DESIGNING A MACHINE LEARNING-BASED SYSTEM TO PREDICT MONTHLY ELECTRICITY AND WATER BILLS FOR HOUSEHOLD BUDGETING

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CHAPTER I

INTRODUCTION

Creating a budget involves allocating your money to cover both necessities and discretionary spending. While this process may seem straightforward, the real challenge lies in accurately predicting future expenses. Even the most carefully planned budgets can be disrupted by unforeseen costs, making financial management a complex task.

BACKGROUND OF THE STUDY

Amid rising prices and financial uncertainty, household budgeting has become increasingly essential, particularly when managing utility costs. Proper budgeting helps families allocate their resources effectively, ensuring that bills are paid on time while also allowing for future planning and emergency expenses. Utilities like electricity and water often account for a significant portion of household expenditures, making their management a priority in any financial plan.

A recent study conducted at Tarlac State University in 2024 explored the budgeting practices of Financial Management students amid rising inflation and economic challenges. This research highlighted the importance of financial education in strengthening students' budgeting skills, emphasizing that early exposure to money management—such as handling allowances—plays a critical role in fostering responsible spending habits.

A well-structured budget provides a comprehensive overview of spending patterns, enabling individuals to identify inefficiencies and make necessary adjustments. With the continued rise in utility costs, monitoring consumption and adjusting behaviors—such as reducing energy use or addressing leaks—become vital to avoiding unnecessary expenses. Budgeting also contributes to financial stability, helping households prepare for fluctuations in utility bills due to seasonal changes or lifestyle shifts (Guiding Wealth., 2023).

According to Britt and Grable (2021), financial stress, financial literacy, and financial behaviors among young adults living independently are closely linked. Their study found that young adults with lower financial literacy tend to experience higher levels of financial stress, leading to poor budgeting habits. To mitigate this, the authors stress the importance of financial education programs that aim to enhance budgeting behavior.

Moreover, effective budgeting can alleviate financial stress by providing individuals with greater control over their finances, enabling them to save for emergencies. This shift from reactive to proactive utility management empowers households to make informed financial decisions. However, predicting utility bills remains a challenging task due to various influencing factors, including fluctuating consumption patterns, weather conditions, and household size. For example, seasonal variations, such as increased air conditioning use in the summer or higher water consumption during droughts, can complicate forecasting efforts (Raviprabhakaran et al., 2024).

In addressing these prediction challenges, machine learning (ML) has proven to be an invaluable tool. Studies show that ML models can significantly improve budgeting accuracy by processing real-time data, enabling more informed financial decisions (Deloitte, 2020). Research also supports the use of machine learning algorithms for predicting personal expenditures, thus enhancing financial planning and management (Ahmed et al., 2022). By analyzing historical data and considering variables such as weather patterns, consumption habits, and household demographics, ML algorithms can generate more accurate forecasts for electricity and water usage (Torculas et al., 2023). Advanced techniques like Extreme Gradient

Boosting offer more reliable predictions, helping households better anticipate costs and manage their budgets (Matos et al., 2024).

Integrating ML-based systems into household budgeting can transform financial management from a reactive to a proactive process, allowing families to navigate dynamic utility expenses and prepare for unexpected fluctuations more effectively (Abdul Rauf et al., 2023).

STATEMENT OF THE PROBLEM

Financial management challenges among young adults, particularly college students, continue to be a pressing issue due to insufficient budgeting skills and financial literacy education. A national survey revealed that 59% of college students have considered dropping out due to financial stress, with 80% reporting negative impacts on mental health (PR Newswire, 2023). Furthermore, 57% of students indicated difficulty in managing unexpected expenses of $500, reflecting limited financial preparedness and poor budgeting skills (Inside Higher Ed, 2023). Rising inflation has also exacerbated these issues, as 61% of students reported changes in their saving and spending habits due to economic pressures (PR Newswire, 2023). These budgeting struggles are linked to a lack of formal financial education, as only 26% of young adults received financial literacy training in schools, leaving the majority ill-equipped to handle personal finances effectively (Financial Times, 2023). Such findings emphasize the need for integrating comprehensive financial education into curricula to better prepare students for managing expenses and alleviating financial stress.

A survey from the National Endowment for Financial Education (NEFE) revealed that a significant number of young adults, especially college students, struggle with managing recurring expenses such as utility bills due to a lack of formal financial education. Despite the growing importance of financial literacy, schools often fail to provide practical training on budgeting for day-to-day financial commitments, leaving many individuals unprepared for managing expenses such as electricity and water bills (National Endowment for Financial Education, 2020). Cavite State University - Imus Campus college students, who are transitioning into adulthood, face the challenge of managing fluctuating utility expenses without formal education on budgeting and forecasting. With factors such as weather, seasonal changes, and household size significantly influencing utility consumption, there is a need for a system that not only aids in budgeting but also accurately predicts monthly utility bills.

This study seeks to address the following questions:

1. What are the key factors, including weather, season, and household size, that influence monthly utility consumption?
2. How can the analysis of past monthly electricity and water bills improve predictions of future consumption and costs?
3. How accurate and reliable is the proposed machine learning-based system in predicting utility costs?
4. How can the proposed system enhance CVSU Imus college students' ability to manage utility expenses effectively?

Objectives of the Study

This study aims to develop a machine learning-based system for predicting monthly electricity and water bills, with the following specific objectives:

1. To identify and analyze key factors influencing utility consumption, including:
    a) Weather conditions
        i. Temperature
        ii. Humidity Level

b) Seasonal variations

i. Summer

ii. Winter

iii. Holidays

c) Household-specific variables

i. Number of occupants

ii. Household size

iii. Appliances usage

iv. Behavioral patterns

v. Water source

vi. Electricity source

2. To compare historical monthly bills of electricity and water to identify consumption patterns and trends.

3. To design and implement a machine learning-based predictive model capable of forecasting monthly utility bills.

4. To evaluate the accuracy and reliability of the predictive model using metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE).

This study ultimately seeks to empower CVSU Imus students with a predictive tool that combines the benefits of accurate forecasting with practical budgeting assistance, addressing both immediate financial needs and long-term literacy in utility management

TIME AND PLACE OF THE STUDY

The study will be conducted from January 2025 to June 2025. The research will take place at Cavite State University (CvSU) Imus Campus, where college students will participate as respondents.

CvSU Imus Campus has been chosen as the study location due to its diverse student population, which is expected to provide valuable insights into the budgeting challenges faced by young adults managing their utility expenses. Data collection, surveys, and discussions with students will be facilitated within the campus to ensure accessibility and relevance to the target population.

This timeline will allow adequate time for data gathering, system development, model training, and validation, culminating in the deployment, and evaluation of the proposed machine learning-based predictive system. The involvement of the institution and its students is anticipated to play a key role in the successful execution of this study.

SCOPE AND LIMITATION OF THE STUDY

This study focuses on developing a machine learning system to predict monthly electricity and water bills for households, using historical consumption data, weather patterns, and household demographics. It aims to improve budgeting by applying regression models and neural networks to forecast future bills. Data will be collected from utility companies, weather APIs, and household surveys, with model performance validated using metrics like RMSE and MAE.

However, the study has limitations. The accuracy depends on the quality and availability of data, with any missing or inconsistent data potentially impacting results. The model may be region-specific due to varying weather patterns and utility structures. External factors, such as sudden changes in rates or appliance use, might also affect predictions. Additionally, data privacy concerns must be addressed to comply with laws, and complex models may require significant computational resources. The model's ability to generalize across different households could also be limited.

DEFINITION OF TERMS

Artificial Neural Networks (ANNs) - are computational models inspired by the human brain's structure and function. Composed of interconnected nodes (neurons) organized into layers, ANNs process and learn complex data patterns, making them suitable for tasks such as image recognition, language processing, and predictive modeling.

Budgeting - is the process of creating a plan to allocate financial resources, typically by estimating income and expenses over a specific period. It serves as a tool for managing finances, ensuring expenditures align with financial goals and available resources.

Electricity Consumption (kWh) - is the amount of electrical energy used by a device, household, or system, measured in kilowatt-hours (kWh). One kWh represents the energy consumption of a 1-kilowatt device running for one hour. It is the standard unit for billing electricity usage.

Energy Management - refers to the systematic process of monitoring, controlling, and optimizing energy consumption in buildings, industries, or households. It aims to reduce energy costs, improve efficiency, and minimize environmental impact.

Financial Forecasting - involves predicting future financial outcomes based on historical data, trends, and economic indicators. It helps organizations and individuals plan budgets, investments, and resource allocation effectively.

Machine Learning - is a subset of artificial intelligence (AI) that enables systems to learn from data and improve their performance on a specific task without explicit programming. It involves training algorithms to identify patterns and make decisions or predictions based on input data.

Resource Optimization - is the process of efficiently allocating and utilizing resources—such as time, energy, money, or manpower—to maximize output, reduce waste, and achieve specific objectives. It is often applied in logistics, production, and financial planning.

Support Vector Machines (SVMs) - are supervised learning algorithms used for classification and regression tasks. They work by finding the optimal hyperplane that separates data points into distinct categories, maximizing the margin between classes for better predictive accuracy.

Water Usage (m^3) - refers to the volume of water consumed, typically measured in cubic meters (m^3). One cubic meter is equivalent to 1,000 liters. This measure is commonly used to track and bill water consumption in households or industry.

THEORETICAL FRAMEWORK OF THE STUDY

This study integrates key concepts from financial behavior theory, machine learning, and resource optimization to develop a system for predicting monthly electricity and water bills, aimed at improving household budgeting. According to financial behavior theory, individuals' financial decisions, including budgeting, are influenced by psychological factors and financial literacy (Ajzen, 1991). Poor financial literacy, especially in young adults, often leads to ineffective budgeting practices, particularly when managing recurring expenses like utility bills (Britt & Grable, 2021). Financial education, particularly early exposure to money management, has been shown to improve responsible budgeting behavior (Lusardi & Mitchell, 2020).

The study’s core relies on machine learning (ML) theory, which employs supervised learning models like Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Decision Trees to predict utility consumption patterns based on historical data (Goodfellow et al., 2016). These models analyze patterns in past data to forecast future utility costs, helping individuals make informed financial decisions (Deloitte, 2020). By providing predictions of electricity and water bills, ML can enable households to proactively adjust their consumption and avoid unexpected financial stress.

Additionally, **resource optimization models** highlight the importance of using predictive data to allocate household resources more efficiently (Raviprabhakaran et al., 2024). Machine learning systems, which provide timely and accurate predictions, transform financial management from a reactive process to a proactive one. This proactive approach empowers households to adjust behaviors—such as reducing energy usage or fixing leaks—thereby saving money and optimizing their resources (Torculas et al., 2023).

Finally, **financial literacy** plays a crucial role in the effective management of utility expenses. Research indicates that individuals with higher financial literacy are better equipped to manage fluctuating utility costs (Britt & Grable, 2021). By integrating machine learning into financial education, this study seeks to enhance budgeting practices and reduce financial stress, offering a more sustainable approach to household financial management

CHAPTER II

REVIEW OF RELATED LITERATURE AND STUDIES

2.1 Introduction to Bill Prediction

Bill prediction refers to the process of estimating future utility costs, such as electricity and water bills, based on historical usage data, external factors, and trends. It utilizes statistical methods and machine learning techniques to forecast expenses, enabling households and businesses to anticipate costs and make informed financial decisions (Smith & Johnson, 2020).

Bill prediction systems analyze consumption patterns and external factors like seasonal changes, tariffs, and occupancy rates to produce accurate forecasts. These systems are increasingly integrated into smart home technologies and mobile applications, providing real-time monitoring and alerts to users (Chen et al., 2021).

2.2 Budgeting

Budgeting is the process of creating a plan to allocate financial resources effectively to meet specific goals. It involves estimating income, setting spending limits, and tracking expenses to ensure financial stability (Jones, 2019., ResearchGate. 2024).

According to Miller (2020), budgeting not only facilitates saving but also promotes financial discipline by prioritizing essential expenses and identifying areas for cost-cutting. In the context of utility management, budgeting often involves using predictive tools to estimate monthly expenses, enabling consumers to prepare for fluctuating costs.

2.3 Machine Learning

Machine learning is a subset of artificial intelligence (AI) that allows computer systems to learn from data, identify patterns, and make predictions or decisions without being explicitly programmed (Mitchell, 1997). It employs algorithms to analyze historical data, extract features, and improve performance over time as more data becomes available.

Recent studies have demonstrated the successful application of machine learning models, including artificial neural networks (ANNs), support vector machines (SVMs), and decision trees, in diverse domains such as financial forecasting, energy management, and resource optimization (Zhang & Hadavandi, 2021; Zheng et al., 2021). These models enhance prediction accuracy, automate decision-making processes, and optimize resource utilization.

2.4 Related Studies and Projects

2.4.1 Using Machine Learning to Predict Residential Building Net Electrical Consumption

Pratama (2023) employed a machine learning approach to predict electricity consumption in residential buildings, focusing on building-specific characteristics such as size, insulation quality, and number of occupants. The study utilized Gradient Boosting models and Support Vector Regression to create predictions with over 90% accuracy. In addition to energy consumption, Pratama’s (2023) research explored how incorporating demographic data, such as income levels and lifestyle habits, enhanced the system's ability to forecast costs. The study also highlighted the significance of these predictions in guiding energy-efficient retrofits for older buildings, further reducing household energy expenses.

Similarly, Lee and Park (2020) implemented a neural network model to forecast electricity bills in smart homes. Their study emphasized the importance of feature selection, including time-of-use pricing and daily consumption trends, to improve prediction performance.

Another research by Zhang et al. (2021) applied deep learning algorithms to smart meter data, integrating seasonal variations and appliance-specific load profiles. The results demonstrated that machine learning could outperform traditional statistical methods in forecasting utility costs.

2.4.2 A Predictive Machine Learning Framework for Optimizing Residential Electricity Consumption

Smith and Taylor (2023) proposed a comprehensive machine learning framework to optimize residential electricity consumption. Their study introduced advanced algorithms such as Extreme Gradient Boosting (XGBoost) and LightGBM, which outperformed traditional linear models in forecasting energy usage with minimal computational cost. The framework also included a feedback mechanism, where predicted energy consumption was used to suggest behavioral changes, such as reducing peak-time energy use or upgrading to energy-efficient appliances. By integrating this predictive system into smart home setups, the study demonstrated a 12% reduction in energy costs for participating households, showcasing its practical application.

In addition, Singh et al. (2021) utilized Long Short-Term Memory (LSTM) networks for time-series prediction of water consumption. The study highlighted that the inclusion of IoT-enabled smart meters significantly enhanced data collection, leading to better predictions.

2.4.3 Hybrid Approaches for Multi-Utility Bill Prediction

A study by Patel and Sharma (2022) combined machine learning techniques with optimization algorithms to create a hybrid system for predicting both electricity and water bills. The system dynamically adjusted predictions based on user feedback, improving accuracy over time.

Furthermore, Zhou et al. (2023) explored ensemble learning methods, combining multiple algorithms to enhance predictive performance for multi-utility bills. Their research demonstrated the practical application of AI-driven tools for resource management and budgeting in residential and commercial sectors.

2.4.4 Prediction of Individual Household Energy Bills Using Deep Learning

Matsuoka and Tamura (2020) designed a deep learning model for predicting household energy bills, focusing on electricity consumption. The model utilized historical energy usage data combined with weather variables such as temperature, humidity, and seasonal trends to generate accurate forecasts. Their study revealed that incorporating weather data significantly improved prediction accuracy, reducing forecast errors by up to 15% compared to traditional regression models. They emphasized the application of this system in reducing household financial stress by enabling proactive budgeting and early preparation for high utility bills.

2.4.5 Electricity Billing and Consumption Prediction Using Machine Learning

Gupta and Verma (2021) investigated the use of machine learning models, including Random Forest, Support Vector Machines, and Neural Networks, for predicting electricity usage and billing amounts. Their study highlighted the strength of ensemble methods like Random Forest in handling noisy data and improving prediction reliability. Additionally, they analyzed how different socioeconomic factors, such as household income and appliance usage, impact energy consumption. Their results showed that incorporating these variables improved prediction accuracy, making the system more robust for diverse user profiles. This research demonstrated the potential of ML in empowering households to better allocate resources and reduce unnecessary expenses.

2.4.6 AI Residential Electricity Bill Prediction

Mukka (2022) presented a practical application of AI for predicting monthly electricity bills through an open-source GitHub project. The system employed supervised learning techniques, including Linear Regression and Decision Trees, to forecast bill amounts based on historical consumption data and real-time usage trends. The project included a user-friendly interface that allowed households to input their data and receive personalized budget recommendations. Mukka's work emphasized accessibility, making AI-based solutions available to households with limited technical expertise. Additionally, the project demonstrated how such systems could be scaled and integrated with utility provider platforms to offer real-time cost analysis and alerts.

2.4.7 End-to-End Machine Learning for Predicting Household Electricity Bills

Rauf et al. (2024) introduced an end-to-end machine learning system capable of predicting household electricity bills. The system used neural networks to process vast datasets, including weather patterns, consumption histories, and dynamic pricing models from utility providers. The research emphasized the importance of incorporating real-time data, such as hourly consumption rates, to generate highly accurate forecasts. Rauf et al. also demonstrated the integration of their system with mobile applications, enabling users to monitor their energy costs and receive recommendations on energy-saving practices. Households using the system reported a 15% decrease in unexpected bill surges, showcasing its practical utility in proactive financial management.

2.5 Synthesis of Related Studies

The reviewed studies highlight the growing role of machine learning in predicting monthly utility bills. Key findings emphasize the importance of historical data, external factors, and advanced algorithms in improving prediction accuracy.

Integrating smart meters and IoT devices further enhances data collection, enabling real-time monitoring and cost estimation.

The studies also reveal the potential for hybrid approaches, which combine multiple models and techniques to handle complex patterns and anomalies in consumption data. These findings provide a foundation for the current study, which aims to develop a machine-learning-based application for predicting monthly bills and assisting with budgeting decisions

CHAPTER III

METHODOLOGY

This study employs a quantitative and experimental research methodology, similar to approaches used in prior studies, to develop a machine learning-based system for predicting monthly electricity and water bills. An experimental research design is used to create and test the predictive model, focusing on the collection and analysis of quantitative data to ensure objective results. Historical data on electricity and water consumption, weather patterns, and household demographics will be gathered through surveys, utility company databases, and APIs, following methods seen in studies such as "Electricity Consumption Prediction Using Machine Learning" (Reddy et al., 2023). This data will be preprocessed through cleaning and normalization before being used to train and test machine learning algorithms, such as regression models or neural networks, as validated by research like "Machine Learning to Predict Student Performance".

The development process involves designing the system architecture, including data preprocessing, model training, and the implementation of a prediction module. The model’s performance will be evaluated using statistical metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE), a standard in similar predictive modeling studies (Elhabyb et al., 2024). A structured implementation plan will outline timelines for data collection, system development, testing, and deployment. This methodology ensures a systematic approach to achieving the study’s objectives while providing reliable and practical solutions for household budgeting.

MATERIALS

The materials required for this study include both digital and physical resources to support data collection, model development, and system implementation. The primary materials consist of historical electricity and water billing records, which can be sourced from utility companies or household surveys. Additionally, weather data is essential and can be accessed through APIs or publicly available meteorological databases. Household demographic information will also be collected via surveys or existing datasets to provide contextual factors influencing consumption patterns.

To process and analyze the data, a computer with sufficient computational power is necessary, equipped with software tools such as Python or R for implementing machine learning algorithms. Libraries like TensorFlow, Scikit-learn, or PyTorch will be utilized for model training and validation. An integrated development environment (IDE), such as Jupyter Notebook or PyCharm, will support coding and experimentation. For documentation and reporting, word processing and spreadsheet tools like Microsoft Word and Excel are required. Finally, access to online resources, such as academic journals and tutorials, will aid in refining the methodology and validating the findings. These materials collectively enable the successful execution of the study's objectives.

EXPERIMENTAL UNITS

The experimental units of this study are the households whose historical electricity and water billing data, demographic details, and consumption patterns are analyzed. These households serve as the primary source of data and represent the varying factors that influence utility consumption, such as family size, income level, and lifestyle habits. Each household’s data will be treated as an individual observation, providing insights into how specific variables—such as weather conditions, seasonal changes, and demographic characteristics—affect monthly utility bills. By using these experimental units, the study aims to develop and validate a machine learning-based system that accurately predicts future utility expenses, ensuring its relevance and applicability to real-world scenarios.

PLANNED EXPERIMENTAL DESIGN

The planned experimental design for this study will follow a systematic approach to collect, preprocess, and analyze data for developing and validating a machine learning-based system to predict household electricity and water bills.

1. Data Collection:

   • Source: Historical electricity and water bills from households, weather data (e.g., temperature, humidity), and household demographic information (e.g., family size, income, appliance usage).

   • Procedure: Data will be gathered through APIs from utility companies, weather databases, and surveys conducted with household participants to obtain demographic information.

2. Sampling and Experimental Units:

   • Sampling Method: A random selection of households across various students of Cavite State University Imus Campus with varying household sizes and income levels. These households will serve as experimental units, with each providing data on their electricity and water consumption patterns, weather influence, and demographic profile.

   • Control Variables: Factors such as weather conditions, and household demographics (e.g., the number of residents, type of appliances used) will be controlled to isolate their impact on consumption patterns.

3. Data Preprocessing:

   • The collected data will be cleaned and transformed to handle missing values, outliers, and inconsistencies. This may involve standardizing consumption figures, handling missing weather data, and encoding categorical variables such as household size.

4. Model Development:

   • A machine learning model, likely starting with regression algorithms such as random forests, gradient boosting, or more advanced models like neural networks, will be trained on the processed data. The model will be designed to predict future utility bills based on the input features (household demographics, historical usage, and weather data).

5. Validation and Evaluation:

   • The model will be validated using various evaluation metrics, such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), to assess prediction accuracy.

   • A cross-validation technique will be employed to ensure robustness and generalizability of the model across different datasets.

6. Ethical Considerations:

   • The study will ensure participant privacy by anonymizing demographic data and following ethical guidelines for data collection, ensuring informed consent for survey participation, and compliance with local data protection laws.

7. Implementation:

- The final model will be deployed as a prediction tool that can be used by households to forecast their future utility bills, helping them plan their finances more effectively.

This experimental design is structured to ensure reliable, unbiased results while also addressing the complexity of predicting utility bills using machine learning.

APPENDICES

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ACTIVITY	2024										2025						
	M	A	M	J	J	A	S	O	N	D	J	F	M	A	M	J	J
Proposal Drafting																	
Proposal Defense																	
System Design																	
System Development																	
System Testing																	
System Evaluation																	
System Implementation																	
Manuscript Preparation																	
Final Oral Defense																	
Manuscript Review																	

Appendices 1. Gantt Chart

RESEARCH TITLE	**DESIGNING A MACHINE LEARNING-BASED SYSTEM PREDICTING MONTHLY ELECTRICITY AND WATER BILLS FOR HOUSEHOLD BUDGETING**																							
TIMELINE OF ACTIVITIES																								
ACTIVITY	JAN				FEB				MAR				APR				MAY				JUN			
	W1	W2	W3	W4	W1	W2	W3	W4	W1	W2	W3	W4	W1	W2	W3	W4	W1	W2	W3	W4	W1	W2	W3	W4
Research and Literature Review																								
Data Collection and Preprocessing																								
Model Selection and Training																								
Algorithm Evaluation and Optimization																								
Implementation of System																								
Testing and Validation																								
Report Writing and Thesis Draft																								
Final Revisions and Submission																								

Appendices 2. Timetable of Activities

REFERENCES

Ahmed, M. S., et al. (2022). Machine learning for personal finance: A survey. IEEE Access, 10, 20973-20997.

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes,* 50(2), 179-211.

Britt, C. L., & Grable, J. (2021). Financial literacy and financial well-being. *In Handbook of financial literacy* (pp. 3-20). Edward Elgar Publishing.

Chen, X., Zhang, Y., & Wang, J. (2021). Smart grid: A review. *Renewable and Sustainable Energy Reviews,* 148, 106349.

Deloitte. (2020). Artificial intelligence (AI) in financial services: *From concept to execution.* Deloitte Insights.

Elhabyb, K., Baina, A., Bellafkih, M., & Deifalla, A. F. (2024). Machine learning algorithms for predicting energy consumption in educational buildings. *International Journal of Energy Research.* https://doi.org/10.1155/2024/6812425

Financial Times. (2023, February xx). *Only 1 in 4 young adults received financial education at school, study shows.* Retrieved from https://www.ft.com/

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press. Retrieved from http://www.deeplearningbook.org

Gupta, S., & Verma, A. (2021). Electricity billing and consumption prediction using machine learning. *International Journal of Engineering Research & Technology* (IJERT), 10(3), 127-132. Retrieved from https://www.ijert.org

Jones, T. M. (2019). *The essentials of personal finance*. McGraw-Hill Education. Retrieved from https://www.mheducation.com

Lee, J., & Park, J. (2020). Short-term electricity load forecasting for smart homes using artificial neural network. *Energies,* 13(22), 6047. https://doi.org/10.3390/en13226047

Lucero, M. A., et al. (2024). Budgeting practices of financial management students of Tarlac. *Digital Journal of Philippine Studies*, 1(1), 45-60.https://digijournalphils .com/wp-content/uploads/2024/08/Lucero-at-al-SC-0524-017-Formatted.pdf

Lusardi, A., & Mitchell, O. S. (2020). Financial literacy and retirement preparedness: Evidence and implications for financial education programs*. In Financial literacy around the world* (pp. xx-xx). Oxford University Press.

Matos, F. A., et al. (2024). Extreme gradient boosting for time series forecasting: A review. *Artificial Intelligence Review*, 47(2), 293-329.

Matsuoka, T., & Tamura, K. (2020). Prediction of individual household energy bills using deep learning. *Energy and Buildings*, 210, 109924.

Miller, M. H. (2020). Behavioral finance and investor psychology. Routledge.

Mitchell, T. M. (1997). Machine learning. McGraw-Hill.

Mukka, S. (2022). AI residential electricity bill prediction [GitHub repository].

Patel, M., & Sharma, A. (2022). Hybrid approach for multi-utility bill prediction using machine learning and optimization. *International Journal of Engineering Research & Technology* (IJERT), 11(9), 798-802.

Pratama, A. S. (2023). Using machine learning to predict residential building net electrical consumption. *Journal of Building Engineering*, 61, 106712.

Rauf, A., Khan, M. A., & Ahmad, N. (2024). End-to-end machine learning for predicting household electricity bills. *IEEE Transactions on Smart Grid*, 14(3), 1821-1830.

Raviprabhakaran, T., Singh, S., & Kumar, A. (2024). Resource optimization in cloud computing: A comprehensive review. *Journal of Ambient Intelligence and Humanized Computing,* 15(1), 1-24.

Reddy, G. V., Aitha, L. J., Poojitha, C., Shreya, A. N., Reddy, D. K., & Meghana, G. S. (2023). Electricity consumption prediction using machine learning. *E3S Web of Conferences,* 391, 01048. https://doi.org/10.1051/e3sconf/202339101048

Singh, A., Kumar, S., & Singh, R. (2021). Water consumption prediction using long short-term memory (LSTM) networks. *Journal of Water Resource and Protection,* 13(04), 246-254.

Smith, J., & Johnson, D. (2020). Household budgeting: *A practical guide*. Wiley.

Smith, M., & Taylor, J. (2023). A predictive machine learning framework for optimizing residential electricity consumption. Energy and Buildings, 276, 111704.

Torculas, R., et al. (2023). Optimizing resource allocation in cloud computing environments using machine learning: A review. Journal of Parallel and Distributed Computing, 173, 108-128.

Zhang, G., & Hadavandi, S. (2021). Deep learning for financial time series forecasting: A review. Digital Signal Processing, 110, 102916.

Zhang, Y., Li, Y., & Chen, H. (2021). Deep learning for smart meter data analysis: A review. IEEE Internet of Things Journal, 8(18), 14068-14086.

Zheng, Y., Qin, T., & Li, R. (2021). Deep learning for energy management systems: A review. Renewable and Sustainable Energy Reviews, 141, 106014.

Zhou, Y., Chen, X., & Wang, J. (2023). Ensemble learning for multi-utility bill prediction. IEEE Transactions on Sustainable Computing.