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Simulation-Based Assessment of QRIS Adoption Scenarios and Transaction Efficiency among Indonesian MSMEs

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Abstract

QRIS stands for Quick Response Code Indonesian Standard, which is considered to be an alternative for payment digitalization of micro-, small and medium-sized enterprises (MSMEs). The issue is that previous studies consider adoption in a dichotomous manner and focus mainly on behavioral intention rather than operations. This paper suggests a simulation-based estimation of the impact of adoption intensity defined as QRIS transactions share on transaction efficiency of MSMEs. A synthetic dataset was created by means of statistical distributions with four hundred synthetic MSMEs across five industries in Indonesia being used. In order to estimate the impact, a benchmark scenario and five adoption scenarios (from 20% up to 100%) were analyzed. In order to estimate the performance, the author used the following components: payment time, transaction cost, errors in the recording process, failures probability, reconciliation time, and processing capacity to calculate the weighted Transaction Efficiency Index (TEI). To propagate uncertainty, a Monte Carlo simulation with one thousand iterations was implemented. The results have shown that average TEI increases from 0.653 to 0.782 in case of digital dominance. Average payment time is reduced by 19.9% and the cost of monthly payments is reduced by 11.2%. It should be noted that there is a trade-off as a result of adoption – QRIS failure exposure increases from 1.8% to 6.8% of transactions. The metamodel estimated with regression shows that there is a positive influence of adoption intensity on TEI ($\beta=0.170$; $p<0.001$) which is significantly improved by internet reliability and digital literacy of MSMEs. The sensitivity analysis revealed that such factors as cash processing time and QRIS processing time play the key role in the model.

Keywords: QRIS, MSMEs, Digital Payment, Transaction Efficiency, Monte Carlo simulation

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1. Introduction

The payment systems in the developing nations are moving away from cash-based transactions to using digital tools, and the MSMEs have been playing a critical role in this transformation process. Digitalization benefits the merchants with quicker services to customers, more detailed transaction reports, less involvement in physical cash transactions, and a wider variety of payments for the consumers (Angelicia et al., 2024; Demirgüç-Kunt et al., 2022; Humphrey et al., 2001). In Indonesia, the process has been fast-tracked with the introduction of the Quick Response Code Indonesian Standard (QRIS) which is an interoperable QR payments system in Indonesia, developed by Bank Indonesia (Indonesia, 2019).

The operational benefit of digital payments, however, is not determined solely by the availability of the technology. Realized efficiency depends on the intensity of use, transaction volume and value, the digital readiness of the business owner, the quality of internet connectivity, processing fees, consumer acceptance, and the merchant's ability to integrate payment data with bookkeeping (Jack & Suri, 2014; OECD, 2021). Owning a QRIS code is therefore not equivalent to using QRIS actively: two merchants with identical signage may route very different shares of their transactions through the digital channel. This study consequently distinguishes between MSMEs that merely provide QRIS and MSMEs for which QRIS is the dominant payment method.

QRIS can be positioned as a standardization instrument for QR-based payments that lowers the fixed cost of accepting digital money for small merchants (Adawiyah, 2025; Indonesia, 2019; Nafisa et al., 2022). Its potential benefits include

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faster checkout, elimination of change-making, lower cash-handling risk, automatic digital transaction records, easier reconciliation, greater consumer convenience, and integration opportunities with digital bookkeeping applications (Aryowiloto et al., 2024; Humphrey et al., 2001; Muhammad Hilmansyah Lukman et al., 2025; Raza et al., 2017). At the same time, QRIS introduces its own frictions: merchant discount rates and connectivity costs, dependence on network availability, failed or delayed transactions, limited digital literacy, difficulties in verifying payment proofs, settlement delays, and possible mismatches between payment evidence and actual transactions (Schierz et al., 2010; Zhou, 2013). Whether the benefits outweigh the frictions at a given level of usage is fundamentally an empirical and computational question.

However, much of the research in digital payments looks into intention to use, ease of use, usefulness, satisfaction, trust, and similar constructs of acceptance (Davis, 1989; Irma Trimulyawati et al., 2024; Rabbani & Herman, 2024; Rogers, 2003; Venkatesh Morris, M. G., Davis, G. B., & Davis, F. D, 2003). Although such frameworks explain why both merchants and customers use a particular technology, they fail to shed light on the changes taking place inside an MSME due to the rising number of QRIS payments. What needs to be done is conducting research to understand the effects of the usage of QRIS payments in terms of actual performance factors: payment speed, transaction costs, cash handling costs, error rate, capacity, and reconciliation efficiency.

Previous research has largely concentrated on the users' intention or perception, but not transactional efficiency per se (Davis, 1989; Gefen et al., 2003). Methodological gap: the bulk of empirical literature is based on survey data. There are very few studies using simulation approach and comparing several levels of QRIS adoption in the face of parameter uncertainty, whereas simulation is a widely accepted tool for assessing operational efficiency of a system before its actual implementation (Banks et al., 2010; Law, 2015). Analytical gap: the adoption of the technology is usually described with a dichotomous variable (0 = non-user, 1 = user). However, there may be two micro, small and medium enterprises (MSMEs) which “use QRIS” but show a lot of disparity in the proportion of transactions processed through the system. This research uses the continuous measure of adoption – the proportion of QRIS transactions. Contextual gap: the effect of QRIS might be conditional upon variables like sector, size of the firm, transaction volume, network quality, and owners' digital literacy.

The study pursues seven objectives: (1) to develop a synthetic dataset representing transaction characteristics of QRIS-using Indonesian MSMEs; (2) to build a simulation model linking QRIS adoption intensity to transaction efficiency; (3) to measure changes in time, cost, errors, and capacity across adoption scenarios; (4) to compare impacts across sectors and MSME characteristics; (5) to identify the adoption scenario yielding the highest transaction efficiency; (6) to conduct sensitivity analysis on key model parameters; and (7) to derive recommendations for MSMEs and policymakers.

The novelty lies in the combination of (i) a continuous measure of QRIS adoption intensity, (ii) a composite Transaction Efficiency Index integrating time, cost, accuracy, reliability, reconciliation, and capacity, (iii) scenario-based comparison of adoption levels, (iv) Monte Carlo propagation of parameter uncertainty, (v) explicit modeling of MSME heterogeneity, and (vi) systematic sensitivity and robustness analysis. To the best of the author's knowledge, these elements have not previously been integrated in a single reproducible model for the Indonesian QRIS context.

From the theoretical perspective, the paper uses digital payments adoption using Transaction Cost Economics, technology adoption theories, network effects, and operational efficiencies as lenses. The methodology of the paper gives a detailed and replicable simulation model where the parameters of the model are re-estimable based on different merchant types. In terms of practice, the model will help MSMEs to predict the potential advantages and barriers of increasing their transactions using QRIS. On the other hand, from the policy point of view, the paper will be able to identify which MSMEs need digital literacy, better connectivity, or accounting before adoption.

2. Literature Review

2.1. Digital Payment Adoption

Digital payments either replace or complement physical money in transmitting value through electronic media. In the extant literature, factors such as accessibility, speed of transactions, interoperability, perceived usefulness, perceived ease of use, trust, security, and facilitating conditions have been found to influence adoption (Davis, 1989; Rogers, 2003; Venkatesh Morris, M. G., Davis, G. B., & Davis, F. D, 2003; Venkatesh et al., 2003). With merchants, considerations such as processing costs relative to costs of managing cash become important and form the basis of the transaction-cost approach espoused here (Baumol, 1952; Jack & Suri, 2014).

2.2. QRIS Adoption Intensity

Adoption needs to be considered on a scale rather than a single state. There are five levels identified: availability (there is QRIS but it is seldom used), adoption (only a small percentage of users engage in digital transactions), moderate adoption (both digital and physical cash transactions are equally divided), high adoption (QRIS is the predominant transaction system), and dominance in digital transactions (most of the transactions happen through QRIS). These levels of adoption are demonstrated in the simulation scenarios mentioned in Section 3 where the usage of QRIS is fixed at 20%, 40%, 60%, 80%, and 100%.

2.3. Tansaction Cost Economics

According to TCE theory, the choice of exchange institutions depends on the transaction cost of conducting business (Coase, 1937; Saragih et al., 2025; Williamson, 1985). In applying the concept to payment systems, the relevant transaction costs go beyond just the fees, and include the time spent conducting the payment transactions, cash management, change management, cash deposits, error correction, records reconciliation, and failure cost of transactions. The total transaction cost for any MSME i thus becomes:

$$TC_i = C_processing,i + C_cash,i + C_error,i + C_reconciliation,i + C_failure,I \quad (1)$$

Switching from cash payments to QRIS changes the cost vector in such a way that cash-related components decline and processing and connectivity components increase, resulting in a net effect which is empirically dependent on usage frequency and merchant features.

2.4. Technology Adoption and Digital Readiness

The adoption of technology framework, which starts from the Technology Acceptance Model to UTAUT, assumes that the benefits of the innovation are dependent on the ability of the user to use the technology (Davis, 1989; Venkatesh Morris, M. G., Davis, G. B., & Davis, F. D, 2003). With regard to payment systems for MSMEs, the readiness variables are digital literacy, usefulness, ease of use, infrastructural reliability, owner's experience, and employees' capabilities (OECD, 2021; Oliveira et al., 2016). The low level of literacy is translated into poor operational efficiency through slow processing of payments, error-prone record-keeping, and long time needed to reconcile digital data.

2.5. Operational and Transaction Efficiency

Transaction efficiency is defined as the ability to perform transactions with reduced time, cost, and resource expenditure (Porter, 1998). For the purpose of this study, transaction efficiency is modeled as a six-factor concept that comprises of speed, efficiency in terms of costs, accuracy, reliability, processing power, and reconciliation efficiency. Combining all the factors above into one index is done through the standard normalization and weighting process (OECD & Centre, 2008).

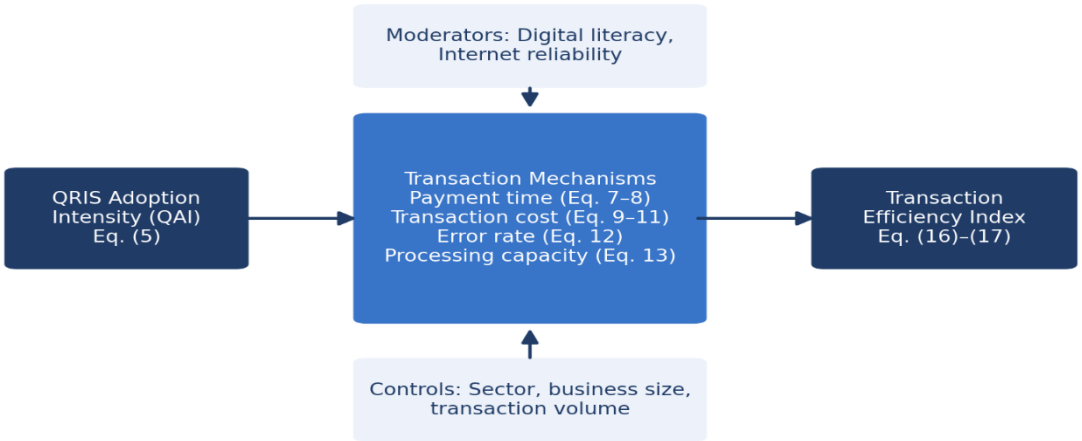

Figure 1. QRIS framework adoption intensity and transaction efficiency

2.6. Network Externality

The utility of a payment device grows in proportion to the number of trading partners that use and accept the payment method (Katz & Shapiro, 1985). The QRIS system has very strong two-way network externalities, where the benefit for merchants is proportional to the increasing number of consumers who adopt the service. These network benefits are not uniform since they depend on the local infrastructure and the nature of the customers of each MSME.

2.7. Conceptual Framework

Central to the research is the proposed causative link between QRIS Adoption Intensity and Transaction Efficiency as mediated by Transaction Mechanisms. Transaction mechanisms include time of payments, transaction costs, error rates, failure rate, reconciliations time, and processing capability. The role of digital literacy and internet stability is that of moderating variables while sector, firm size, and transaction size are considered control variables.

2.8. Hypothesis Development

Based on TCE mechanism, the higher levels of QRIS utilization are linked with lower levels of cash counting, change making, and manual record keeping, resulting in shorter payment times and lower costs, and hence increasing the index value (Hypotheses H1-H3). The usage of digital records will reduce the occurrence of record keeping errors in contrast to manual cash management (H4). As savings per period increase with higher transaction volumes, higher volume traders are expected to experience greater gains (H5). The ability to make gains from adoption will be contingent on how effectively one can use the technology, suggesting that digital literacy and internet reliability will positively moderate the results (H6). Finally, structural differences in terms of volume, value, and services indicate sector-specific differences (H7). The hypotheses are:

Table 1. Hypothesis QRIS

Code	Hypothesis
H1	An increase in the proportion of QRIS transactions has a positive effect on the MSME Transaction Efficiency Index.
H2	An increase in the proportion of QRIS transactions lowers average payment completion time.
H3	Greater QRIS usage reduces MSME cash-handling costs.
H4	Greater QRIS usage reduces transaction recording and reconciliation errors.
H5	The effect of QRIS adoption on transaction efficiency is stronger for MSMEs with high transaction volume.
H6	Digital literacy and internet connection reliability strengthen the relationship between QRIS adoption and transaction efficiency.
H7	The impact of QRIS adoption on transaction efficiency differs across business sectors.

3. Methods

3.1. Research Design

The research uses quantitative design with scenario analysis and Monte Carlo simulation (Banks et al., 2010; Harahap et al., 2023, 2026; Law, 2015). It is not a national survey designed for estimating the true situation with all Indonesian MSMEs; instead, it builds a computational model of fictitious Indonesian MSMEs with chosen rational parameter values and studies how transaction efficiency reacts to different levels of QRIS adoption under controlled uncertainty. The research is conducted in ten steps: (1) defining variables, (2) generating a synthetic dataset, (3) building baseline, (4) designing scenarios of adoption, (5) computing transaction indicators, (6) calculating Transaction Efficiency Index, (7) running Monte Carlo simulation, (8) comparing between scenarios, (9) conducting sensitivity analysis, and (10) validating and robustifying the results. All calculations were carried out in Python (NumPy/SciPy/statsmodels) with a constant seed, which means that all figures and tables in this paper can be reproduced exactly.

3.2. Unit of Analysis and Simulated Population

The unit of analysis will be one individual MSME firm. In this study, the synthetic population is made up of 400 MSMEs, which are divided into five sectors to reflect MSME operations in Indonesia: food and beverage (100), retail (100), services (75), fashion and craft (75), and miscellaneous local enterprises (50). These numbers denote the sample size generated in a simulation, not an estimation of a population. The sector determines the location parameters of distributions of volume, value, and cash service time.

3.3. Synthetic Data Generation

Synthetic data are generated from statistical distributions matched to the character of each variable (Banks et al., 2010). Variables concentrated around a mean, such as cash service time and the digital literacy score, follow a normal distribution:

$$X \sim N(\mu, \sigma^2) \quad (2)$$

Economic variables with right-skewed behavior, such as monthly transaction volume and average transaction value, follow a log-normal distribution:

$$X \sim \text{Lognormal}(\mu, \sigma^2) \quad (3)$$

Proportion-type variables, such as the baseline QRIS share, failure rates, and recording error rates, follow a beta distribution:

Table 2. Research variables and operational definitions

Variable	Code	Indicator	Scale
QRIS adoption intensity	QAI	Proportion of QRIS transactions	Ratio
Monthly transaction volume	MTV	Transactions per month	Ratio
Average transaction value	ATV	Average monetary value (IDR)	Ratio
Payment processing time	APT	Seconds per transaction	Ratio
Cash handling cost	C_cash	Monthly cash-related cost (IDR thousand)	Ratio
Digital transaction cost	C_digital	Monthly digital payment cost (IDR thousand)	Ratio
Transaction error rate	ER	Incorrect or unmatched transactions (%)	Percentage
Transaction failure rate	TFR	Failed QRIS transactions (%)	Percentage
Reconciliation time	RT	Hours per month	Ratio
Processing capacity	PC	Transactions processed per hour	Ratio
Digital literacy	DL	Technology capability score (0–100)	Interval
Internet reliability	IR	Connection reliability score (0–1)	Interval
Business size	BS	Micro or small enterprise	Nominal
Business sector	SEC	Type of business	Nominal
Transaction Efficiency Index	TEI	Composite efficiency score (0–1)	Index

Table 3. Simulation parameters and probability distributions

Parameter	Distribution / value
Cash service time (s)	Normal(44, 7^2), sector-adjusted, clipped [25, 75]
QRIS base processing time T_base (s)	Constant 21
Network penalty λ (s)	Constant 18
Literacy handling penalty κ (s)	Constant 10
Failure retry time (s)	Constant 35
Base QRIS failure rate	Beta(2, 62), amplified by $(1 + 1.8(1-IR))(1 + 1.6 \cdot QAI(1-IR))$, damped by literacy
Cash error rate	Beta(3, 69), literacy-damped
QRIS error rate	Beta(2, 118), literacy-damped
Monthly transaction volume	Lognormal(6.95, 0.45^2), sector-adjusted
Average transaction value (IDR)	Lognormal(10.35, 0.50^2), sector-adjusted
Digital literacy (0–100)	Normal(64, 13^2), clipped [20, 98]
Internet reliability (0–1)	Beta(6.0, 2.6), clipped [0.30, 0.995]
Cash handling components (IDR thousand per 100 cash tx)	Counting 9.0; change 6.5; storage 5.0; deposit 7.5
QRIS merchant discount rate	0.3% of digital transaction value
Connectivity cost	IDR 55 thousand per month when QAI > 0
Error correction / failure recovery cost	IDR 14 / 6 thousand per affected transaction
Reconciliation time (h per 100 tx)	Cash 1.15; QRIS 0.42, literacy-adjusted
Baseline QRIS share QAI_0	Beta(2.2, 5.0), readiness-adjusted, clipped [0.02, 0.92]

$$X \sim \text{Beta}(\alpha, \beta) \quad (4)$$

Categorical distributions govern sector membership and derived business size. Table 1 lists the research variables and Table 2 and 3 documents the generating distributions and model parameters, which constitute the full assumptions of the study.

3.4. QRIS Adoption Intensity

QRIS Adoption Intensity is defined as the proportion of QRIS transactions to all transactions of MSME i:

$$QAI_{\mathrm{i}} = \frac{N_{QRIS,i}}{N_{Total,I}} \quad (5)$$

$$0 \leq \mathrm{QAI_i} \leq 1 \quad (6)$$

where N_QRIS,i is the number of QRIS transactions and N_Total,i the total number of transactions of MSME i.

3.5. Simulation Scenarios

Six different scenarios are examined: the baseline scenario (S0) where each MSME keeps its adopted share (the mean value of the adopted share equals to 0.322), and five counterfactual scenarios where the adopted share of QRIS is kept fixed to 20%, 40%, 60%, 80%, and 100%, respectively. The last scenario, namely S5, may be regarded as the stress test and not a recommendation for all transactions to be done through digital channels.

3.6. Transaction Time Model

Average payment time blends cash and QRIS service times according to the adoption share:

$$APT_{\mathrm{i}} = (1 - QAI_{\mathrm{i}}) \cdot T_{cash,i} + QAI_{\mathrm{i}} \cdot T_{QRIS,I} \quad (7)$$

QRIS service time responds to connection quality, operator capability, and failure retries:

$$T_{QRIS,i} = T_{base} + \lambda(1 - IR_{\mathrm{i}}) + \kappa(1 - DL_{\mathrm{i}}) + F_{\mathrm{i}} \quad (8)$$

where T_base is the base QRIS processing time, IR_i is internet reliability, DL_i is digital literacy, F_i is the expected additional time from failed or repeated attempts, and λ, κ are penalty coefficients. F_i equals the effective failure probability multiplied by the retry time.

3.7. Transaction Cost Model

Total monthly payment cost sums five components:

$$TPC_{\mathrm{i}} = C_{cash,i} + C_{digital,i} + C_{error,i} + C_{failure,i} + C_{reconciliation,I} \quad (9)$$

$$C_{cash,i} = (1 - QAI_{\mathrm{i}})\left(C_{counting,i} + C_{change,i} + C_{storage,i} + C_{deposit,i}\right) \quad (10)$$

$$C_{digital,i} = QAI_{\mathrm{i}}\left(C_{processing,i} + C_{connectivity,i}\right) \quad (11)$$

The design of the system inherently allows for a tradeoff, where raising QAI leads to a reduction in the cash components, while at the same time increasing the processing (MDR) and connectivity components, along with a secondary dependency cost factor that is proportional to the square of the ratio of digital content over unreliable networks.

3.8. Transaction Error Model

The blended recording error rate mixes channel-specific rates:

$$ER_{\mathrm{i}} = (1 - QAI_{\mathrm{i}}) \cdot ER_{cash,i} + QAI_{\mathrm{i}} \cdot ER_{QRIS,I} \quad (12)$$

Errors in cash involve miscalculations, wrong change given, loss of receipts, and wrong balance of cash. QRIS involves errors in amounts, invalid transaction proof, late confirmations, misdelivery of transactions, and failure to transact after the money has already been deducted. The rates for both channels are reduced by digital literacy, where the QRIS rate is more affected.

3.9. Processing Capacity

$$PC_{\mathrm{i}} = \frac{3600}{APT_{\mathrm{i}}} \quad (13)$$

Hourly processing capacity is the reciprocal of average payment time; shorter service times translate directly into more customers served per hour.

3.10. Data Normalization and the Transaction Efficiency Index

Benefit-type indicators (processing capacity) are normalized by:

$$r_{ij} = \frac{(x_{ij} - \min(x_j))}{(\max(x_j) - \min(x_j))} \quad (14)$$

Cost-type indicators (payment time, total cost, error rate, failure rate, reconciliation time) are normalized by:

$$r_{ij} = \frac{(\max(x_j) - x_{ij})}{(\max(x_j) - \min(x_j))} \quad (15)$$

Normalization is performed on the pooled data of all six conditions so that scores are comparable across scenarios. The Transaction Efficiency Index is the weighted sum of the normalized indicators:

$$TEI_i = \Sigma_j w_j r_{ij}, \ \Sigma_j w_j = 1 \quad (16)$$

Table 4. Weights of the Transaction Efficiency Index

Indicator	Type	Weight
Payment processing time (APT)	Cost	0.20
Total payment cost (TPC)	Cost	0.20
Transaction error rate (ER)	Cost	0.15
Transaction failure rate (TFR)	Cost	0.10
Reconciliation time (RT)	Cost	0.15
Processing capacity (PC)	Benefit	0.20
Total		1.00

TEI values are interpreted using five classes: very low (0.00–0.20), low (0.21–0.40), moderate (0.41–0.60), high (0.61–0.80), and very high (0.81–1.00).

3.11. Monte Carlo Simulation

Parameter uncertainty in service times, network failures, transaction volumes, cash-handling costs, error rates, and adoption intensity is propagated by Monte Carlo simulation (Law, 2015). In each of 1,000 iterations, a fresh synthetic population of 400 MSMEs is drawn, all six conditions are evaluated, indicators are normalized, and per-scenario mean TEI values are stored. Summary statistics comprise the mean, standard deviation, median, 5th and 95th percentiles, and 95% confidence intervals. Scenario contrasts on the paired iteration-level distributions are tested with paired t-tests and Wilcoxon signed-rank tests.

3.12. Statistical Analysis

Beyond scenario comparison, a regression metamodel is estimated on a continuous-adoption experiment in which each MSME of an independent population is assigned a uniformly random QAI in [0, 1]. The base specification is:

$$TEI_i = \beta_0 + \beta_1 QAI_i + \beta_2 DL_i + \beta_3 IR_i + \beta_4 \ln(MTV_i) + \beta_5 BS_i + \beta_6 SEC_i + \varepsilon_i \quad (17)$$

Moderation by digital literacy and by network quality is tested with interaction models:

$$TEI_i = \beta_0 + \beta_1 QAI_i + \beta_2 DL_i + \beta_3 (QAI_i \times DL_i) + \beta X_i + \varepsilon_i \quad (18)$$

$$TEI_i = \beta_0 + \beta_1 QAI_i + \beta_2 IR_i + \beta_3 (QAI_i \times IR_i) + \beta X_i + \varepsilon_i \quad (19)$$

All models use heteroskedasticity-robust (HC3) standard errors.

3.1 Sensitivity Analysis

One-at-a-time (OAT) sensitivity analysis perturbs ten structural parameters by ±20% and records the resulting mean TEI at the moderate-high scenario S3, visualized as a tornado chart (Saltelli et al., 2008). Complementarily, Spearman rank correlations between MSME-level inputs and TEI quantify which merchant characteristics drive efficiency within a scenario.

3.13. Model Validation

Validity involves five validation tests. Face validity: all directional associations were tested on their conceptual validity. Parameter validity: extremes, average values, and distributions were checked in line with feasible ranges for Indonesian micro-merchants. Internal validity: equations and coding were checked for the production of consistent and replicable

results using the same seed. Testing under extreme conditions: the model was tested at QAI=0 and QAI=1 as well as when there is severely degraded internet stability. Robustness testing: changes in the population size, iteration number, and weights of TEI were investigated to ensure that the main order of scenarios is retained.

3.14. Ethical and Reporting Considerations

All data used are artificial and involve no real-life identification of any MSMEs. The findings cannot be considered official estimates of the country's situation, as artificial values are used to analyze the model and no cause-and-effect relationship can be stated without confirmation through real-life transactional data.

4. Result and Discussion

4.1. Characteristics of the Simulated Dataset

The population under reference consists of 400 synthetic MSMEs that include 100 in food and beverages, 100 in retail, 75 in services, 75 in fashion and craft, and 50 other local businesses. Based on the simulated turnover per month, 273 are micro firms, while 127 are classified as small firms. The simulated QRIS adoption level results in 0.322 (SD 0.172), which ranges between 0.022 and 0.888, whereby the majority of the simulated merchants adopt the QRIS but still operate primarily on cash basis. The monthly number of transactions is 1,094 (median 951), and the average transaction value is IDR 38,000. The digital literacy rate is 63.8 (SD 12.6), and the internet reliability is 0.706. See Table 3 for sectoral characteristics.

Table 5. Characteristics of the synthetic MSME dataset by sector

Sector	Simulated MSMEs	Mean monthly volume	Mean value (IDR thousand)	Mean QAI_0
Food and beverages	100	1564	29	0.334
Retail	100	1216	35	0.331
Services	75	731	52	0.300
Fashion and craft	75	789	48	0.327
Other local businesses	50	912	31	0.304
Total	400			

4.2. Descriptive Statistics

Table 4 reports descriptive statistics of the main simulation variables under the baseline condition.

Table 6. Descriptive statistics of simulation variables (baseline S0)

Variable	Mean	SD	Min	Median	P75	Max
QAI (proportion)	0.322	0.172	0.022	0.294	0.434	0.888
Monthly transactions	1094	610	167	951	1385	4234
Payment time (s)	40.3	5.5	26.6	40.0	43.9	55.6
Total cost (IDR thousand)	1054	610	242	892	1329	5756
Error rate (%)	3.14	1.66	0.43	2.85	3.92	10.42
Failure exposure (%)	1.84	2.06	0.01	1.15	2.31	17.20
Reconciliation (h/month)	10.0	5.8	0.8	8.8	12.8	36.3
Capacity (tx/hour)	91	13	65	90	97	135
TEI	0.653	0.083	0.382	0.657	0.708	0.855

4.3. Baseline Transaction Conditions

With a baseline scenario, the average time taken by a transaction is 40.3 seconds, while the cost incurred each month due to payments is IDR 1,054 thousand. The average percentage of recording errors in the combined system is 3.14%, while the proportion of transactions exposed to QRIS failures is 1.84%. On average, each month takes 10.0 hours in reconciliation procedures, while the system can handle 91 transactions per hour.

4.4. QRIS Adoption Scenario Comparison

Table 5 compares the six conditions on all primary indicators, and Table 6 reports the Monte Carlo TEI summary with 95% confidence intervals and efficiency classes.

Table 7. Comparison of QRIS adoption scenarios (reference run, mean values)

Scenario	Payment time (s)	Cost (IDR thousand)	Error (%)	Failure (%)	Capacity (tx/h)	TEI
S0 (baseline)	40.3	1054	3.14	1.84	91	0.653
S1 (20%)	41.9	1073	3.43	1.01	88	0.630
S2 (40%)	39.4	1040	2.88	2.20	93	0.667
S3 (60%)	36.9	990	2.51	3.38	98	0.704
S4 (80%)	34.7	970	1.97	5.25	105	0.740
S5 (100%)	32.3	936	1.48	6.79	113	0.782

Table 8. Transaction Efficiency Index across scenarios (Monte Carlo, 1,000 iterations)

Scenario	Mean TEI	SD	95% CI	P5–P95	Class
S0 (baseline)	0.672	0.015	[0.671, 0.673]	0.647–0.697	High
S1 (20%)	0.651	0.016	[0.650, 0.652]	0.625–0.677	High
S2 (40%)	0.684	0.015	[0.683, 0.685]	0.659–0.708	High
S3 (60%)	0.716	0.013	[0.715, 0.717]	0.695–0.739	High
S4 (80%)	0.750	0.012	[0.749, 0.750]	0.729–0.770	High
S5 (100%)	0.784	0.012	[0.783, 0.785]	0.764–0.803	High

The MEAN TEI increases strictly from S1 to S5, and each counterfactual above the baseline share is an improvement on S0. There are two features that deserve special attention. First, S1 (forced 20% share) is worse than the baseline (0.630 vs. 0.653), as the baseline population is already adopting cash with 32% efficiency, so forcing merchants to use cash decreases efficiency. Second, the increase in TEI with every 20-point adoption step is not equal: +0.037 from S1 to S2, +0.037 to S3, +0.036 to S4, and +0.042 to S5. The steps in the middle are slightly flatter – reflecting the process of diminishing returns driven by the increased risk of failures – but the last step is back up again as all cash handling expenses are removed completely. All pairwise contrasts between the means in Monte Carlo are statistically significant: S5-S0 contrast produces mean difference of 0.112 ($t(435) = 435.3$, $p < 0.001$; Wilcoxon $p < 0.001$), while even the S5-S4 contrast is significant (mean difference 0.034, $p < 0.001$).

4.5. Payment Time and Capacity

The average time taken to make payments reduces from 40.3 seconds at the baseline stage to 36.9 seconds at S3 and 32.3 seconds at S5, which means there is a reduction of 19.9% compared to the baseline. This is because capacity is the inverse of the service time; thus, there is an increase in capacity from 91 to 113 transactions per hour, which is a 24.4% increase.

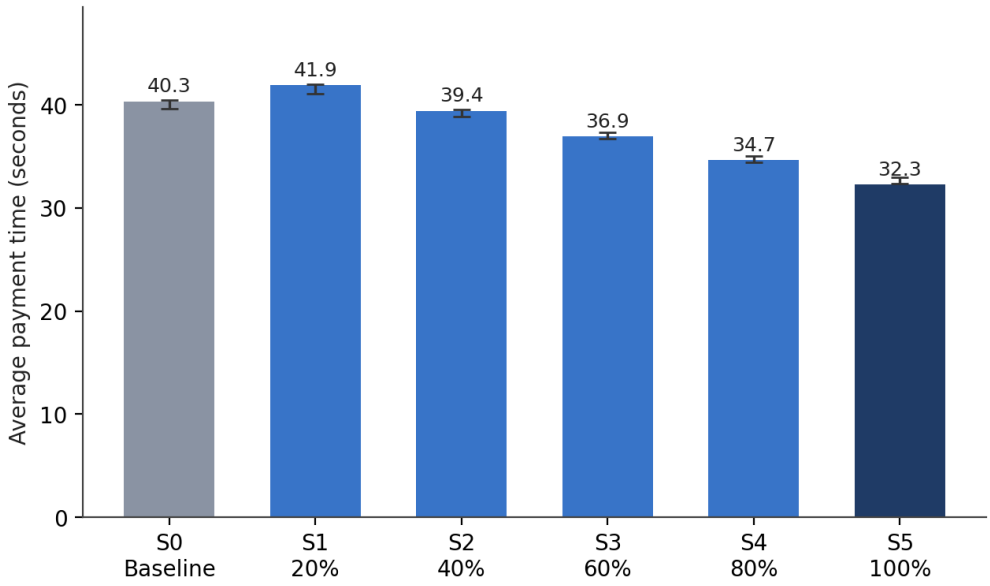

Figure 2. Average payment processing time across QRIS adoption scenarios

4.6. Transaction Cost Analysis

Figure 3 shows the breakdown of the cost of monthly payments. Cash processing drops from IDR 208 thousand to zero at S5, whereas digitization and connectivity climb from IDR 93 to 174 thousand, and failure recovery from IDR 119 to IDR 468 thousand. The overall outcome continues to be positive, as the cost falls by 11.2% at S5 (IDR 1054 → 936 thousand). Nonetheless, there is a major change in the structure of the costs, with an evolution from cost intensive cash processing to fee and infrastructure driven digitization.

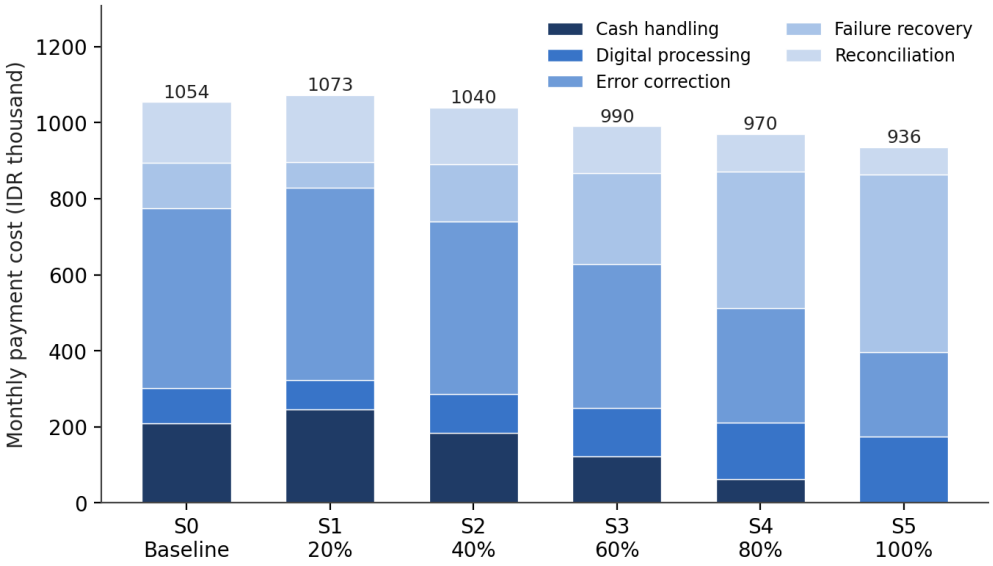

Figure 3. Composition of monthly transaction costs under different QRIS adoption scenarios (totals above bars, IDR thousand)

4.7. Error and Failure Analysis

The two measures of reliability have contrasting trends (see Figure 4). The joint error ratio in recording comes down from 3.14% at baseline to 1.48% at S5, which is a drop of 52.8%, because of the replacement of the manual cash ledger system with automated digital accounting. However, QRIS failure risk, as a measure of failure or retry of the digital transaction over the total number of transactions, increases from 1.84% to 6.79%, since each transaction depends on the network connection and congestion effects build up with poor connections.

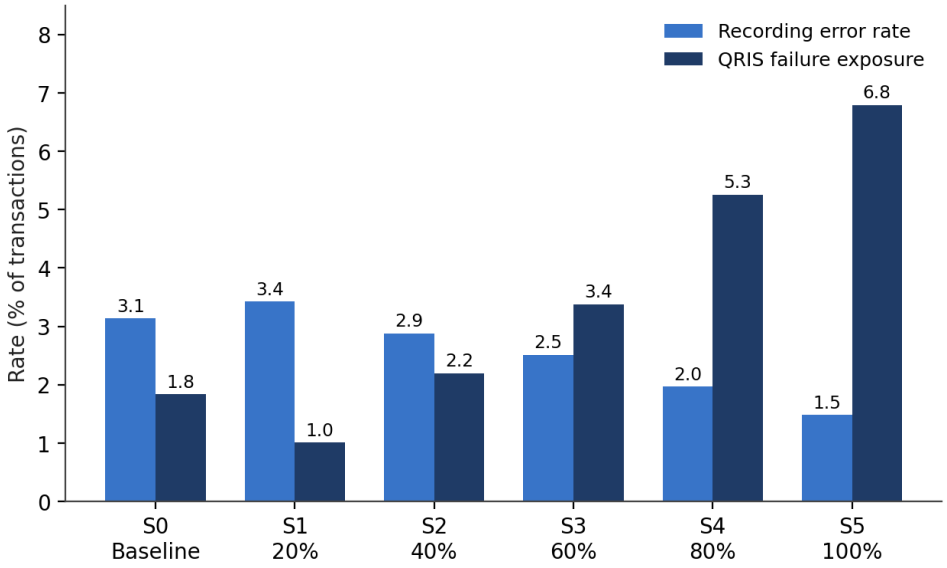

Figure 4. Recording error rate and QRIS failure exposure by adoption scenario

4.8. Transaction Efficiency Index

Figure 5 illustrates the complete distribution of per-MSME TEI. The mean value of the TEI starts off at 0.653 (high class) and goes up to 0.782 (high class) by S5. There is an expansion of the distribution in intermediate situations followed by a contraction in S5, implying that heterogeneity in connectivity and literacy plays the most critical role in the transitional area. For the per-MSME level, the best situation would be S5 for 67.0%, S4 for 21.5%, and S3 and below for the rest 11.5%.

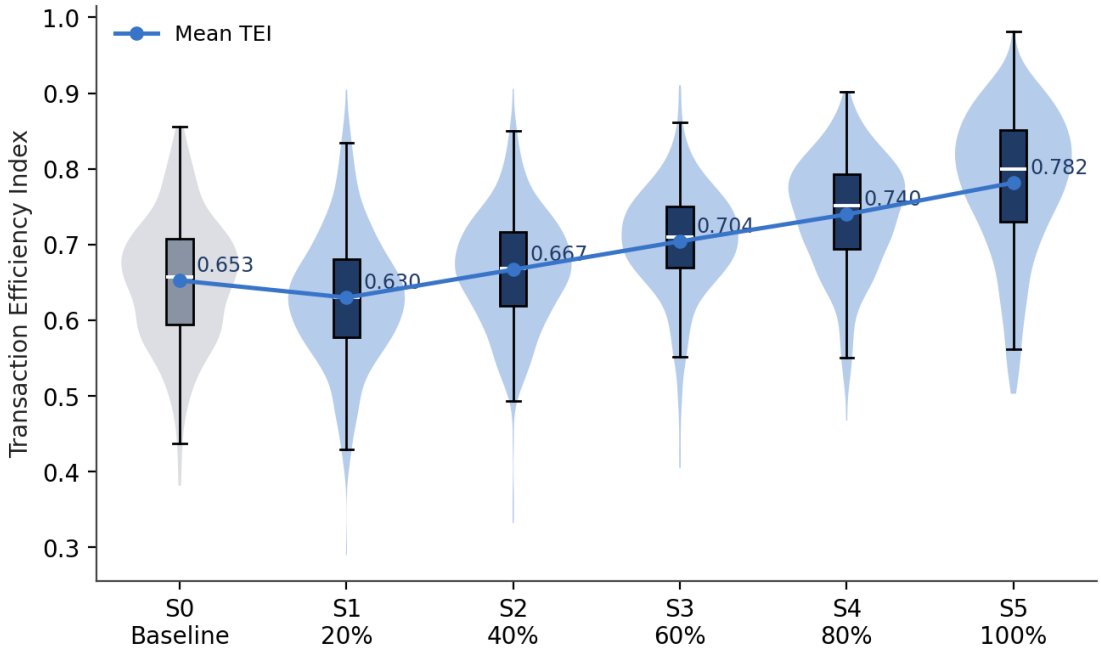

Fig 5. Transaction Efficiency Index across QRIS adoption scenarios (violin: per-MSME distribution; line: mean)

4.9. Sectoral and Size Comparison

The mean values of each sector are shown in Table 9 and Figure 6. The most efficient sector is the services sector (with a score of 0.783 at S5) and fashion and craft (with 0.797), because smaller transaction volume reduces the impact of absolute costs while the bigger ticket value decreases the per transaction friction. The food and beverages sector is the least efficient sector (with a score of 0.610 at S0) and shows the biggest improvement in absolute terms (0.151 TEI points to S5) – because of the high volume of transactions. Micro enterprises are better than small enterprises at all stages (0.719 at S3 vs. 0.673).

Table 9. Sectoral mean TEI across adoption scenarios

Sector	S0	S1	S2	S3	S4	S5
Food and beverages	0.610	0.582	0.621	0.664	0.713	0.762
Retail	0.648	0.626	0.661	0.709	0.743	0.790
Services	0.691	0.666	0.707	0.732	0.755	0.783
Fashion and craft	0.674	0.652	0.694	0.724	0.750	0.797
Other local businesses	0.656	0.647	0.670	0.703	0.749	0.780

4.10. Monte Carlo Simulation Results

Figure 7 shows the distribution of the average TEI per iteration. It can be seen that the distributions of the six scenarios are mostly different except for the S0-S2 scenario where there is overlap due to the baseline falling between 20% and 40% of the counterfactual. There is very little variability in the iteration level results (Standard deviation of 0.012 – 0.016).

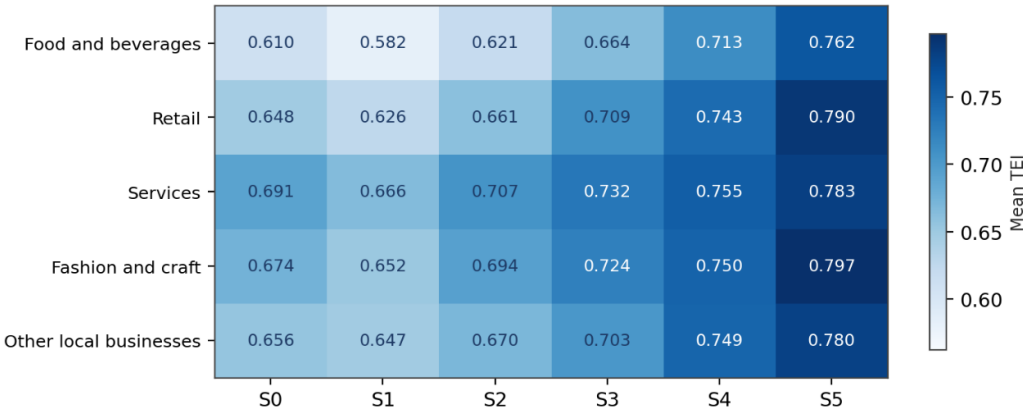

Figure 6. Sectoral efficiency heatmap of mean TEI by scenario

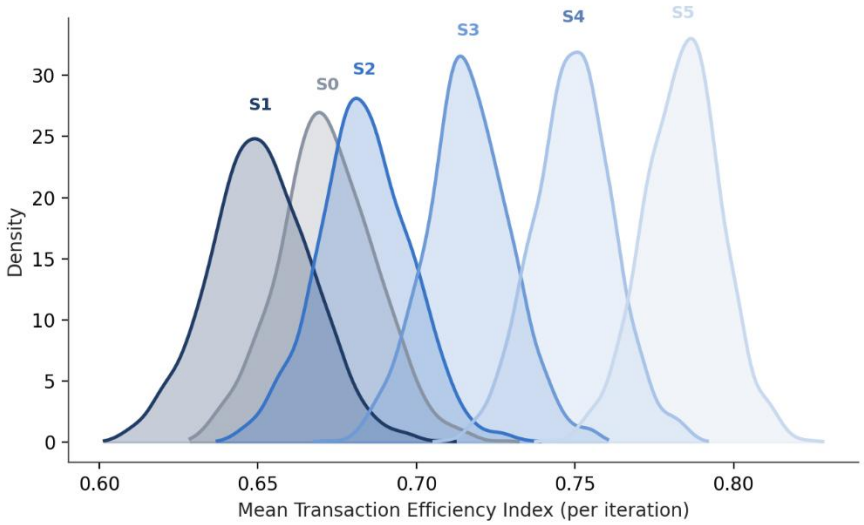

Figure 7. Monte Carlo distribution of mean Transaction Efficiency Index

4.11. Regression Metamodel Results

Table 10 reports the metamodel estimated on the continuous-adoption experiment (Eq. 18). QRIS adoption intensity is the strongest positive driver of TEI ($\beta = 0.170$, $p < 0.001$); internet reliability ($\beta = 0.203$, $p < 0.001$) and digital literacy ($\beta = 0.157$, $p < 0.001$) also raise efficiency, while log transaction volume reduces the normalized index ($\beta = -0.071$, $p < 0.001$) through its cost-level channel. The model explains 57.2% of TEI variance. The interaction models (Eq. 19–20) show that the adoption effect is significantly strengthened by digital literacy ($\beta = 0.236$, $p = 0.022$) and by internet reliability ($\beta = 0.311$, $p < 0.001$): the same increase in QRIS share buys more efficiency for capable, well-connected merchants.

Table 10. Regression metamodel of the Transaction Efficiency Index (HC3 robust errors)

Variable	Coefficient	Std. error	t-value	p-value
QRIS adoption intensity	0.170	0.013	13.08	< 0.001
Digital literacy	0.157	0.026	5.94	< 0.001
Internet reliability	0.203	0.024	8.54	< 0.001
ln(Monthly volume)	-0.071	0.009	-8.14	< 0.001
Business size (small = 1)	0.004	0.008	0.49	0.625
QAI × DL (Eq. 19)	0.236	0.103	2.29	0.022
QAI × IR (Eq. 20)	0.311	0.086	3.64	< 0.001
R^2 (Eq. 18) = 0.572; sector dummies included				

4.12. Sensitivity Analysis

Figure 8 represents the tornado diagram of ±20% perturbation analysis one parameter at a time at S3 (mean TEI for base case = 0.716). The leading parameters here are the time to make cash payment (swing = 0.030) and internet reliability (swing = 0.014). The third important parameter in terms of impact on TEI is the base processing time of QRIS and λ parameter. Cost-related parameters have relatively low swing values because efficiency in this case depends more on time and reliability than on costs. At the merchant side, Spearman correlations confirm the order of importance: TEI at S3 is positively correlated with internet reliability ($\rho = 0.386$, $p < 0.001$) and digital literacy ($\rho = 0.147$, $p = 0.003$); negatively – with cash service time ($\rho = -0.573$) and transactions volume ($\rho = -0.504$).

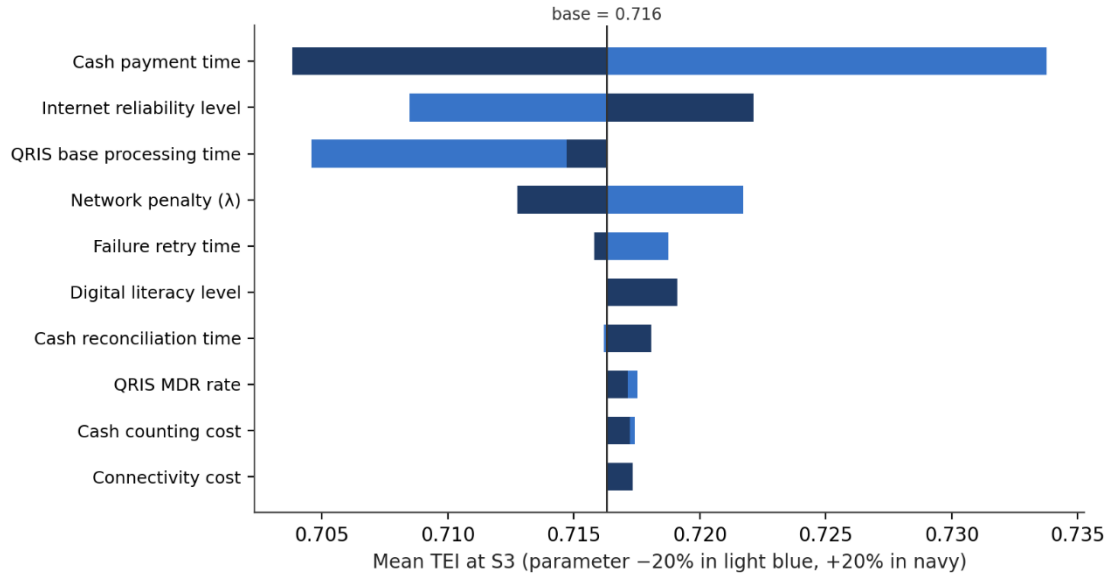

Figure 8. Tornado chart of one-at-a-time parameter sensitivity (mean TEI at scenario S3)

4.13. Robustness and Extreme-Condition Testing

Table 11 illustrates robustness test results. Changing the population size to 300 or 500 MSMEs, halving the number of Monte Carlo iterations, and using uniform weights (1/6 each) instead of expert ones do not affect the ranking order; the leading scenario stays the same (rank stability verified). The test on extreme conditions results in realistic outputs: at QAI = 0, the average transaction time equals 44.0 seconds, and capacity is 84 tx/h; at QAI = 1, it falls down to 32.3 seconds, with a capacity of 113 tx/h. With highly degraded infrastructure (average reliability ≈ 0.27), the TEI curves flatten significantly—S3 (0.670), S4 (0.675), and S5 (0.677) are virtually indistinguishable—thus proving that the need for very high adoption is no longer justified.

Table 11. Robustness testing: mean TEI by scenario under alternative configurations

Configuration	S0	S1	S2	S3	S4	S5
Reference (N = 400)	0.653	0.630	0.667	0.704	0.740	0.782
N = 300	0.668	0.646	0.680	0.714	0.748	0.784
N = 500	0.677	0.656	0.688	0.720	0.752	0.787
500 iterations	0.672	0.651	0.683	0.716	0.750	0.784
Equal weights	0.700	0.683	0.710	0.736	0.762	0.789

The 19.9% simulation of decrease in payment duration is brought about by the removal of cash-related micro-tasks such as cash counting, making change, manually entering data, and verifying cash balances. In addition, there are situations under which the speed gain is reduced, and that is unreliable networks ($\lambda(1-IR)$), hesitation on the part of the operators when they are poorly literate in digital payments ($\kappa(1-DL)$) and retry errors, all of which increase the processing time in seconds. As these factors are proportional to exposure to failure from adoption, it is the merchants who benefit from both reliable networks and high adoption who enjoy higher speed gain, and not just large QRIS adoption.

However, the results do not support the assumption that QRIS decreases all cost elements. On the contrary, the simulation shows the emergence of the structural substitution effect: while cost of handling cash becomes 0 (from IDR 208 to 0 thousand), the cost of digital transactions, connection, and failure handling grows (up to IDR 642 from 213 thousand). The 11.2% of the saving effect appears possible only due to the higher costs related to the handling of cash which are substituted by new cost elements related to the digital technology. From the point of economic optimum, the scenario with minimum total cost of the payment transaction for the given merchant is considered optimal rather than with maximum adoption. The sensitivity analysis suggests that this trade-off is more sensitive to the change in time and reliability than the MDR parameter.

Digitalization cuts the blended error rate by 52.8% and lowers reconciliation time from 10.0 to 4.5 hours per month. Nevertheless, the framework considers reconciliation efficiency to be conditioned on literacy, implying that the merchants should be able to identify whether transactions have been completed or not, match payment proof to sales, and take into account the time difference between the transaction and payment receipt. Where this condition does not hold, the efficiency gains of digitalization are partially offset by the slowness of digital reconciliation – providing a specific mechanism for the QAI x DL interaction.

MSMEs are different in nature, and the simulation captures the impact that results from their differences. The variations between sectoral TEI levels are statistically significant (H7), and micro and small firms have different cost structures. The per MSME optimum differs depending on the scenario, where 67.0% of MSMEs reach their peak level, 21.5% peak at 80%, with others reaching lower peaks. For the scenario of very poor connectivity, the S3-S5 graph flattens out, with the TEI difference being 0.007 TEI levels. This renders the effort to digitalize redundant for anything above moderate levels. Thus, the claim “one scenario applies to all MSMEs” is contradicted by the simulation itself.

In terms of total economic impact (TEI), S5 generates the highest mean TEI of 0.784, with a confidence interval of [0.783, 0.785] for 95%. However, there are three reservations to this apparently positive result. First, the test of S5 is the ultimate stress test of total digitization, where the exposure to failure of S5 is 6.79%, which is roughly 3.7 times higher compared to the base scenario, and the businesses that lack the cash-based option bear the whole cost of every failure. Second, the marginal benefits decrease in the middle range, so that S4 contributes 67.6% to the overall improvement from the base scenario to S5. Third, the conditional analysis based on the quality of the infrastructure shows that the optimal value decreases with decreasing infrastructure reliability. In summary, it is reasonable to say that this is an infrastructure dependent high-adoption optimum.

As part of the Transaction Cost Economics approach, the empirical examination regards the digitalization of payment as a quantitative restructuring of the transaction cost vector, rather than merely a net cost shift, and proves that this restructuring depends on intensity. In the context of Technology Adoption Theory, it is proved that the actual gains do not depend on the adoption/ intention to adopt but on intensity of usage coupled with readiness for operations—the very QAI × DL and QAI × IR interactions represent the embodiment of “facilitating conditions” in numeric form. As for the literature related to network externalities, the research brings to light the reverse side of dependence: with the digital portion tending to one, the quality of networks becomes a limitation rather than an amenity.

In the paper, an entirely documented framework is provided starting with synthetic population design, scenarios generation, composite indicator, Monte Carlo simulation propagation, regression metamodeling, One At A Time (OAT) sensitivity analysis, and finally robustness or extreme condition test. All the parameters used are clearly described in Table 2, and all the results can be reproduced from a certain random seed. The framework can be re-parameterized to fit the QR criteria of another country or merchant population or even calibration with real-world transaction data where available.

The merchants can simply implement the logic of the model by aiming for a QRIS market share percentage that falls in the high adoption bracket, instead of seeing the presence of a QR code as an end in itself. It is expected that cost saving on handling cash will outweigh fees at an MDR of 0.3%. Before increasing the market share, all attention should be given to making sure that the personnel are skilled at payment authentication and digital reconciliations. The level of connectivity must be checked, as it is the key environmental factor determining the benefits that the business stands to gain.

5. Conclusion

This study describes a replicable simulation model which makes a clear connection between the level of adoption of QRIS and MSME transaction efficiency via various mechanisms such as time, cost, error, failure, reconciliation, and capacity. Under the conditions of the model’s assumptions and parameterization, the simulation results show that

increasing the share of QRIS transactions to the level of dominance compared to the current average of 32% will bring: (i) increase in the mean transaction efficiency from 0.653 to 0.782; (ii) 19.9% decrease in the mean payment time; (iii) 11.2% decrease in the total monthly payment cost; (iv) 52.8% decrease in the recording errors; and (v) 24.4% increase in hourly service capacity - along with 3.7 times increase in the exposure to failures of digital transactions.

There are three key results. Firstly, the efficiency is affected not by the adoption but its intensity level – the continuous variable QAI turned out to be the best predictor of the composite index ($\beta = 0.170$, $p < 0.001$). Secondly, there is conditionality of the effect - digital literacy and connectivity have an important impact on the effect of adoption, and in case of poor connectivity, the advantage of very high adoption becomes negligible. Finally, the efficiency frontier is the result of a certain compromise – the 80% adoption rate brings almost all efficiency gains possible at much lower risks of dependence on the infrastructure and thus the conclusion is "as digital as possible, considering infrastructure limitations, with cash as a backup option."

The results above refer to the behavior of the established model and not to the condition of all Indonesian MSMEs as such. Further studies need to be conducted in order to confirm the parameters using actual data from merchant transactions; establish longitudinal studies on the model; examine agent-based modeling and system dynamics models with built-in consumer-merchant interactions; conduct geospatial analysis for different parts of Indonesia; tackle fraud and cyber security; include digital bookkeeping behaviors; and employ machine learning techniques to actual transaction streams for distribution estimation.

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