of financial literacy. The results of this research may be used by policymakers, financial educators, and families to advance financial literacy, boost financial well-being for families, and improve financial management practices.

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