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Digital Transformation and Operational Efficiency: A Two-Stage DEA Approach in Electricity Distribution Units in Central Java and the Special Region of Yogyakarta

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Abstract: This study examines the impact of digital transformation, facilitated by the PLN Mobile application, on the operational efficiency of the Customer Service Units (UP3) under PT PLN (Persero) Distribution Main Unit (UID) Central Java and the Special Region of Yogyakarta. The Digital Transformation Index (DTI), constructed from the ratio of PLN Mobile users to total customers and the ratio of digital complaints to total complaints, serves as a proxy for digital transformation. The analysis covers 78 Decision Making Units (DMUs) over the period 2020–2025. Technical efficiency is measured using input-oriented Data Envelopment Analysis (DEA) under both Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS) assumptions. Subsequently, a two-limit Tobit regression model (0–1) is employed to assess the effect of DTI and operational parameters, including the number of customers, network coverage index, capacity index, and structure index on efficiency scores. The findings indicate average efficiency scores of 0.755 (CRS) and 0.791 (VRS). The number of customers significantly affects efficiency, while the capacity index exhibits a positive relationship at the 10% significance level. In contrast, the Digital Transformation Index (DTI) does not demonstrate statistical significance. These results suggest that operational capacity plays a more substantial role in explaining efficiency variations than the intensity of digitalization, and that increased digital adoption does not automatically translate into improvements in internal operational efficiency.

Keywords: Digital Transformation, PLN Mobile, Operational Efficiency, Data Envelopment Analysis, Tobit Regression.

INTRODUCTION

Digital transformation is increasingly viewed as a strategic mechanism to improve operational efficiency, system reliability, and service delivery in the electricity sector. The International Energy Agency notes that power-system digitalization can reduce operating costs by around 5% when supported by process optimization, better asset utilization, and fewer

service disruptions (International Energy Agency, 2017). Such gains require complementary adjustments in organizational processes, governance, and operational capabilities.

PT PLN (Persero) has accelerated customer service digitalization through PLN Mobile (PT PLN (Persero), 2020). In PLN UID Central Java and the Special Region of Yogyakarta, digital service adoption reached 12,980,791 downloads and 2,998,407 transactions in 2025 (as of August), with an application rating of 4.907 (Bidang Niaga & Manajemen Pelanggan, 2025). This adoption reflects a shift in service interaction patterns (Uribe-Linares et al., 2023). This raises the question of whether increasing digitalization improves internal operational efficiency at the UP3 level.

This study therefore examines whether higher digitalization intensity is associated with improvements in internal technical efficiency at the UP3 level, rather than customer service quality outcomes. Within the Structure–Conduct–Performance (SCP) framework, when market structure is relatively stable as in regulated electricity distribution, performance differences are more likely driven by variations in organizational conduct (Lipczynski et al., 2005; Setiawan, 2023). Accordingly, PLN Mobile-based digital transformation is conceptualized as a conduct shift that may alter service processes and workflow standardization at the operational unit level.

Prior digital transformation research highlights that performance gains materialize when digital technologies enable process integration, coordination, and capability development (Baiyere et al., 2020; Bharadwaj et al., 2013; Vial, 2019). While studies in utilities and energy sectors report positive links between digital transformation and efficiency (Lin & Xie, 2023; Wang & Xia, 2024), the evidence is largely based on firm-level indicators and different institutional settings, leaving limited unit-level evidence for regulated public utilities.

To operationalize digital transformation intensity at the unit level, this study constructs a Digital Transformation Index (DTI) using operational data: the ratio of PLN Mobile users to total customers and the ratio of digital complaints to total complaints. This composite measure captures the intensity of digital service utilization at the UP3 level and enables comparability across units and time (Kotarba, 2017; Zou et al., 2024).

Operational efficiency is measured using input-oriented DEA under CRS and VRS assumptions (Banker et al., 1984; Charnes et al., 1978; Cooper et al., 2011), followed by a second-stage Tobit model to examine determinants of bounded efficiency scores (Antonelli & De Bonis, 2019; Badunenko & Tauchmann, 2018). This approach allows contextual factors influencing efficiency scores bounded within the interval $[0,1]$ to be analyzed systematically (Tobin, 1958). DEA has been extensively applied in electricity distribution studies to examine efficiency variations across operational entities (Çelen, 2013; Zhao et al., 2018).

Although research on digital transformation and operational efficiency has expanded rapidly, the two streams are often examined separately, particularly in regulated public utilities. This study integrates digital transformation into the Structure–Conduct–Performance framework by conceptualizing the Digital Transformation Index (DTI) as a shift in organizational conduct and examining its relationship with operational efficiency as an internal performance dimension at the UP3 level. Unlike prior studies relying on firm-level indicators, the DTI is constructed from operational data at the $UP3 \times \text{year}$ level and analyzed using a two-stage DEA–Tobit approach, providing a more granular understanding of efficiency variation across operational units. In addition, this study contributes to the two-stage DEA literature by applying the DEA–Tobit framework to analyze efficiency determinants at the operational unit level within a regulated electricity distribution system, thereby extending existing efficiency studies that predominantly focus on firm-level analysis.

METHOD

Research Design and Data Sources

This study employs a quantitative approach using a panel data design at the UP3 level. The unit of analysis consists of 13 Customer Service Units (UP3) under PT PLN (Persero) Distribution Main Unit (UID) Central Java and the Special Region of Yogyakarta over the period 2020–2025, resulting in 78 observations (13 UP3 × 6 years). The dataset comprises secondary operational data obtained from the company's internal information systems, including operational resource data, job completion performance, service standard compliance, and indicators of digital service utilization. Digital transformation is treated as the explanatory variable, while operational efficiency is positioned as the internal performance variable.

Measurement of Digital Transformation

Digital transformation is operationalized as a Digital Transformation Index (DTI), constructed from the ratio of PLN Mobile users to total customers and the ratio of complaints submitted through digital channels to total complaints. The selected indicators are intended to capture digital service channel adoption intensity at the UP3 level. In customer-facing service digitalization, adoption is most directly observed through (i) the extent to which customers migrate to the digital platform (user penetration) and (ii) the share of service interactions conducted via digital channels (digital complaint share). The digital transformation literature highlights that early-stage transformation in service organizations is commonly manifested as a shift of customer interactions from traditional channels to digital platforms, making these front-end utilization metrics a practical and observable proxy for adoption intensity (Baiyere et al., 2020; Vial, 2019).

The index is subsequently normalized using the min–max scaling method and aggregated with equal weights, following established practices in composite index construction (Nardo et al., 2005). The normalization formula is expressed as follows:

$$DTI_{it} = \frac{X_{it} - X_{min}}{X_{max} - X_{min}}$$

where i denotes the UP3 unit and t represents the year of observation. The DTI is treated as a continuous variable reflecting the intensity of digital transformation at the UP3 level.

Equal weighting is used because both indicators are viewed as equally important from an operational perspective: the ratio of PLN Mobile users reflects the breadth of customer migration to the digital platform, while the ratio of digital complaints captures the intensity of digitally mediated service interaction. Nevertheless, this approach assumes equal contribution across indicators, and no formal sensitivity analysis is conducted under alternative weighting schemes, so the index may be somewhat sensitive to different weighting structures. In addition, because the DTI is constructed from front-end utilization metrics, it should be interpreted as a practical proxy for digital service channel adoption intensity rather than a definitive measure of digital transformation, as it does not fully capture deeper dimensions such as back-office integration, workflow redesign, or end-to-end process automation.

Measurement of Operational Efficiency Using Data Envelopment Analysis (DEA)

Operational efficiency is measured using input-oriented Data Envelopment Analysis (DEA) under two assumptions: Constant Returns to Scale (CRS/CCR) and Variable Returns to Scale (VRS/BCC). DEA measures the relative efficiency of Decision Making Units (DMUs) without imposing a parametric production function (Banker et al., 1984; Charnes et al., 1978; Cooper et al., 2011). The estimations are conducted using DEAP version 2.1. The input-oriented VRS DEA model is formulated as follows:

$$\min_{\theta, \lambda} \theta$$

subject to the following constraints:

$$\begin{aligned} \sum_{j=1_1}^n \lambda_j x_{ij} &\leq \theta x_{io} && \forall i = 1, \dots, m \\ \sum_{j=1_1}^n \lambda_j y_{rj} &\geq y_{ro}, && \forall r = 1, \dots, s \\ \sum_{j=1_1}^n \lambda_j &= 1, && \lambda_j \geq 0 \quad \forall j \end{aligned}$$

where $\theta \in [0,1]$ denotes the technical efficiency score of DMU o ; x_{ij} and y_{rj} represent the i -th input and the r -th output of DMU j , respectively, λ_j denotes the intensity weight, and the constraint $\sum \lambda_j = 1$ captures the Variable Returns to Scale (VRS) assumption. The adequacy of the number of observations follows the model discrimination criterion:

$$n \geq \max \{m \times s, 3(m + s)\}$$

With two inputs and three outputs, the minimum required number of DMUs is 15. This study employs 78 DMUs, thereby satisfying the methodological adequacy criterion (Dyson et al., 2001). The input variables in the DEA model consist of the number of operational employees and normative working hours. The service output variables include the number of jobs completed on time, the Service Level Agreement (SLA) fulfillment rate, and the number of resolved complaints. The technical efficiency score (θ) ranges from 0 to 1, where a value of 1 indicates that the unit operates on the efficient frontier.

An input-oriented DEA model is used because UP3 units have greater control over operational inputs than over output realization. Resource variables such as employees and working hours can be managed internally, while service outputs are partly shaped by demand conditions and case characteristics beyond the unit’s full control. Therefore, the input-oriented specification is more appropriate for assessing the efficiency of resource utilization at the UP3 level.

Tobit Regression

Since DEA efficiency scores are bounded within the interval 0–1 and include observations censored at the upper limit ($\theta = 1$), a two-limit Tobit model is employed (Greene, 2018; Tobin, 1958). The specification of the Tobit model in this stage is formulated as follows:

$$\theta_{jt}^* = \beta_0 + \beta_1 DTI_{jt} + \beta' Z_{jt} + \varepsilon_{jt}, \quad \varepsilon_{jt} \sim N(0, \sigma^2)$$

with the following observation mechanism:

$$\theta_{jt} = \begin{cases} 0, & \text{if } \theta_{jt}^* \leq 0 \\ \theta_{jt}^*, & \text{if } 0 < \theta_{jt}^* < 1 \\ 1, & \text{if } \theta_{jt}^* \geq 1 \end{cases}$$

The two-limit censoring mechanism at 0 and 1 is applied because DEA efficiency scores are restricted to the interval [0,1] (Banker & Natarajan, 2008). The use of second-stage regression

follows established practices in analyzing the determinants of efficiency, taking into account the bounded nature of DEA scores and the implications of censoring for statistical inference, as discussed by (Badunenko & Tauchmann, 2018). The primary independent variable is the Digital Transformation Index (DTI), representing a shift in organizational conduct. The control variables include the number of customers, Network Coverage Index, Capacity Index, and Structure Index, which capture differences in operational characteristics across UP3 units. The model is estimated with a lower limit of 0 and an upper limit of 1, using robust standard errors clustered at the unit level (Greene, 2018). The Tobit estimation is performed using Stata 14.

RESULTS AND DISCUSSION

Digital Transformation Index

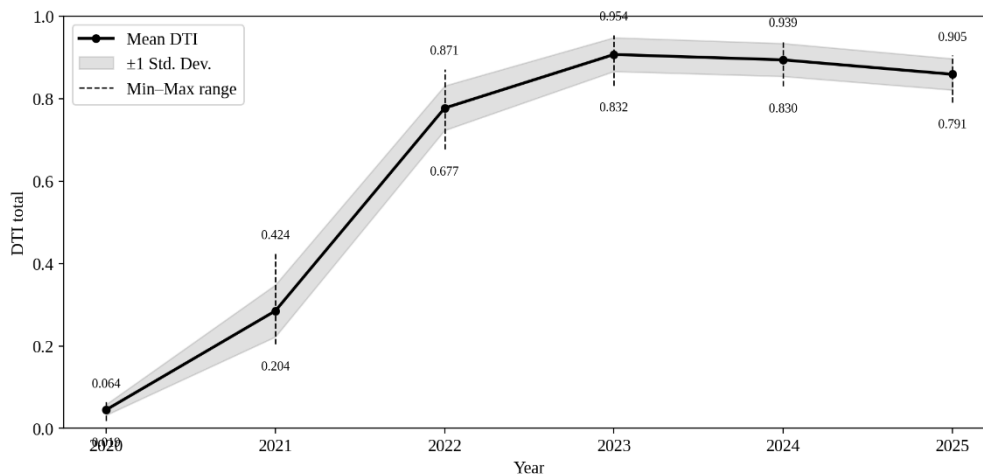
The Digital Transformation Index (DTI) generates 78 UP3-year observations for the period 2020–2025. The index ranges from 0.019 to 0.954, with an overall mean of 0.628, indicating substantial variation in the intensity of digital service utilization across units and over time.

Table 1. Descriptive Statistics of the Digital Transformation Index (DTI) by Year (2020–2025)

Year	Min	Max	Mean	Std
2020	0.019	0.064	0.045	0.013
2021	0.204	0.424	0.285	0.063
2022	0.677	0.871	0.777	0.054
2023	0.832	0.954	0.907	0.041
2024	0.830	0.939	0.894	0.040
2025	0.791	0.905	0.859	0.038

Source: Primary Data Processing, 2025.

Table 1 reports the descriptive statistics of the Digital Transformation Index (DTI) by year. The results indicate a rapid increase in digital service utilization during the early phase of digital transformation. The mean DTI rises from 0.045 in 2020 to 0.777 in 2022 and reaches 0.907 in 2023. After this period, the index stabilizes at a relatively high level during 2024–2025. Figure 1 illustrates the temporal trend of the average DTI across the study period.



Source: Primary Data Processing, 2025.

Figure 1. Trend of the Average Digital Transformation Index (DTI), 2020–2025

This pattern indicates that the adoption of PLN Mobile as a digital service channel expanded rapidly during the early years of implementation and subsequently reached a maturity stage where digital service utilization became relatively stable across units. Despite this convergence at higher levels of digitalization, variation across UP3 units remains observable.

DEA Results: Distribution of Technical Efficiency (CRS and VRS)

Technical efficiency is estimated under two assumptions: Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS). The CRS model measures overall technical efficiency, whereas the VRS model isolates pure technical efficiency by controlling for scale effects (Banker et al., 1984; Cooper et al., 2011).

Table 2. Classification of UP3 Units Based on Mean Efficiency and Volatility

Model	Mean	Minimum	Maximum	Efficient Units	Percentage Efficient
CRS	0.755	0.485	1.000	4	5.1%
VRS	0.791	0.485	1.000	11	14.1%

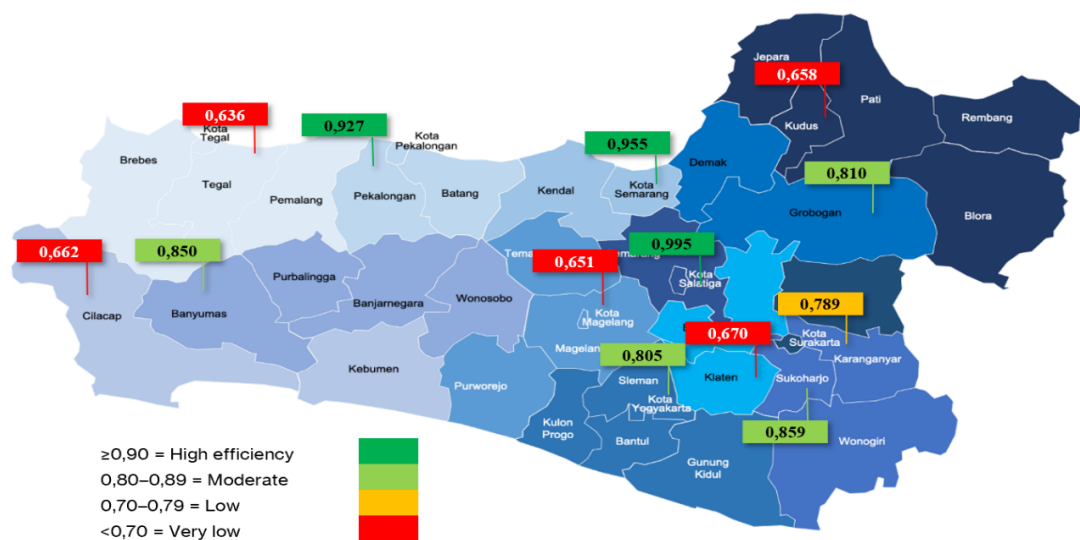
Source: Primary Data Processing, 2025.

Under the CRS assumption, the average efficiency score of 0.755 indicates that, on average, each DMU could potentially reduce its input usage by approximately 24.5% while maintaining the same level of output. Only 4 out of 78 DMUs (5.1%) achieve full efficiency under this assumption. Under the VRS assumption, the average efficiency score increases to 0.791, implying an average pure technical inefficiency of 20.9%. A total of 11 DMUs (14.1%) reach the efficiency frontier under the VRS model. The difference in the number of efficient DMUs between the CRS and VRS models suggests the presence of scale inefficiency in several units. Specifically, 7 DMUs are efficient under VRS but not under CRS, indicating that these units are technically efficient in a pure sense but are not operating at an optimal scale. Overall, 67 DMUs (85.9%) remain below the VRS frontier, while 74 DMUs (94.9%) fall below the CRS frontier.

These findings confirm that the majority of service units still have substantial room for efficiency improvement, both in terms of technical performance and scale optimization.

Spatial Distribution DEA-VRS Technical Efficiency Scores

Figure 2 presents the spatial distribution of the average DEA-VRS efficiency scores across the 13 UP3 units over the 2020–2025 period. The mapping reveals substantial variation in technical efficiency among service units (UP3), despite the standardization of operational procedures.



Source: Primary Data Processing, 2025.

Figure 2. Spatial Distribution of the Average DEA-VRS Technical Efficiency Scores (2020–2025)

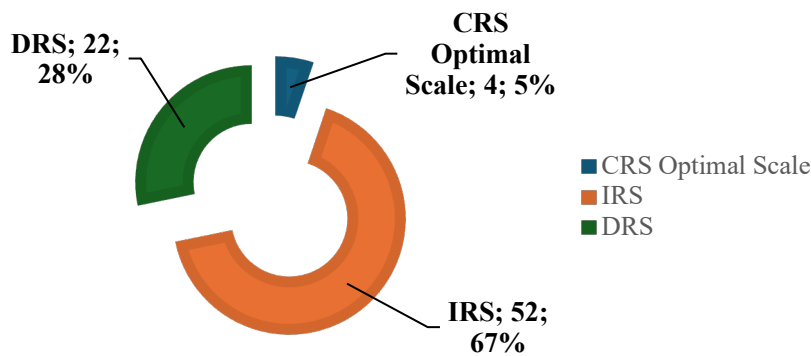
Three units fall into the high-efficiency category (≥ 0.90), representing 23.1% of the total UP3 units, namely Salatiga (0.995), Semarang (0.955), and Pekalongan (0.927). In contrast, five units (38.5%) are classified as very low efficiency (< 0.70), including Tegal (0.636) and Magelang (0.651). High-efficiency units are concentrated in the central area, whereas lower-performing units are more dispersed across the western and parts of the northern regions. This pattern indicates the presence of operational performance heterogeneity that cannot be fully explained by differences in digital transformation intensity alone.

Scale Efficiency and Returns to Scale (RTS)

Scale Efficiency (SE) is calculated as the ratio of CRS efficiency to VRS efficiency, expressed as follows:

$$SE = \frac{TE_{CRS}}{TE_{VRS}}$$

An SE value of 1 indicates that a unit operates at the optimal scale, whereas a value below 1 reflects the presence of scale inefficiency (Cooper et al., 2011). The average Scale Efficiency of 0.955 suggests that, on aggregate, approximately 4.5% of potential efficiency is lost due to suboptimal scale operations.



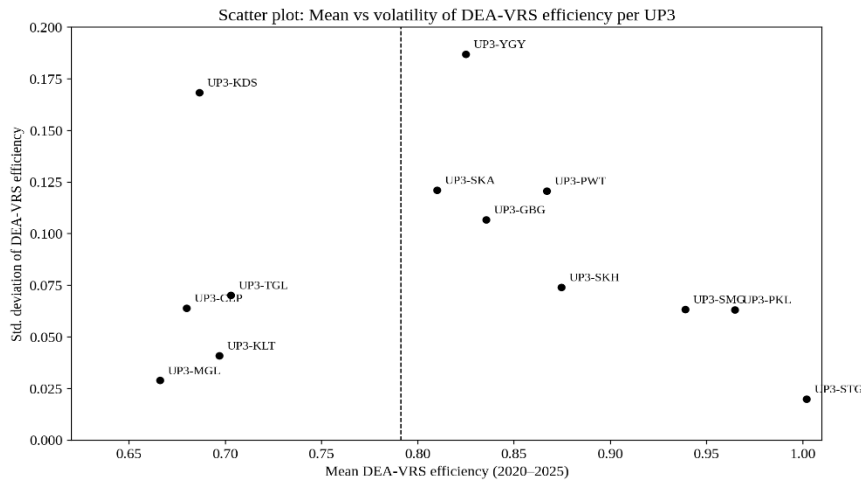
Source: Primary Data Processing, 2025.

Figure 3. Distribution of Scale Efficiency (SE) (n = 78 DMUs)

A total of 66.7% of DMUs operate under Increasing Returns to Scale (IRS), indicating that most units remain below their optimal scale and have the potential to increase output through proportional input expansion. In contrast, 28.2% of DMUs exhibit Decreasing Returns to Scale (DRS), suggesting the presence of potential operational overcapacity. Only 5.1% of DMUs operate at the optimal scale under Constant Returns to Scale (CRS).

Mean–Volatility Analysis of DEA-VRS Efficiency

To evaluate the temporal consistency of efficiency performance, a mean–volatility analysis is conducted by plotting the average DEA-VRS efficiency scores against the annual standard deviation for each UP3 (see Figure 5).



Source: Primary Data Processing, 2025.

Figure 4. Mean–Volatility Scatter Plot of DEA-VRS Efficiency Scores for Each UP3 (2020–2025)

The results indicate that Salatiga (0.995) and Semarang (0.955) are positioned in the high mean–low volatility quadrant, reflecting both high and stable efficiency throughout the observation period. In contrast, Tegal, Magelang, and Kudus fall within the low mean quadrant, indicating relatively low efficiency performance that persistently remains below the overall average (0.791).

To further clarify the classification of each unit’s position, the quadrant summary is presented as follows:

Table 3. Classification of UP3 Units by Mean Efficiency and Volatility

Quadrant	Criteria	UP3
High Mean – Low Volatility	Mean $\theta > 0.791$ with Low Volatility (SD)	Salatiga, Semarang
High Mean – Higher Volatility	Mean $\theta > 0.791$ with Moderate Volatility (SD)	Pekalongan, Sukoharjo
Low Mean – Moderate Volatility	Mean $\theta < 0.791$	Tegal, Magelang, Kudus, Cilacap, Klaten
Near Mean	Mean $\theta \approx 0.791$	Surakarta

Source: Primary Data Processing, 2025.

The disparity between the highest performing unit (0.995) and the lowest performing unit (0.636) amounts to 35.9 percentage points. This pattern reinforces the view that efficiency variation is more strongly driven by differences in operational capacity and internal management practices than by external structural factors.

Efficiency Frontier Structure, Peer Units, and DEA Slack Analysis

Based on the DEA-VRS estimation across 78 DMUs, 7 DMUs attain the efficiency frontier ($\theta = 1$) and serve as frontier-defining units. These efficient DMUs originate from three UP3 units, namely Yogyakarta (2021), Semarang (2023–2025), and Salatiga (2021, 2022, and 2024).

Table 4. Frontier Units and Frequency of Occurrence as Peers (DEA-VRS)

Kode DMU	Kode UP3	UP3	Year	Frontier Status (VRS)	Peer Frequency
DMU-14	UP3-YGY	Yogyakarta	2021	Efficient	4
DMU-40	UP3-SMG	Semarang	2023	Efficient	59
DMU-41	UP3-SMG	Semarang	2024	Efficient	2
DMU-42	UP3-SMG	Semarang	2025	Efficient	7
DMU-44	UP3-STG	Salatiga	2021	Efficient	28

DMU-45	UP3-STG	Salatiga	2022	Efficient	31
DMU-47	UP3-STG	Salatiga	2024	Efficient	37
Other DMUs	–	–	–	Inefficient	0

Source: Primary Data Processing, 2025.

Semarang 2023 (DMU-40) serves as a reference unit 59 times, making it the most dominant frontier-defining unit. Salatiga also demonstrates strong consistency as a frontier benchmark, particularly in 2024 (37 times), 2022 (31 times), and 2021 (28 times). Other DMUs never serve as peers, as they do not lie on the efficiency frontier. The concentration of peer references among a limited number of DMUs indicates that the frontier structure is centralized rather than dispersed.

DEA Slack Analysis

Table 5 summarizes the average slack values for input and output variables, indicating potential sources of inefficiency.

Table 5. Average Slack Values of Inputs and Outputs (n = 78 DMUs)

Variable	Type	Mean Slack	Minimum	Maximum
Operational Employees	Input	0.000	0.000	0.000
Normative Working Hours	Input	0.000	0.000	0.000
Jobs Completed on Time	Output	1,261.07	0.000	13,513.00
Resolved Complaints	Output	381.50	0.000	13,495.00
SLA Fulfillment Rate	Output	0.008	0.000	0.049

Source: Primary Data Processing, 2025.

The slack analysis results indicate that inefficiency is predominantly driven by the output side rather than the input side. The largest average slack is observed in the Timely Job Completion variable, amounting to 1,261.07 units, with a maximum value of 13,513.00. This is followed by Resolved Complaints, which records an average slack of 381.50 and a maximum of 13,495.00. In contrast, slack in the SLA Compliance Rate variable is relatively small (mean = 0.008; maximum = 0.049). Meanwhile, the average slack values for both input variables are 0.000, indicating that inefficiency is not attributable to non-radial input excess after proportional adjustment through the efficiency score (θ). This pattern suggests the presence of output shortfalls, whereby the available input capacity has not yet been translated into optimal service output levels. Efficiency improvement efforts should focus more on enhancing process productivity and optimizing service output achievement rather than reducing operational resources.

Tobit Regression: Impact of Digital Transformation on Operational Efficiency

The Tobit model is employed because DEA efficiency scores are bounded within the interval of 0 to 1, with observations censored at the upper limit ($\theta = 1$) (Greene, 2018; Tobin, 1958). The two-stage DEA–Tobit approach follows the recommendation of Banker and Natarajan (2008), whereby technical efficiency scores are treated as a limited dependent variable to examine the determinants of inefficiency. Estimation is conducted using Stata 14 with a two-limit Tobit specification ($ll = 0, ul = 1$) and robust standard errors clustered at the UP3 level.

Table 6. Tobit Regression Results (Operational Efficiency as the Dependent Variable, n = 78)

Variable	Coefficient	Std. Error	p-value
Digital Transformation Index (DTI)	-0.0046978	0.0400963	0.907
Number of Customers	-3.94×10^{-7}	1.17×10^{-7}	0.001
Network Coverage Index	-0.3427378	0.2420513	0.161
Capacity Index	0.3262355	0.1845226	0.081

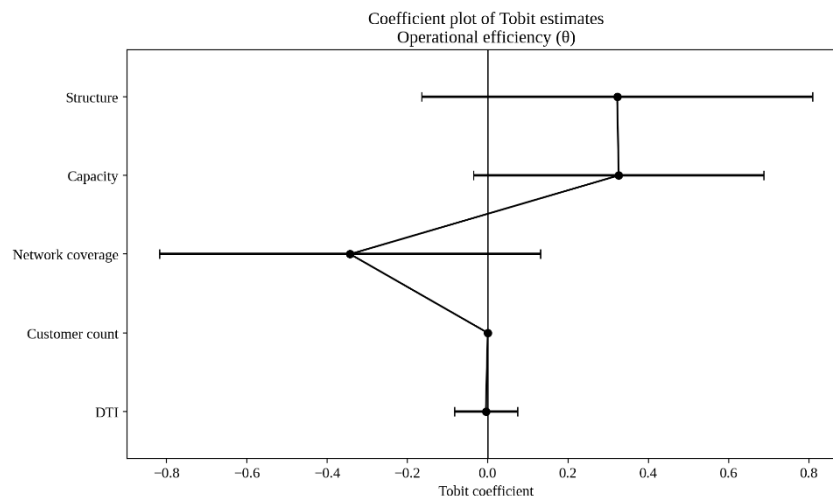
Structure Index	0.3223659	0.2484896	0.199
Constant	1.084692	0.0911875	0.000

Source: Primary Data Processing, 2025.

Note:

Model Statistics: N = 78; two-limit Tobit model (ll = 0, ul = 1) with standard errors clustered at the UP3 level; $F(5,73) = 5.67$; $\text{Prob} > F = 0.0002$; Log pseudolikelihood = 21.817; 0 left-censored, 67 uncensored, and 11 right-censored observations at $\theta \geq 1$; $\sigma = 0.145$.

The Tobit model is statistically significant overall ($F(5,73) = 5.67$; $\text{Prob} > F = 0.0002$), indicating that the explanatory variables jointly account for variation in bounded efficiency scores. To enrich model evaluation, the estimation also reports a log pseudolikelihood of 21.817 under the two-limit Tobit maximum-likelihood framework. These statistics complement the coefficient estimates by providing additional information on overall model performance. To visualize the direction and magnitude of the effects of each independent variable on operational efficiency, a coefficient plot based on the Tobit estimation with 95% confidence intervals is presented as follows:



Source: Primary Data Processing, 2025.

Figure 7. Coefficient Plot of Tobit Regression Estimates

The model is statistically significant overall ($\text{Prob} > F = 0.0002$), indicating that the independent variables jointly explain variations in efficiency scores. The Digital Transformation Index (DTI) does not exhibit a statistically significant effect on operational efficiency ($p = 0.907$). The extremely small coefficient (-0.0047) suggests that increased digitalization intensity is not associated with changes in technical efficiency within this model. The number of customers has a negative and statistically significant effect ($p = 0.001$). The negative coefficient implies that an increase in customer load reduces technical efficiency, indicating that operational capacity has not fully adapted to the growth in the customer base. The Capacity Index shows a positive effect at the 10% significance level ($p = 0.081$), suggesting that increased capacity tends to improve operational efficiency. Meanwhile, the Network Coverage Index and Structure Index are not statistically significant ($p > 0.10$), indicating no observable effect on efficiency in this model. A total of 11 observations are censored at the upper limit ($\theta = 1$), confirming the presence of frontier units within the sample. These findings indicate that efficiency variation is more sensitive to capacity-related factors and service load pressures than to the intensity of digital transformation.

Discussion

The DEA findings indicate that the average technical efficiency is 0.791 under the VRS assumption, with only 14.1% of DMUs reaching the efficiency frontier. The gap between CRS and VRS efficiency scores, along with the dominance of Increasing Returns to Scale (IRS) conditions, suggests that scale inefficiency remains substantial and that many units operate below the optimal scale. These results are consistent with empirical findings in the electricity distribution sector, where scale mismatch and heterogeneity in operational environments are often identified as primary sources of inter-unit inefficiency (Çelen, 2013; Zhao et al., 2018). Accordingly, the findings reinforce the view that efficiency issues in regulated utilities are not solely technical in nature, but also structural at the level of operational scale.

As a simple robustness consideration within the DEA framework, efficiency is estimated under both CRS and VRS assumptions. Whereas the CRS model captures overall technical efficiency, the VRS model isolates pure technical efficiency by controlling for scale heterogeneity. The higher mean efficiency under VRS than under CRS indicates that a portion of the observed inefficiency is associated with scale mismatch rather than purely technical factors. This finding suggests that efficiency variation across UP3 should be interpreted not only as a reflection of managerial performance, but also as a consequence of differences in operating scale.

The regulated and relatively stable structure of the electricity distribution industry tends to limit performance variation arising from changes in market structure. Within the Structure–Conduct–Performance (SCP) framework, the literature suggests that when market structure remains relatively constant, performance differences are more likely to be driven by changes in organizational conduct (Lipczynski et al., 2005). In this context, digital transformation through PLN Mobile can be positioned as a shift in conduct. That is, the implementation of digital platforms represents a behavioral and managerial adjustment within the organization. However, the empirical results indicate that such changes do not automatically translate into improvements in internal operational efficiency.

This diagnosis is further supported by the slack analysis, in which the indicators of timely job completion and complaint resolution suggest that inefficiency is primarily driven by output shortfalls rather than input wastage. Non-radial inefficiency components often indicate that the ideal level of output cannot be achieved even when inputs have been proportionally utilized, as emphasized in slack-based DEA approaches (Tone, 2001). These findings imply that strengthening service process productivity is more critical than reducing operational resources in efforts to improve efficiency. Given this pattern, alternative DEA formulations such as the slack-based measure (SBM) may offer additional insight in future research. Unlike radial models, SBM explicitly incorporates slack values and can therefore provide a more refined assessment of non-radial inefficiency across operational units. From a managerial perspective, this finding implies that efficiency improvement should focus less on reducing operational resources and more on improving service process execution. In practical terms, UP3 units should strengthen work scheduling, improve coordination in service completion, and accelerate complaint-resolution workflows so that existing inputs can be translated more effectively into timely job completion, SLA fulfillment, and service recovery outcomes.

The Tobit regression in the second stage of the analysis indicates that the Digital Transformation Index (DTI) does not have a statistically significant impact on operational efficiency. This result is not fully consistent with several studies that report a positive correlation between digital transformation and efficiency in the utilities or energy sector (Lin & Xie, 2023; Wang & Xia, 2024). This discrepancy suggests that the impact of digitalization is highly contextual and depends on how digital transformation is measured, the depth of process changes, and the operational characteristics at the UP3 level.

Another possible explanation for the very small and statistically insignificant DTI coefficient is a time-lag effect between digital adoption and efficiency outcomes. Increases in digital channel utilization may occur relatively quickly, but improvements in internal operational efficiency often require a longer adjustment period because the benefits of digitalization depend on process integration, workflow adaptation, learning effects, and complementary organizational changes. As a result, front-end digital adoption may not immediately translate into measurable gains in technical efficiency within the same observation period.

The conventional two-stage DEA–Tobit framework is not without methodological limitations, particularly because DEA efficiency scores are generated in the first stage and then used for second-stage inference. Prior studies have proposed bootstrap-based procedures, such as the Simar–Wilson approach, to improve statistical validity. While this study employs a two-limit Tobit model as a commonly used specification for bounded efficiency scores, with standard errors clustered at the UP3 level, the absence of bootstrap correction should be acknowledged. Accordingly, the estimated relationships are interpreted as associative rather than strictly causal.

The DTI components primarily reflect the level of digital channel utilization on the service interaction (front-end) side. The digital transformation literature emphasizes that efficiency gains typically emerge when digitalization evolves beyond mere channel shifting toward end-to-end process transformation. Such transformation involves the orchestration of organizational capabilities, cross-functional data integration, workflow standardization, and back-office automation (Baiyere et al., 2020; Bharadwaj et al., 2013; Vial, 2019; Westerman et al., 2014). When digitalization remains focused on customer interaction channels, its impact tends to be limited to service accessibility rather than internal efficiency. The most immediate benefits therefore appear in the form of improved service accessibility and user experience. Improvements in internal efficiency require deeper organizational adjustments and may take longer to materialize in productivity-related performance metrics.

The results for the control variables support this argument. The number of customers shows a negative and statistically significant effect on efficiency, indicating that increasing service load can reduce efficiency when operational capacity and coordination are not adequately adjusted. Rising service demand and operational complexity may place pressure on technical performance if not accompanied by corresponding capacity adjustments. These findings are consistent with the public sector efficiency literature (Afonso & Aubyn, 2005; Gupta & Verhoeven, 2001; Hauner & Kyobe, 2010).

The Capacity Index shows a tendency toward a positive effect, indicating that capacity readiness and infrastructure adequacy are important prerequisites for efficiency. DEA studies in electricity distribution networks also identify sufficient capacity and effective network management as central determinants of efficiency improvement (Çelen, 2013). Capacity can therefore be viewed as an enabling mechanism through which digital transformation may translate into improvements in operational efficiency.

From an operational policy perspective, these results suggest that the efficiency effects of digitalization depend on capacity alignment. Expanding digital adoption without corresponding improvements in operational readiness, coordination, and execution capability may primarily produce a shift in service channels rather than measurable gains in internal efficiency. This pattern is consistent with the view that digitalization without process reengineering primarily produces a service channel shift rather than an end-to-end transformation of operational workflows. Consequently, efficiency gains are more likely to materialize when digital initiatives are paired with process redesign, integration, and execution capability improvements. Accordingly, PLN should complement digital expansion with end-

to-end process integration and capacity strengthening so that increased digital interaction can be translated into higher operational performance at the UP3 level.

From a methodological perspective, the two-stage DEA approach separates the measurement of relative efficiency from the evaluation of its determinants. DEA efficiency scores are bounded within the interval $[0,1]$, and potential measurement error in the first stage has implications for statistical inference in the second stage. Previous studies emphasize that the estimation of efficiency determinants should account for censoring issues and potential bias in subsequent regression analysis (Banker & Natarajan, 2008; Dyson et al., 2001). Alternative methods, including truncated regression and bootstrapping procedures, have been developed to strengthen estimation validity within the two-stage DEA framework (Anang, 2022; Badunenko & Tauchmann, 2018; Fernandes et al., 2018). The Tobit regression results are therefore interpreted as indicative associative relationships rather than conclusive causal claims.

CONCLUSION

This research examines whether service digital transformation through PLN Mobile affects operational efficiency across 13 Customer Service Units (UP3) under PT PLN (Persero) Distribution Main Unit (UID) Central Java and the Special Region of Yogyakarta during the 2020–2025 period. The results indicate that most units remain below the efficiency frontier. The second-stage Tobit regression shows that the intensity of digital transformation, represented by the Digital Transformation Index (DTI), does not have a statistically significant effect on variations in operational technical efficiency. The number of customers is negatively and significantly associated with efficiency, while the Capacity Index shows a tendency toward a positive relationship.

Overall, increased use of digital customer service channels at the UP3 level has not directly translated into improvements in internal technical efficiency during the observation period. This suggests that digital transformation initiatives should be complemented by operational scale and capacity alignment to translate digital adoption into efficiency improvements. Efficiency variation appears to be more strongly influenced by service load pressures and operational capacity readiness than by the intensity of front-end digitalization.

This study has several limitations. First, the second-stage analysis relies on a conventional two-limit Tobit model without bootstrap correction, which may limit the robustness of statistical inference. Second, the Digital Transformation Index is constructed from front-end service utilization metrics and therefore does not fully capture deeper process digitalization. Third, the findings are limited to UP3 units within PLN UID Central Java and the Special Region of Yogyakarta, and their generalizability to other institutional settings should therefore be considered with caution.

From an industrial engineering and operations management perspective, this study contributes by integrating multi-input and multi-output efficiency measurement based on DEA with determinant analysis using a regression model bounded within the $[0,1]$ interval. This approach provides a systematic quantitative evaluation framework for regulated public utility organizations. The construction of a digital transformation index based on operational data at the UP3 level also extends the measurement of digitalization from the aggregated firm level to the technical unit level, providing a basis for benchmarking and evidence-based process improvement.

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