ISSN: 2338-8412 e-ISSN : 2716-4411

Ekombis Review – Jurnal Ilmiah Ekonomi dan Bisnis
Available online at : https://jurnal.unived.ac.id/index.php/er/index
DOI: https://doi.org/10.37676/ekombis.v13i4

Advance Meter Infrastructure (AMI) Users Behaviour And Electricity Performance Predictive Model: An Implementation Of Ami Program Review In Indonesia

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How to Cite :
Fitri, Siallagan, M. (2025). Advance Meter Infrastructure (AMI) Users Behaviour And Electricity Performance Predictive Model: An Implementation Of Ami Program Review In Indonesia . EKOMBIS REVIEW: Jurnal Ilmiah Ekonomi Dan Bisnis, 13(4). doi: https://doi.org/10.37676/ekombis.v13i4

ARTICLE HISTORY
Received [05 May 2025]
Revised [24 September 2025]
Accepted [29 September 2025]

KEYWORDS
Advanced Metering Infrastructure (AMI), Customer Behaviour, PLN Service Performance, Customer Satisfaction.

ABSTRACT

The advancements of electricity metering in Indonesia have remained the focus by PT Perusahaan Listrik Negara (PLN) in distributing electricity. The Advanced Metering Infrastructure (AMI) initiative started in 2020 aimed to enhance service quality, reduce non-technical losses, and support the integration of renewable energy sources. The AMI implementation still considered to have many challenges considering its high implementation cost, uneven distribution of communication networks, and customer acceptance to the technology in Indonesia. The research aimed to develop the predictive model to identify critical parameters for AMI implementation success based on customer behaviour analysis. The success presented by the customer satisfaction level were found to have low correlation with the electricity and technical performance variables. Identified critical parameters were AMI implementation period, comfort features, AMI ease of use, and troubleshooting responses, which directly related to the customers. An internal performance monitoring is recommended to enhance services provided by PLN with predictive and active troubleshooting responses. The stage of socialization and education in both before and after AMI implementation are found to be critical to get the customer experience and satisfaction review to achieve its targeted impact.

INTRODUCTION

Indonesia's electricity sector has undergone significant advancements, transitioning from conventional analog meters to digital and smart metering systems. Historically, electricity consumption was measured using analog meters, which required manual readings, often leading to billing inaccuracies and inefficiencies in energy distribution. To address these challenges, PT Perusahaan Listrik Negara (PLN), Indonesia's state-owned electricity company, has introduced the Advanced Metering Infrastructure (AMI) as part of its modernization efforts. AMI integrates smart meters, communication networks, and data management systems to enable real-time monitoring, improve billing accuracy, and enhance the efficiency of electricity distribution.

The implementation of AMI in Indonesia officially began in 2020, with PLN gradually rolling out smart meters across nationwide. In 2023, over 1.2 million smart meters had been installed, achieving 93.54% of the targeted rollout across eight provinces. The initiative aims to enhance energy efficiency, reduce non-technical losses, and improve service reliability. Despite these efforts, several challenges persist, including high implementation costs, infrastructure limitations, and varying levels of consumer acceptance. Many customers remain unfamiliar with AMI's benefits, leading to potential resistance to adoption.

This study seeks to examine the critical factors influencing AMI implementation success, particularly from the customers' perspective. Understanding customer satisfaction and behavior is essential for optimizing AMI adoption and ensuring long-term benefits. The research also aims to develop a predictive model for AMI user behavior, utilizing statistical analysis to identify key determinants of customer satisfaction. By evaluating factors such as technology reliability, ease of use, accuracy, comfort, and troubleshooting response, this study provides insights into how AMI implementation impacts service quality and consumer perception.

The contributions of this study aim to support PLN and other stakeholders in developing strategic policies and implementation frameworks that maximize the benefits of AMI while addressing potential challenges. By identifying the key drivers of customer satisfaction and behavioral responses to AMI, this research contributes to Indonesia's broader goal of modernizing its energy infrastructure and achieving a more sustainable, efficient, and customer-centric electricity network.

LITERATURE REVIEW

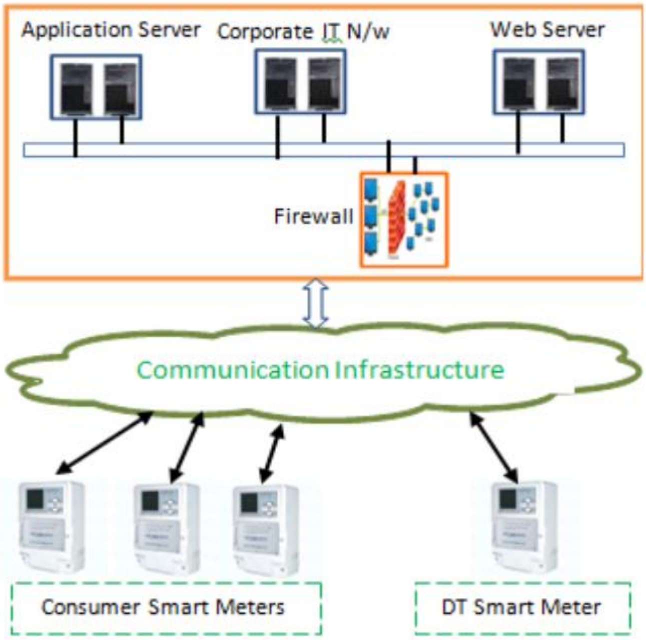
Advance Meter Infrastructure

Advanced Metering Infrastructure (AMI) serves as a fundamental component in the evolution of Smart Grids, especially in distribution systems. The main role of AMI is to enable bidirectional communication between consumers and the utility's Smart Grid Control Center, allowing for real-time remote monitoring and management of energy usage and various system parameters. The incorporation of meter data analytics is essential in the AMI framework, enabling utilities to enhance resource management and business processes efficiently (Li & Hu, 2012).

AMI is defined as a system that measures, collects, transfers, and analyzes energy usage data, while enabling communication with metering devices. This enables end users to engage in reducing peak demands and contributing to the overall energy management process (Smith & Zhang, 2019). Moreover, AMI systems can execute remote commands, including the disconnection or reconnection of loads, thereby improving grid control.

The essential elements of AMI infrastructure comprise smart meters, communication networks, Meter Data Acquisition Systems (MDAS) or Meter Data Management (MDM) (Brown et al., 2020). Smart meters serve as intermediaries between utilities and consumers, quantifying multiple energy parameters. Their main role is to monitor energy consumption; however, they also produce significant data that provides detailed insights into the electricity delivery system, thereby enhancing the efficiency of distribution utilities and improving power quality for consumers (Johnson & Lee, 2021).

Figure 1 Advance Meter Infrastructure (AMI) topology



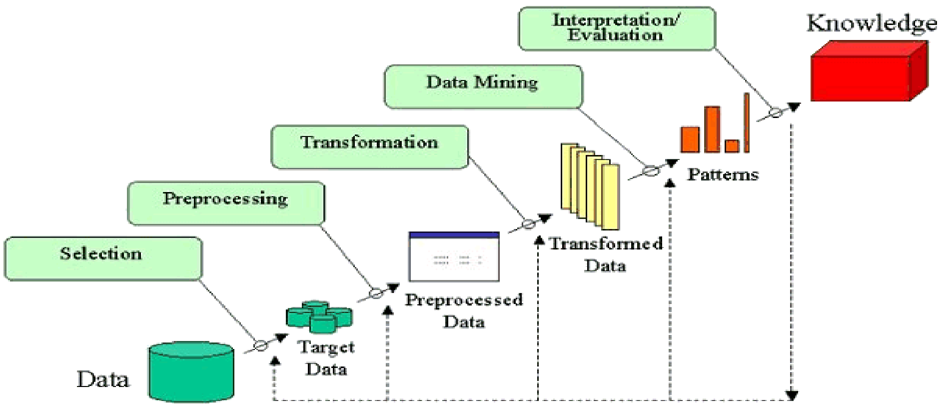
The data produced by smart meters is essential for various smart grid applications, supporting advanced data analytics tasks including monitoring energy consumption patterns, detecting tampering, managing outages, enabling automated demand response, and offering energy feedback to consumers. This data allows consumers to adopt informed energy management practices, enhancing efficiency and sustainability in energy consumption (Doe & Smith, 2018).

Data Mining Process

Knowledge discovery in database (KDD) are the process commonly done in finding the best interest from the data provided and making some critical decisions. There are various of methods in mining the data for an analysis, industry follows 2 popular schemes known as Cross-Industry Standard Process for Data Mining (CRISP-DM) and SEMMA (Sample – explore – modify – model – asses) (Azevedo & Santos, 2008).

As part of KDD process, data mining mainly focuses on patterns extracted and enumerated from the collected data (Fayyad et al., n.d.).

Figure 2. Knowledge discovert in database (KDD) steps

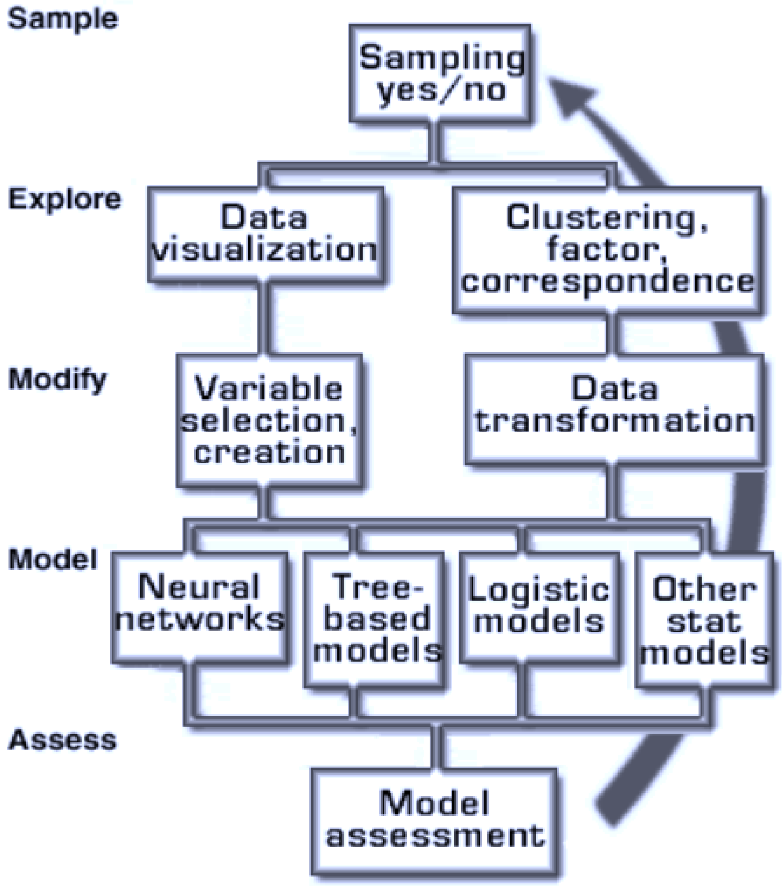


As described in Figure 2, the process of data mining considering methods in extracting knowledge by the specification of measurement and thresholds as per requirements. The data mining are the following stages along with any pre-processing, sub-sampling or even data transformation in KDD process before ended with the evaluation stage. The development of findings in the application domain preceded KDD process aligns with prior knowledge and the goals from the end-user. Knowledge generated from the KDD process then shall be continued into the deployment stage to incorporates the system with the knowledge (Fayyad et al., n.d.).

METHODS

In this study, a predictive model is constructed systematically, following the SEMMA method. The model is selected due to its simplicity and focus on the modelling process as the research aim to generate predictive model of the customer satisfaction behavior. SEMMA method designed to capture the predictive model that quantifies the impact of AMI on the service quality metrics of PT PLN performance.

Figure 3 SEMMA methodology



Using structured processes such as sampling, exploration, modification, modeling, and assessment (evaluation), the model is convinced to be both scientifically sound and useful in real-world situations. PT PLN will be able to optimize its AMI strategy and make measurable improvements in service quality as the result of the findings, which will provide actionable insights. SEMMA method can be described as below:

Table 1. SEMMA Method Descriptions

Steps	Description
Sample	During this stage, the data sampling was done by extracting a tiny fraction of a huge data collection that contains important information while still being manageable.
Explore	At this stage of the process, an exploration of the data by looking for unexpected trends (outliers) and anomalies is conducted to obtain understanding and ideas. Descriptive analysis, summary statistics, visualization, and correlation analysis, these techniques will be used to uncover underlying patterns from the data sets.
Modify	This stage conducts modification of the data through the creation, selection, and transformation of variables to refines the model selection process. New variables may be derived to quantify some parameter analysis, as well as data normalization and scaling techniques may also be applied to ensure all variables contribute equally to the model. This step optimizes the dataset for predictive modeling by reducing noise and highlighting the most significant variables.
Model	At this stage of the process, data modelling process is conducted through the means of statistical techniques and/or with the help of modelling tools (software) to find a structural pattern of the data combination to give the best fit model to predict the outcomes Multivariate statistical methods, such as regression analysis, will be used initially to establish baseline relationships between AMI implementation metrics and service quality outcomes. Advanced machine learning algorithms, including Random Forest and Gradient Boosting, will then be employed to handle non-linear relationships and interactions among variables. These techniques are well-suited for discovering complex patterns in high-dimensional data. Cross-validation will be used to assess the reliability and generalizability of the models. This stage will yield a predictive model capable of quantifying the impact of AMI on PT PLN's service quality metrics.
Assess	At this final stage of the process, data examination is conducted by evaluating the utility and reliability of the findings from the decision-making process and estimating its performance confidence. Performance metrics such as R-squared, Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) will be used to assess how well the model fits the data. Sensitivity analysis will test the robustness of the model by simulating different scenarios, such as varying levels of AMI implementation or regional characteristics.

RESULTS

Many variables that defines electricity performance and user behaviour characteristics with the AMI system implemented. These continuous multi-variables can be further analysed using multivariate regression analysis to find the best model that fits the targeted prediction. Multivariate regression analysis is a statistical technique used to determine the correlation between a single dependent variable and multiple independent variables. It aims to utilize available independent variables with values that can predict the selected dependent variable (Fox, 2016). Each independent variable is assigned a weight through regression analysis techniques to validate its predictive capability. These weights indicate the relative contribution of each independent variable to the overall prediction and help interpret the influence of each factor in making accurate predictions (Xiumin, 2013).

This research aims to develop the best-fit model for analyzing electricity performance and user behavior with AMI implementation. Data on AMI user electricity consumption was collected from the utility provider, while a customer satisfaction survey was conducted to obtain comprehensive insights into AMI user behavior. Based on the collected data, multivariate regression analysis can be performed using Microsoft Excel or more advanced statistical tools such as SPSS or R. However, dataset modification may be necessary to refine the model and ensure it aligns with the study's objectives.

Multivariate regression analysis can be done with the 3 types of data, they are cardinal, ordinal and nominal data. Data modifications that have been done to align with the data required for regression analysis are:

- Data Selections
- Data Conversions
- Data Transformation

Based on the data collected, a pre-process categorization of the data can be done. As the customer satisfaction is the main concern of this research, it is found that both variables of “Rekomendasi AMI” and “Kepuasan AMI” are the 2 (two) parameters that represents customer satisfaction level to the AMI implementation, hence a new variable of “Cust_Satisfaction” is introduced and defined as the dependent variable. The rest of the data parameter will not be categorized and used as the independent variables.

Based on the analysis, the regression model can be considered effective in predicting customer satisfaction, however checking the p-values, residual, and other assumptions will be beneficial to check model reliability.

The coefficient values from the regression model indicating changes within the dependent variable (customer satisfaction) that influenced by changing each of the independent variable values. Besides the coefficient value, the p-values indicating the impact significances of each the variables statistically. P-value of < 0.05 means the variable has a significant impact on customer satisfaction while vice versa, a p-value >0.05 indicating the independent variable is not significantly influencing the dependent variable (customer satisfaction).

Other factor that needs to be improved is the multicolinearity check which based on the results, some predictors are still having the Variance Inflation Factor (VIF) beyond 5 and 10, which might indicate that some predictors are potentially correlated with the other predictors. Removing the insignificant & potentially multicollinear to the other independent variables, will give the regression analysis results as below:

Table 2 Regression model performance

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.940[a]	.883	.881	.808	.883	450.341	4	239	<.001

Selection Criteria				
Akaike Information Criterion	Amemiya Prediction Criterion	Mallows' Prediction Criterion	Schwarz Bayesian Criterion	Durbin-Watson
-98.977	.122	5.000	-81.491	1.870

a. Predictors: (Constant), Nyaman AMI, Periode AMI, Respons Keluhan, Kemudahan AMI
b. Dependent Variable: Cust_Satisfaction

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	.426	.192		2.220	.027		
	Periode AMI	.588	.092	.183	6.420	<.001	.604	1.657
	Kemudahan AMI	.273	.075	.163	3.647	<.001	.246	4.058
	Respons Keluhan	.544	.070	.321	7.725	<.001	.283	3.529
	Nyaman AMI	.636	.075	.385	8.527	<.001	.240	4.167

a. Dependent Variable: Cust_Satisfaction

The improved regression analysis showed: Multiple R (0.940) the correlation coefficient still showed a value of multiple R close to 1 suggesting a very strong positive correlation, meaning the model explains a significant portion of the variation that defines the customer satisfaction.

R-Square (0.883) after removing some independent variables that have a low statistically low significant to the model (P > 0,05) the coefficient of determination showed a still an R-Square of 0.883 means 88,3% of the variations in the predicted customer satisfaction values are explained by the predictors in the model which indicating a very strong model fit.

Adjusted R-Square (0.881), the R-Square and the adjusted R-Square (0.883 vs. 0.881) are very close to each other, this could mean that the current predictors are already relevant hence removing more independent variables will not change the model significantly.

Autocorrelation Test (Durbin-Watson = 1,870), to ensure the significance reliability of each regression parameter's the Durbin-Watson test was conducted and the results of 1,870 showed acceptable (range 1,5 – 2,5) and no autocorrelation is detected.

Finally, based on the improved model test the conclusion of the multi linearity regression analysis showed a model that:

- All predictors (independent variables) are statistically significant
- No multicollinearity concerns
- The model is well-fitted with high adjusted R-square (0,881)
- No unnecessary variables are bloating the model.

The resulted regression analysis showed that the model can be written as below:

Customer Satisfaction (Y)

= 0,588 * Periode AMI +0.636 * AMI Comfort + 0,273
*** AMI Convenience + O,544 * Complaint Response + 0,426**

The results showed:

- Periode AMI → clear positive trend (the longer periode of AMI implementation increases customer satisfaction)
- Kenyamanan AMI → strong positive trend (the more comfort features provided by AMI performance leads to higher satisfaction)
- Kemudahan AMI → still a significant factor to the customer satisfaction with less positive effect compared to the others
- Response Keluhan → Strong positive relationship to the customer satisfaction when handling customer complaints responsively.

DISCUSSION

Based on the research results, areas of improvements are identified, and actions of improvements can be recommended. Based on the identified areas of improvements, a recommendation matrix can be proposed as below:

Table 3 Action Of Improvements Proposal

No	Areas of Improvements	Significance	Actions of Improvements
1	Comfort of using AMI	Most Significant	Socialization of AMI features to the users, periodic education and promotion of the AMI features to the users.
2	Period of using AMI	Highly Significant	Before & after survey of the customer experience and satisfaction to the AMI implementation users.
3	Troubleshooting Response	Highly Significant	Dedicated performance monitoring team to complete exisiting local resolution team.
4	Ease of use of AMI	Less Significant	Socialization of AMI features to the users, periodic education and promotion of the AMI features to the users.

Based on the analysis and discussion above, as the follow up of the proposed actions of improvements, the study recommend 2 strategic actions as the improvements of AMI implementation to improve customer satisfaction of AMI users.

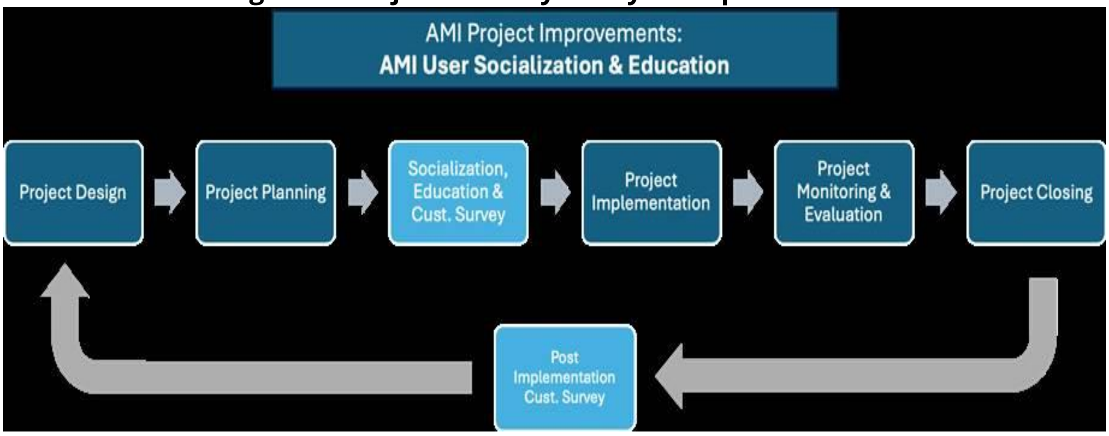
1. Technical improvement:

Improvement in the technical department related to the completion of the technical resolution team that currently operating at each of the unit branch of PT PLN. The existing standby resolution teams are working based on the routine maintenance schedule and customer complaint orders. As the AMI technology provided a comprehensive and real time performance monitoring system, an adjustment is needed to improve troubleshooting response of the resolution team. An internal performance monitoring (centralized or local) is recommended to add predictive and active response of the system troubleshooting. A predictive system maintenance can be done based on the system failure predictions and current system performance, while an active response system troubleshooting can improve resolution downtime of the system.

2. Non- Technical improvement:

As the non-technical improvement, alternative of AMI implementation strategy is proposed with the stage of socialization and education to the potential AMI users. A before and after survey of AMI implementation is proposed to identify its customer satisfaction rate from the AMI implementation plan can be measured up to the post AMI implementation to check if it is aligned with the targeting impact. Figure 4 showed the interruption of socialization & education of AMI technology to the users within AMI implementation project life cycle.

Figure 4. Project delivery life-cycle improvements



CONCLUSION

Based on the research discussion, some conclusions can be derived from the analysis considering to the research objectives.

1. The first objectives is to identify the critical factor that decide the success of AMI implementation in Indonesia. Based on the research analysis the AMI implementation success defined as customer satisfaction, while some critical factors that determine customer satisfaction are found to be AMI implementation period, comfort features, ease of use, and troubleshooting responses.
2. Another objective of the research is to develop a predictive model of AMI targeted customer behavior that represents AMI implementation success. The success parameter defined as the customer satisfaction. The predictive model developed using multivariate regression analysis showed the parameter of comfort features of AMI ("Kenyamanan AMI") has the most significant positive impact (+ 0,636) to the customer satisfaction of AMI users. The AMI implementation period ("Periode AMI") following with the impact coefficient of + 0,588. The AMI trouble shooting response, showing its impact to the customer satisfaction of AMI users with the coefficient of +0,544 and AMI ease of use become the last parameters with less significance (+0,273) while considered to be significant to the customer satisfaction. The model developed have the multi R of 0,940 and an R-Square of 0,883 which means that the model explained 88,3% of the described customer satisfaction value based on the indicated predictors.

SUGGESTION

Improvements on AMI project implementation not only impacted to the users but also to the utility provider (PT PLN). An internal performance monitoring (centralized or local) is recommended to enhance the system troubleshooting with predictive and active response as part of the technical recommendation. It is recommended that the stage of socialization and education to the potential AMI users are provided while running both before and after customer experience and satisfaction survey analysis to see if the implementation achieving its targeted impact.

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