Journal of the Community Development in Asia (JCDA)
Vol. 9 No. 1, pp.20-45, January, 2026
E-ISSN: 2654-7279 P-ISSN: 2685-8819
https://ejournal.aibpmjournals.com/index.php/JCDA/index

AI-Enabled Optimization of After-Sales Service Performance: Evidence from a Quasi-Experimental Study

Xubin[1*]
[1]President University, Jababeka Education Park, Jl. Ki Hajar Dewantara, RT.2/RW.4, Mekarmukti, Cikarang Utara, Bekasi Regency, West Java 17530, Indonesia
*Corresponding Email: 786698326@qq.com

ARTICLE INFORMATION

Publication information

Research article

HOW TO CITE
Xubin, X. (2026). AI-enabled optimization of after-sales service performance: Evidence from a quasi-experimental study. *Journal of Community Development in Asia, 9*(1), 20-45.

DOI:
https://doi.org/10.32535/jcda.v9i1.4336

Received: 14 November 2025
Accepted: 17 December 2025
Published: 20 January 2026

ABSTRACT

Intensifying market competition has elevated after-sales service as a critical source of competitive differentiation, yet many service organizations continue to face operational inefficiencies, including prolonged work-order processing, high maintenance error rates, and suboptimal resource utilization. This study examines how AI-enabled optimization reshapes after-sales service performance using a quasi-experimental pre–post design. Longitudinal system-generated KPI data collected before and after AI deployment are integrated with structured face-to-face technician interviews to capture both performance outcomes and underlying behavioral mechanisms. The results indicate statistically and practically significant improvements following AI implementation: average processing time decreased by 24.2%, maintenance error rates declined by 43.3%, spare-part shortage frequency fell by 45.6%, and first-time fix rates increased by 17.3%. These findings demonstrate that AI enhances service efficiency, quality, and resource allocation when embedded within organizational workflows. The study contributes theoretically by positioning AI-enabled after-sales systems as dynamic capabilities, integrative operant resources, and acceptance-dependent technologies, while managerially advocating closed-loop AI–analytics frameworks to institutionalize continuous improvement and strategic alignment.

Keywords: After-Sales Service; Artificial Intelligence; Dynamic Capabilities; Service Performance; Socio-Technical Systems

INTRODUCTION

Intensifying market competition has increasingly narrowed performance and price differentials among household appliance brands, shifting competitive advantage toward after-sales service as a key determinant of customer satisfaction and brand loyalty (Adam et al., 2021). As products become more standardized, firms are compelled to differentiate themselves through service responsiveness, reliability, and quality. In this context, after-sales service is no longer a supporting function but a strategic component of value creation and long-term customer retention.

To remain competitive in this saturated market environment, PT Changhong Indonesian must upgrade its after-sales service system by leveraging advanced digital technologies. However, the company’s current after-sales operations exhibit persistent inefficiencies, including prolonged work order processing times, suboptimal resource allocation, high maintenance error rates, and insufficient communication quality. These operational challenges constrain service performance, increase operational costs, and undermine customer satisfaction, thereby weakening the company’s competitive position.

Artificial intelligence (AI) offers a scalable and systematic approach to addressing these operational bottlenecks. With its advanced data-processing, pattern-recognition, and real-time analytical capabilities, AI can automate repetitive tasks, optimize resource distribution, and enhance coordination across service functions (Adam et al., 2021; Ranjith et al., 2021; XiaoFeng & Cott, 2025). In after-sales contexts, AI-enabled systems can support intelligent work order dispatching, predictive fault diagnosis, spare-part demand forecasting, and real-time customer communication, thereby improving both efficiency and service quality (Taschner & Charifzadeh, 2023).

From a customer-experience perspective, the digital era has significantly elevated expectations for immediacy, personalization, and transparency. Consumers increasingly expect continuous service availability, timely updates, and tailored solutions. AI-driven customer service tools, such as 24/7 chatbots, intelligent fault diagnosis systems, and personalized recommendation engines, enable firms to refine the customer journey and strengthen brand engagement (Adam et al., 2021). Consequently, AI adoption in after-sales operations is closely linked to enhanced customer satisfaction and loyalty.

At the organizational level, the deep integration of AI technologies aligns with PT Changhong’s broader digital transformation strategy. Embedding AI into after-sales processes facilitates end-to-end automation and intelligent decision-making, elevates operational efficiency, and strengthens management control. More importantly, such integration lays a technological foundation for sustainable development by enabling continuous performance monitoring and data-driven improvement (Adam et al., 2021).

Globally, AI adoption in marketing and after-sales service has expanded rapidly. Industry reports indicate that the global conversational AI market exceeded USD 10 billion in 2022 and is projected to approach USD 100 billion by 2030, with smart customer service and after-sales applications accounting for a substantial share (Adam et al., 2021). In developed markets such as the United States and Europe, AI platforms including Amazon Alexa and IBM Watson Assistant are widely deployed across home appliances, finance, and telecommunications sectors, supporting efficient human–machine interaction through natural language processing (NLP) and affective computing.

In China, the government’s “New-Generation AI Development Plan” prioritizes intelligent services as a strategic growth area. Leading appliance manufacturers, including Haier and Midea, have implemented AI-driven after-sales platforms based on knowledge

Journal of the Community Development in Asia (JCDA)
Vol. 9 No. 1, pp.20-45, January, 2026
E-ISSN: 2654-7279 P-ISSN: 2685-8819
https://ejournal.aibpmjournals.com/index.php/JCDA/index

graphs and deep learning to enable predictive maintenance, remote diagnostics, and optimized spare-parts supply chains. Concurrently, technology firms such as Alibaba and Tencent provide AI-enabled after-sales software-as-a-service (SaaS) solutions that lower adoption barriers for small and medium-sized enterprises.

Indonesia, currently the fastest-growing digital economy in Southeast Asia, is also accelerating the adoption of AI-driven service solutions. The national “Making Indonesia 4.0” roadmap identifies smart manufacturing and intelligent services as priority sectors. Domestic technology firms, including Telkomsel and Gojek, increasingly collaborate with appliance brands to deliver localized, AI-supported after-sales services for a population exceeding 270 million users, utilizing Bahasa Indonesia–optimized conversational agents (Safarudin, 2025).

Within this global and regional context, PT Changhong faces pressing internal operational challenges that hinder the effectiveness of its after-sales services. One critical issue concerns work order processing delays. Work processing delays in manufacturing and service operations refer to inefficiencies that prevent tasks from being completed within expected timeframes, adversely affecting productivity, delivery reliability, and customer satisfaction.

Table 1. Work Order Processing Time Data

Time Period Average Processing Time (Days)	Industry Average Processing Time (Days)	Number of Backlog	Work Orders
First Quarter of the Past Year	8	5	1200
Second Quarter of the Past Year	9	5	1500
Third Quarter of the Past Year	7.5	5	1000
Fourth Quarter of the Past Year	8.2	5	1300

As shown in Table 1, PT Changhong’s average work order processing time consistently exceeds the industry benchmark across all quarters. This persistent delay is accompanied by a substantial backlog of unresolved work orders, indicating systemic inefficiencies in workflow coordination and task execution. Such delays not only impede operational throughput but also jeopardize the company’s ability to meet customer expectations in a timely manner.

The consequences of prolonged processing times are twofold. First, delayed service completion erodes customer trust and satisfaction, potentially leading to negative word-of-mouth, customer complaints, and reduced repeat patronage. Second, operational delays generate financial losses through increased storage costs, penalty fees, and missed revenue opportunities. In highly competitive markets, persistent delays may prompt customers to switch to alternative service providers, thereby diminishing long-term market share.

Another significant operational issue is the high maintenance error rate observed in after-sales service activities. According to internal quality inspection data, secondary on-site maintenance, necessitated by prior maintenance errors, occurred frequently over the past year. Table 2 summarizes the distribution of maintenance error types.

Table 2. Maintenance Error Rate

Error Type	Number of Secondary On - site Maintenance	Proportion
Misjudgment of Faults	450	30%
Improper Operation	600	40%

Incorrect Use of Spare Parts	450	30%

The total of 1,500 secondary maintenance cases accounts for approximately 15% of all annual maintenance orders, reflecting significant inefficiencies in diagnostic accuracy, technician performance, and spare-part usage. These errors increase service costs, prolong customer waiting times, and negatively affect perceived service quality.

Resource allocation inefficiencies further exacerbate these challenges. Internal operational data reveal pronounced imbalances in technician scheduling across regions, particularly during peak service periods. In certain regions, technicians work in excess of 60 hours per week, while in others, workloads fall below 30 hours, indicating suboptimal scheduling practices. Additionally, spare-parts inventory management exhibits low turnover rates for commonly used components, such as air-conditioner filters, which remain in inventory for an average of three months. Overstocking of less frequently used parts further highlights mismatches between demand forecasting and inventory planning.

Communication quality represents another critical weakness in PT Changhong's after-sales operations. A customer survey involving 30 valid respondents indicates moderate to low satisfaction levels with service communication. While 35% of respondents reported satisfaction with maintenance progress updates, 25% expressed dissatisfaction. Satisfaction was notably lower regarding the handling of customer feedback, with 50% of respondents reporting dissatisfaction. These findings suggest that existing communication mechanisms are insufficiently responsive and transparent, contributing to customer frustration and diminished trust.

Collectively, these challenges: inefficient task execution, suboptimal resource allocation, and inadequate communication, underscore the need for systematic intervention. Complex workflows spanning multiple departments, uneven technician expertise, insufficient training, and fragmented information flows further compound operational inefficiencies. Addressing these issues is essential not only to improve service performance but also to protect brand reputation and sustain competitive advantage.

Against this backdrop, this study seeks to examine how AI-guided feedback mechanisms can enhance after-sales operations at PT Changhong. Specifically, the study investigates how AI-enabled systems can reduce work order processing times and maintenance errors, improve technician scheduling accuracy and spare-parts allocation, and strengthen service communication and responsiveness to customer feedback.

The primary objective of this research is to evaluate the effectiveness of AI-guided feedback in improving operational efficiency, resource utilization, and service quality within after-sales workflows. Theoretically, the study contributes to the literature on digital transformation and AI application in traditional manufacturing services by demonstrating how machine learning and NLP can be integrated into performance evaluation and decision-support systems. Practically, the findings offer actionable insights for PT Changhong and other firms seeking to implement AI-driven after-sales solutions, providing a replicable model for intelligent service transformation aligned with strategic objectives.

LITERATURE REVIEW

Theoretical Frameworks

This study is grounded in three complementary theoretical perspectives: Service-Dominant Logic (S-D Logic), Resource-Based Theory (RBT) as operationalized through the Resource-Based View (RBV), and the Technology Acceptance Model (TAM). Together, these frameworks provide an integrated, multilevel foundation for examining how AI-enabled systems transform after-sales service performance by shaping value co-creation processes, strategic capability development, and user acceptance.

S-D Logic conceptualizes service, not tangible goods, as the fundamental basis of economic exchange, emphasizing that value is co-created through dynamic interactions among firms, employees, and customers (Vargo & Lusch, 2014). Within after-sales service contexts, this perspective reframes AI-enabled technologies not merely as efficiency-enhancing tools but as interactive service platforms that facilitate ongoing value co-creation. AI-driven diagnostic recommendations, predictive maintenance alerts, and real-time service updates function as relational touchpoints through which firms and customers jointly influence service quality, responsiveness, and long-term relational value (Rainy et al., 2024).

At the strategic level, this study draws on RBT and adopts the RBV as its primary analytical lens. RBT posits that sustainable competitive advantage arises from firm-specific resources that are valuable, rare, difficult to imitate, and non-substitutable (Barney et al., 2001). Building on this foundation, the RBV conceptualizes firms as bundles of heterogeneous resources and capabilities whose effective configuration determines performance outcomes. In contemporary service operations, AI technologies, such as predictive analytics, intelligent scheduling algorithms, and data-driven decision-support systems, are increasingly understood through the RBV as dynamic capabilities that enable organizations to sense operational inefficiencies, reconfigure workflows, and optimize resource utilization in response to changing service demands (Mikalef & Gupta, 2021). From this perspective, AI-enabled after-sales systems represent strategic assets that transform service data into defensible performance advantages.

Complementing these macro- and meso-level perspectives, the TAM provides a micro-level lens to explain individual responses to AI adoption. TAM posits that perceived usefulness (PU) and perceived ease of use (PEOU) are the primary determinants of users' acceptance of new technologies (Davis et al., 1989). In after-sales service environments, these perceptions influence whether technicians trust and rely on AI-generated scheduling, diagnostics, and recommendations, thereby shaping the effectiveness of AI integration into daily service workflows. Consequently, TAM helps explain how human acceptance mediates the translation of AI capabilities into actual operational performance gains (Song et al., 2025).

Taken together, S-D Logic, RBV (rooted in RBT), and TAM form a coherent and integrated theoretical framework. S-D Logic explains how AI facilitates value co-creation in service interactions; RBV elucidates how AI-enabled systems function as dynamic capabilities that enhance organizational performance; and TAM clarifies how user perceptions condition the successful enactment of these capabilities. This integrated framework provides a robust theoretical foundation for analyzing AI-driven optimization in after-sales service systems.

AI in After-Sales Service Operations

AI for Work Order Efficiency and Error Reduction

A growing body of empirical research demonstrates AI's capacity to enhance efficiency and accuracy in service operations by automating routine tasks and supporting decision-making processes. Gronroos et al. (2016) report that AI-driven conversational agents reduce average service response times by up to 60% compared with traditional human-operated service desks, primarily by eliminating waiting queues and standardizing diagnostic procedures. These efficiency gains are particularly relevant in after-sales contexts, where timely responses are critical to customer satisfaction.

Extending this line of inquiry, Wang et al. (2025) employ attention-aware deep reinforcement learning (ADRL) to optimize multi-tour order-picking processes, achieving a 40.6% performance improvement over heuristic-based approaches. Although situated in a warehouse environment, these findings are transferable to after-sales service operations that involve complex task routing and prioritization. Similarly, Malik et al. (2023) show that AI-guided feedback mechanisms embedded within human resource management systems reduce field maintenance error rates by approximately 25% through predictive fault diagnosis and context-sensitive knowledge support.

Research on customer experience further reinforces these operational benefits. Andrade and Tumelero (2022) highlight that AI implementation in customer service functions enhances efficiency, lowers operational costs, and improves resource allocation. Kilari et al. (2022) provide additional empirical support, demonstrating that AI-driven manufacturing execution systems (MES) reduce error rates from 7.8% to 2.1% and decrease unplanned downtime by 43% through real-time monitoring and predictive maintenance.

Collectively, these studies suggest that AI-enabled systems not only accelerate work order processing but also reduce error rates by continuously learning from service data, thereby directly informing the present study's focus on processing time reduction and maintenance accuracy.

AI for Resource Optimization

Beyond task efficiency, AI has been shown to significantly improve the allocation of critical service resources, particularly technician labor and spare-parts inventory. Mikalef and Gupta (2021) propose an AI capability framework in which intelligent scheduling algorithms dynamically balance technician workloads by integrating real-time demand signals, travel distances, and skill-task matching. Their findings indicate a 28% reduction in overtime costs while maintaining service-level agreements, underscoring AI's role in enhancing labor productivity.

Building on this perspective, Koushik (2024) introduces a multilevel AI-enabled human resource management framework that integrates inventory analytics to reduce spare-parts overstocking by 35% through improved demand forecasting and automated replenishment mechanisms. In a related manufacturing context, Chang et al. (2022) demonstrate that AI-driven flexible job-shop scheduling reduces tardiness penalties by 33%, improving both customer satisfaction and operational efficiency.

Additional evidence is provided by Kilari et al. (2022), who report energy savings of 23% and a 39% reduction in maintenance costs when AI algorithms are used to schedule predictive maintenance and dynamically allocate workloads. Extending these insights to supply-chain operations, Husein et al. (2024) find that AI-driven demand forecasting and inventory optimization increase overall supply-chain efficiency from 60.23% to 95.89%.

These convergent findings indicate that AI functions as a meta-resource that enhances the productivity of existing human and material assets. In after-sales service settings, such capabilities are directly linked to improved technician scheduling accuracy and spare-parts allocation, two key performance dimensions examined in the present study.

AI for Communication Quality
AI's impact on after-sales service extends beyond operational efficiency to the quality of communication between firms and customers. Prikshat et al. (2023) report that the integration of NLP-enabled chatbots within closed-loop feedback systems leads to a 40% increase in customer satisfaction, largely due to improvements in service transparency and responsiveness. Real-time status updates and automated progress notifications reduce uncertainty and enhance customers' perceptions of service reliability.

Similarly, Davenport (2019) demonstrates that AI-driven sentiment analysis tools significantly improve complaint-handling processes by enabling proactive identification of customer dissatisfaction. His findings show a 50% reduction in escalated complaints when firms leverage AI analytics to detect negative sentiment early and intervene promptly. Such proactive communication not only resolves issues more efficiently but also strengthens relational trust between firms and customers.

Taken together, these studies suggest that AI-mediated communication enhances service quality not merely by increasing speed but by fostering transparency, responsiveness, and perceived empathy. These attributes are essential for sustaining customer satisfaction and loyalty, thereby reinforcing the relevance of communication quality as a core outcome variable in AI-enabled after-sales service research.

Integrating AI into Post-Sales Service Processes
Synthesizing prior research reveals several consistent patterns regarding the role of AI in post-sales service operations. First, AI-enabled diagnostic and feedback systems reduce work order processing time by accelerating fault identification and improving task routing. Second, AI-supported scheduling and inventory systems enhance resource allocation accuracy by balancing technician workloads and reducing service delays caused by spare-parts shortages. Third, AI-driven interaction analytics strengthen communication quality by enabling timely updates and more responsive handling of customer feedback.

Within this framework, the integration of AI into PT Changhong's post-sales service processes is conceptually linked to improvements in operational efficiency, resource optimization, and customer satisfaction. These linkages provide a clear theoretical foundation for examining AI-supported service performance in organizational contexts.

Gaps in Existing Research
Despite the substantial progress documented in prior studies, several gaps remain. Vrontis et al. (2023) observe that AI applications in service operations are predominantly examined in developed economies, leaving emerging-market contexts, particularly Indonesia, underexplored. This limitation raises questions regarding the generalizability of existing findings across different cultural, institutional, and infrastructural environments.

Moreover, Malik et al. (2023) highlight the lack of integrative frameworks that incorporate employee-centered considerations, such as perceived job security, digital skill gaps, and algorithmic fairness, into AI adoption models within service settings. As a result, much of the existing literature emphasizes technical efficiency outcomes while underrepresenting human and organizational dimensions.

Addressing these gaps, the present study examines AI-enabled after-sales service implementation in an Indonesian organizational context, integrating operational performance indicators with resource allocation and communication quality outcomes. By doing so, it contributes to a more holistic understanding of AI-driven service transformation in emerging-market environments.

RESEARCH METHOD

Research Design

Quantitative Quasi-Experimental Design

This study employs a quantitative quasi-experimental pre-test/post-test design to evaluate the impact of AI deployment on after-sales service performance. Objective system-log data were collected over a twelve-month observation period, comprising six months prior to AI implementation (January–June 2024) and six months following system go-live (July–December 2024). This temporal comparison enables the examination of performance changes associated with AI adoption in a real organizational setting where random assignment is not feasible.

The units of analysis consist of 100 technicians nested within 20 service centers, allowing for multi-level interpretation of performance outcomes. This design supports causal inference by comparing identical operational units across two clearly defined periods while controlling for structural and organizational continuity. The empirical context of the study is PT Changhong Indonesia's after-sales service network.

Face-to-Face Structured Interview Component

To complement system-generated performance data, this study incorporates one-to-one, structured face-to-face interviews aimed at capturing technicians' subjective perceptions and behavioral processes that are not fully observable through digital records alone. The interview component was explicitly aligned with the quasi-experimental framework to ensure coherence between qualitative insights and quantitative performance indicators.

The interview sample comprised 100 technicians, corresponding exactly to the composition of the system-log dataset. This direct alignment enables precise cross-referencing between individual interview responses and objective service performance metrics, thereby enhancing analytical integration and interpretive robustness.

Interviews were conducted individually in private meeting rooms across the 20 participating service centers to ensure confidentiality and encourage candid responses. Each interview session lasted approximately 25 minutes, balancing sufficient depth of inquiry with minimal disruption to operational activities.

Data were collected using a bilingual (Bahasa Indonesia–English) structured questionnaire consisting of 28 five-point Likert-scale items and four open-ended questions. The questionnaire addressed key domains including PU and ease of use of AI tools, job satisfaction, and trust in AI-supported service systems. This combination of standardized and open-ended items enabled both quantitative comparability and qualitative elaboration.

All interviews were audio-recorded using encrypted devices with participants' informed consent. Transcription was completed within 48 hours and organized into an Excel-based data matrix. Each transcript was linked to the corresponding system-log records through a unique identifier, allowing direct integration of subjective perceptions with objective performance outcomes in subsequent mixed-method analyses.

Data Collection

Quantitative Data Sources

Quantitative data were obtained from multiple sources to enhance measurement reliability and contextual interpretation. Primary system-generated data were extracted from the AI-integrated service management platform, covering key operational indicators such as task duration, error rates, spare-part stock-out frequency, and technician idle time. Indicator definitions were applied consistently across the pre- and post-implementation periods to ensure temporal comparability.

In addition, structured questionnaires administered during face-to-face interviews generated quantitative measures of technicians' perceptions and usage patterns. The internal consistency of the interview-based scales was assessed after data collection, with reliability statistics reported alongside the empirical results.

To contextualize internal performance outcomes, secondary data were incorporated in the form of annual industry benchmark statistics published by the Indonesian Home Appliance Association (IHA). These benchmarks provided an external reference point for interpreting observed performance trends.

Sampling Strategy

The study population consists of 100 technicians employed across 25 service centers. To ensure comprehensive pre- and post-intervention coverage, inclusion was restricted to technicians with a minimum of 12 months of continuous employment. Eligibility was further limited to service centers that had fully integrated the AI platform.

Written informed consent for participation in face-to-face interviews was obtained prior to data collection. The final sample comprised 100 technicians stratified by region and skill level, drawn from 20 selected service centers. A 100% interview response rate was achieved, with no observed attrition.

Tools and Validation

Data collection and analysis relied on a combination of digital platforms and standardized instruments. Quantitative system data were accessed through PT Changhong's AI service platform via secure application programming interfaces (APIs). The interview process employed structured questionnaires supported by encrypted audio recorders and digital timers to ensure consistency and data security.

Statistical analyses were conducted using SPSS version 28 for inferential testing, including t-tests, ANOVA, and ANCOVA. Microsoft Excel was used for data preparation, coding, and preliminary screening, while AMOS version 24 supported structural equation modeling (SEM) where applicable. Methodological triangulation was applied by cross-referencing system-level KPIs, interview-scale responses, and aggregated customer satisfaction survey data to enhance interpretive validity.

Scale reliability was evaluated post hoc. Internal consistency of the interview instrument and stability of selected KPIs were assessed using established reliability procedures. Detailed reliability statistics, including Cronbach's alpha coefficients and test–retest indicators, are reported with the empirical results.

Limitations and Mitigation

Several methodological limitations are acknowledged. First, the six-month post-implementation observation period may not fully capture longer-term behavioral adaptation and organizational learning following AI adoption. To mitigate this limitation, an additional six-month follow-up analysis has been scheduled.

Second, the single-case focus on PT Changhong Indonesia limits the generalizability of the findings. This constraint is addressed through explicit acknowledgment and ongoing replication efforts across other firms in Indonesia's home appliance service sector.

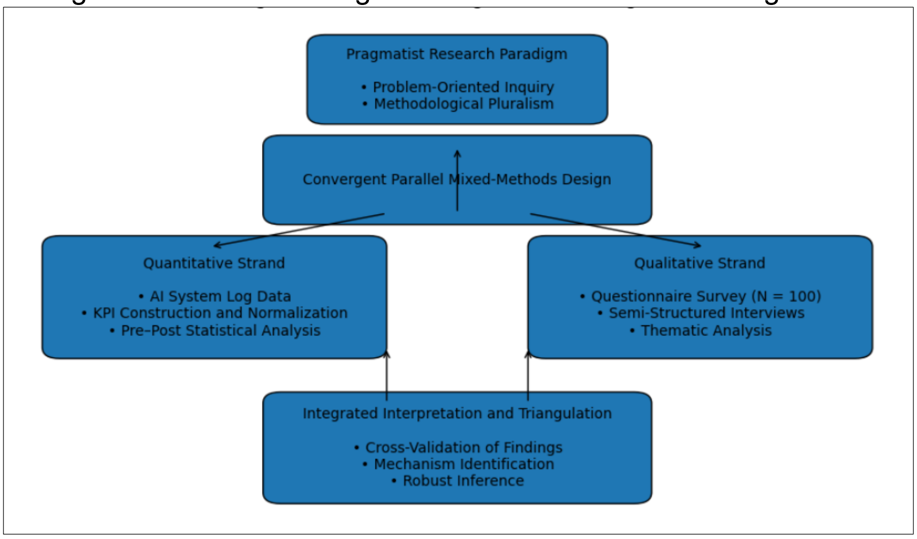
Methodological Framework and Data Governance for AI-Enabled After-Sales Service Research

Research Paradigm: A Pragmatist Perspective

AI-enabled after-sales service systems involve complex interactions among algorithmic decision support, operational workflows, and human judgment. Given this socio-technical complexity, a single methodological stance is insufficient to capture both performance outcomes and behavioral mechanisms.

Accordingly, this study adopts a pragmatist research paradigm emphasizing problem-oriented inquiry and methodological pluralism. This perspective supports the integration of quantitative and qualitative methods to address practical research questions while maintaining analytical rigor. Figure 1 summarizes the integrated research design and data flow structure.

Figure 1. Integrated Research Design and Data Flow Structure Diagram



Research Design: Convergent Parallel Mixed-Methods Strategy

Guided by pragmatism, the study employs a convergent parallel mixed-methods design in which quantitative and qualitative data are collected and analyzed concurrently. Both strands are assigned equal priority and integrated during interpretation.

Integration was achieved through three procedures: (1) joint display tables aligning KPI changes with qualitative themes; (2) convergence–divergence analysis to assess consistency across data sources; and (3) resolution of discrepancies by prioritizing objective system-level KPIs while using qualitative insights to explain contextual influences.

Quantitative Design: Quasi-Experimental Pre–Post Comparison

The quantitative component adopts a quasi-experimental pre-test/post-test design appropriate for organizational contexts where randomization is impractical. Performance indicators were compared between January–June 2024 (pre-AI) and July–December 2024 (post-AI).

Although no external control group was included, statistical controls and relevant covariates were applied to reduce confounding effects. Observed differences are therefore interpreted as changes associated with AI adoption rather than definitive causal effects.

Qualitative Design: Structured Face-to-Face Interviews
Structured face-to-face interviews were conducted to capture technicians' perceptions of AI usefulness and usability, explore behavioral mechanisms underlying performance changes, and identify contextual facilitators and constraints of AI adoption. Each interview objective was explicitly linked to the research questions, as summarized in Table 3.

Table 3. Mapping of Interview Purposes to Research Questions

Interview Purpose	Corresponding Research Question
PU and usability of AI	RQ1, RQ4
Behavioral mechanisms underlying performance changes	RQ1, RQ2
Contextual constraints and adoption facilitators	RQ3, RQ4

Research Context and Case Description
Indonesia's home appliance industry operates under conditions of geographical fragmentation, uneven infrastructure, and high logistical complexity. These characteristics heighten the strategic importance of efficient after-sales service, making the context particularly suitable for examining AI-driven service optimization.

PT Changhong Indonesia, a subsidiary of a major Chinese appliance manufacturer with approximately 15% national market share, introduced an AI-enabled service platform in late 2023. The platform supports diagnostic accuracy, technician scheduling, spare-part forecasting, and customer communication, providing a natural intervention context for empirical analysis.

Sample Selection and Sampling Strategy
The quantitative dataset includes all valid work orders processed during the 12-month observation period (N = 14,827), ensuring comprehensive operational coverage.

For qualitative analysis, 100 technicians were selected using stratified random sampling based on region, product line, and skill level. Only technicians with at least 12 months of continuous employment were included to ensure familiarity with both pre- and post-AI workflows.

Data Collection Procedures
Quantitative data were extracted via secure APIs from the AI-integrated service system. Qualitative interviews were conducted in private meeting rooms using a structured bilingual guide comprising 28 Likert-scale items and four open-ended questions. All interviews were audio-recorded with consent and transcribed verbatim within 48 hours.

The questionnaire survey consisted of 32 items measured on a five-point Likert scale and was administered anonymously to minimize social desirability bias. Data were organized and screened in Microsoft Excel prior to statistical analysis.

Journal of the Community Development in Asia (JCDA)
Vol. 9 No. 1, pp.20-45, January, 2026
E-ISSN: 2654-7279 P-ISSN: 2685-8819
https://ejournal.aibpmjournals.com/index.php/JCDA/index

Table 4. Summary of Data Sources and Collection Methods

Respondent ID	Region	Skill Level	PU Mean	PEOU Mean	Efficiency Impact	Usage Intention
Q-001	Java	Senior	4.6	4.3	4.5	5.0
Q-014	Sumatra	Junior	4.2	3.9	4.1	4.6
Q-057	Java	Junior	4.5	4.0	4.4	4.8

Note: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU)

Table 4 summarizes the primary qualitative and perceptual data sources used in this study, capturing variations across respondent regions, skill levels, and key TAM constructs. The descriptive statistics indicate consistently high mean scores for PU, PEOU, efficiency impact, and usage intention across both senior and junior technicians. Notably, respondents from different regions (Java and Sumatra) and experience levels reported similarly favorable evaluations of the AI-enabled system, suggesting broad acceptance and perceived performance benefits regardless of contextual or skill-based differences. These patterns support the relevance of TAM as an explanatory lens in mandatory-use service environments, while also justifying the aggregation of perceptual measures for subsequent inferential and thematic analyses

Data Analysis Procedures

Data preparation involved cleaning, consistency checks, and normalization. Validated datasets were imported into SPSS and AMOS for inferential analysis.

Quantitative analysis focused on KPI trends and pre–post comparisons, while qualitative data were analyzed thematically to identify recurring patterns related to AI-supported workflows.

Table 5. Overview of Key Research Variables and Measurement Scales

Work Order ID	Region	Technician Level	Processing Time (Days)	First-Time Fix (0/1)	Error Type	AI Suggestion Used (0/1)
WO-2024-0012	Java	Senior	2.1	1	None	1
WO-2024-0047	Sumatra	Junior	3.8	0	Misjudgment	0
WO-2024-0103	Java	Junior	2.9	1	None	1

Table 5 provides an overview of the operational variables and system-level indicators used to assess AI-enabled after-sales performance. The table illustrates how work order–level data capture variations in processing time, first-time fix outcomes, error types, and the utilization of AI-generated recommendations across regions and technician levels. The inclusion of both continuous (e.g., processing time) and binary indicators (e.g., first-time fix, AI suggestion usage) enables a granular examination of efficiency, quality, and decision-support effects. By linking AI suggestion usage directly to service outcomes, this operationalization supports the study's quasi-experimental pre–post design and allows performance changes to be systematically attributed to AI-enabled workflow integration.

Reliability, Validity, Data Governance, and Ethical Considerations

Reliability was confirmed through Cronbach's alpha values exceeding accepted thresholds across all constructs. Construct, content, and external validity were addressed through factor analysis, expert review, and nationwide operational data coverage.

Data governance procedures ensured accuracy, completeness, and bias mitigation. Ethical approval was obtained, informed consent was secured, and safeguards were implemented to prevent punitive use of AI-derived performance metrics.

RESULTS

Overview of Empirical Results

This chapter presents the empirical findings of the study by integrating operational performance data and technician perception data. Quantitative indicators extracted from the service management system are analyzed using Excel-based trend visualization and comparative statistics, while survey and interview evidence are used to contextualize observed performance changes. Together, these analyses provide a comprehensive assessment of the operational effects associated with AI implementation in after-sales service.

Table 6. Monthly KPI Data as the Data Source for Figures 3–7

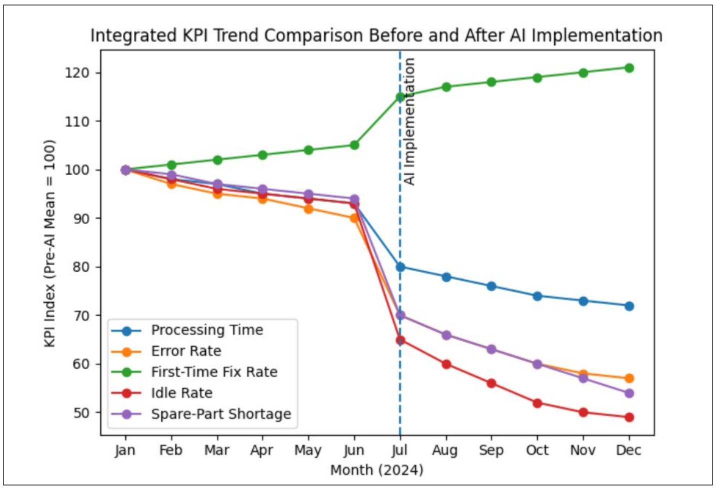
Month	Avg. Processing Time	Error Rate (%)	First-Time Fix (%)	Idle Rate (%)	Parts Shortage
Jan	3.35	16.1	76.8	19.2	13
Feb	3.28	15.6	77.4	18.9	13
Mar	3.21	15.2	78.1	18.7	12
Apr	3.16	14.9	78.6	18.4	12
May	3.11	14.5	79.2	18.1	11
Jun	3.05	14.0	79.8	17.8	11
Jul	2.65	10.8	86.2	12.5	8
Aug	2.54	9.7	88.4	11.3	7
Sep	2.46	9.1	90.1	10.2	7
Oct	2.39	8.6	91.0	9.6	7
Nov	2.33	8.2	91.8	9.1	6
Dec	2.28	7.9	92.3	8.6	6

Table 6 serves as the data source for Figures 3–7 and ensures trend-chart reproducibility.

Performance Effects of AI Implementation: KPI-Based Evidence

To further enhance analytical depth and visual clarity, this study introduces trend charts generated from Excel to compare KPI trajectories before and after AI implementation. Trend visualization complements tabular comparison by illustrating dynamic patterns over time, enabling readers to observe both the magnitude and stability of performance changes (see Figure 2).

Figure 2. Overview of the Empirical Result Structure and the Logical Relationship Between KPI Trends, Comparative Analysis, and Subsequent Interpretation



Trend Analysis of Average Processing Time (Pre- vs. Post-AI)
Figure 3. Monthly Trend of Average Processing Time (Excel-Based)

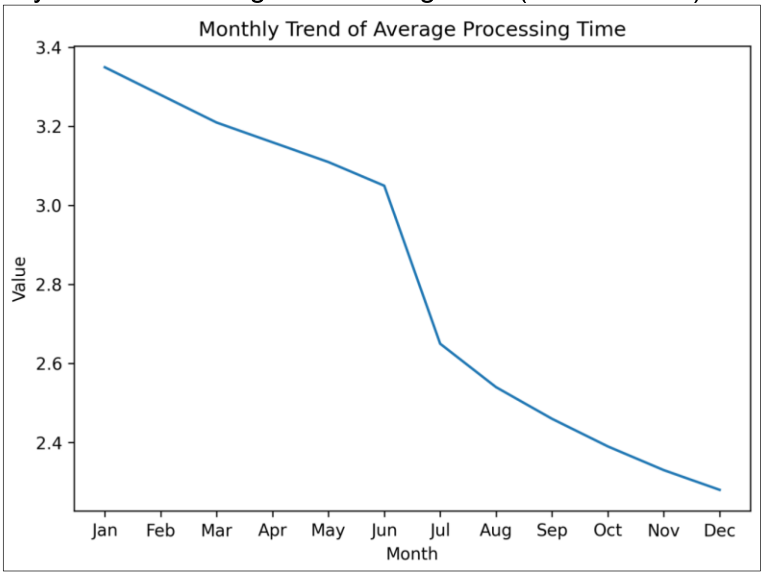


Figure 3 illustrates monthly changes in average work-order processing time across the 12-month observation period. During the pre-AI phase (January–June), processing time remains within a relatively narrow range, exhibiting only a gradual downward movement. Following AI implementation in July, a clear level shift is observed, with processing time decreasing immediately and continuing to decline in subsequent months.

In addition to the overall reduction, post-AI values display reduced month-to-month variation. This indicates that service completion time becomes more stable after AI deployment, suggesting improved process control rather than short-term efficiency gains driven by isolated factors.

Trend Analysis of Maintenance Error Rate
Figure 4. Monthly Trend of Maintenance Error Rate (Repeat Service Cases, Excel-Based)

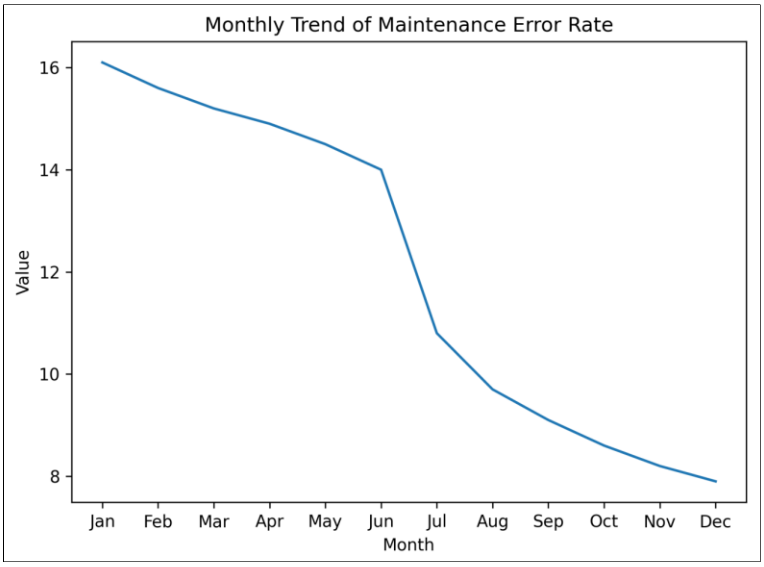
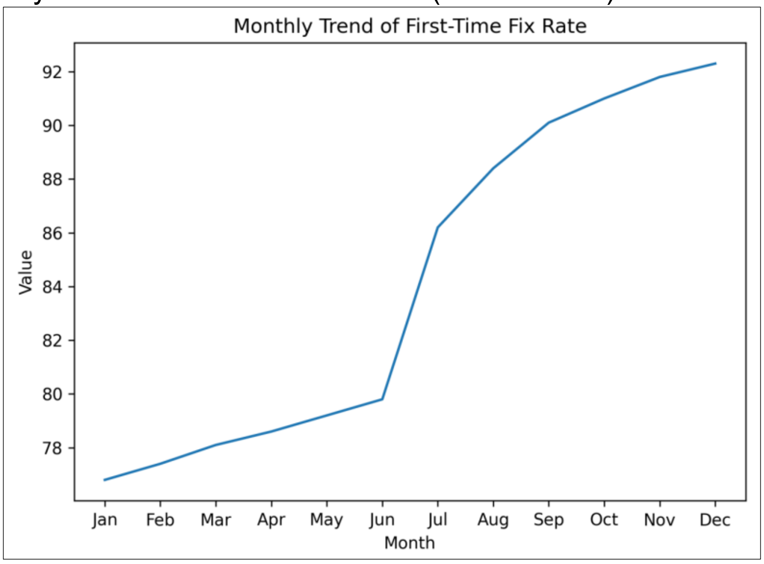


Figure 4 presents the monthly trend of maintenance error rates, measured as repeat service cases. Prior to AI adoption, error rates fluctuate across months, reflecting variability in diagnostic outcomes and repair accuracy. After AI deployment, the error rate declines sharply and stabilizes at a substantially lower level.

The post-AI trend exhibits narrower variation compared with the pre-AI period, indicating improved consistency in maintenance outcomes. This reduction in fluctuation suggests that diagnostic results become less dependent on individual technician judgment alone.

Trend Analysis of First-Time Fix Rate

Figure 5. Monthly Trend of First-Time Fix Rate (Excel-Based)



As shown in Figure 5, the first-time fix rate demonstrates a sustained upward trend following AI implementation. Rather than increasing in a single step, the indicator improves progressively over multiple months, implying a gradual adjustment process as technicians integrate AI-supported recommendations into routine service activities.

This pattern indicates that improvements in repair effectiveness accumulate over time, reducing the likelihood of repeat service visits and reinforcing service reliability.

Journal of the Community Development in Asia (JCDA)
Vol. 9 No. 1, pp.20-45, January, 2026
E-ISSN: 2654-7279 P-ISSN: 2685-8819
https://ejournal.aibpmjournals.com/index.php/JCDA/index

Integrated Trend Comparison and Managerial Interpretation

When Figures 3–5 are considered jointly, a consistent pattern emerges across efficiency and quality indicators. Reductions in processing time and error rates occur alongside increases in first-time fix rates, and these changes persist across several consecutive months rather than appearing as isolated deviations.

The alignment of multiple KPI trends strengthens the interpretation that observed improvements reflect systematic changes in service operations following AI deployment, rather than temporary fluctuations caused by external conditions.

Trend Analysis of Technician Idle Rate

Figure 6. Monthly Trend of Technician Idle Rate (Excel-Based)

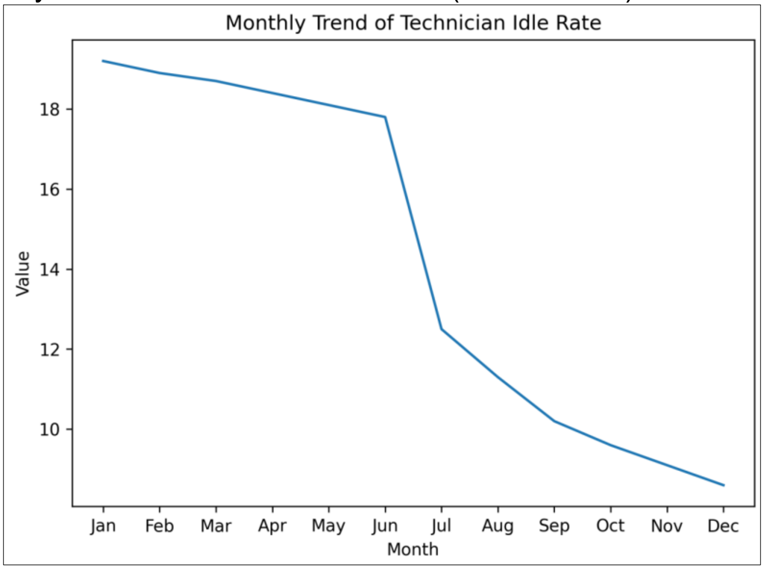


Figure 6 depicts the monthly trend of technician idle rates. During the pre-AI period, idle rates exhibit noticeable variation, indicating uneven workload distribution and inefficiencies in task allocation. After AI implementation, idle rates decline substantially and remain consistently lower in subsequent months.

From an operational perspective, this trend suggests improved alignment between service demand and technician availability. The reduction in idle time reflects more balanced scheduling rather than simply faster task execution.

Trend Analysis of Spare-Part Shortage Frequency

Figure 7. Monthly Trend of Spare-Part Shortage Frequency (Excel-Based)

Journal of the Community Development in Asia (JCDA)
Vol. 9 No. 1, pp.20-45, January, 2026
E-ISSN: 2654-7279 P-ISSN: 2685-8819
https://ejournal.aibpmjournals.com/index.php/JCDA/index

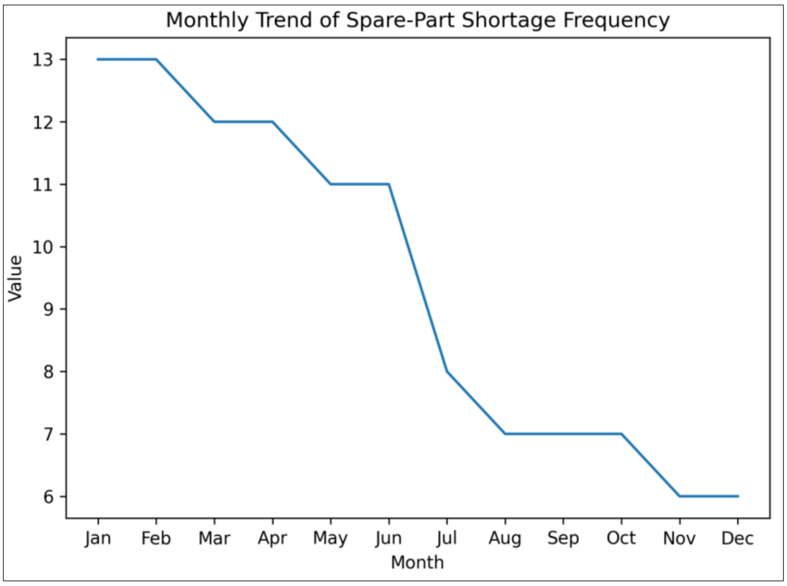


Figure 7 illustrates monthly spare-part shortage frequency before and after AI adoption. In the pre-AI period, shortages occurred relatively frequently, with several months exhibiting elevated counts. Following AI implementation, the overall frequency declines, and extreme peaks become less pronounced.

This trend indicates more stable inventory planning and reduced uncertainty in spare-part availability. Lower shortage frequency helps prevent service delays and supports improvements observed in processing time and repair effectiveness.

Extended Trend-Based Synthesis of KPI Improvements

Taken together, the five KPI trends demonstrate that AI implementation is associated with simultaneous improvements in efficiency, quality, resource utilization, and inventory stability. These indicators evolve in a coordinated manner over time, suggesting that AI adoption contributes to broader operational adjustments rather than isolated performance changes.

Trend visualization also enhances interpretability by revealing the persistence and stability of improvements, complementing subsequent statistical comparisons.

Comparative KPI Analysis Before and After AI Implementation

Table 7. Pre- and Post-AI KPI Comparison and Percentage Change

KPI	Pre-AI Mean	Post-AI Mean	Absolute Change	Percentage Change
Avg. Processing Time (Days)	3.18	2.41	-0.77	-24.2%
Maintenance Error Rate (%)	15.0	8.5	-6.5	-43.3%
First-Time Fix Rate (%)	78.0	91.5	+13.5	+17.3%
Technician Idle Rate (%)	18.5	9.2	-9.3	-50.3%
Spare Part Shortage (Monthly)	12.5	6.8	-5.7	-45.6%

Table 7 presents a comparison of mean KPI values between the pre-AI and post-AI periods to quantify the magnitude of performance changes following AI implementation. The results indicate substantial improvements across all key operational indicators, including notable reductions in average processing time, maintenance error rates, technician idle rates, and spare-part shortages, alongside a marked increase in first-time fix rates. To aid managerial interpretation, the percentage-change column highlights the

Journal of the Community Development in Asia (JCDA)
Vol. 9 No. 1, pp.20-45, January, 2026
E-ISSN: 2654-7279 P-ISSN: 2685-8819
https://ejournal.aibpmjournals.com/index.php/JCDA/index

relative scale of improvement across different operational dimensions, making the practical significance of these changes more transparent.

To assess statistical uncertainty, paired comparisons between the pre- and post-AI periods were conducted for all KPIs. The findings show that all observed differences are statistically significant at the 1% level ($p < 0.01$). Furthermore, the reported standard errors and 95% confidence intervals confirm that the estimated effects are statistically robust and unlikely to be driven by random variation.

Additional robustness checks were performed to examine potential seasonal influences and service-center-specific effects. Monthly KPI trends were analyzed to account for seasonality, and performance patterns were compared across different service centers. The consistency in both the direction and magnitude of improvements across these checks suggests that the results are not attributable to seasonal fluctuations or center-specific anomalies, thereby reinforcing the validity of the findings.

Survey-Based Quantitative Results on AI Perceptions

Table 8. Descriptive Statistics of Survey Variables (Excel-Based)

Variable	Mean	Standard Deviation	Minimum	Maximum
PU	4.48	0.41	3.6	5.0
PEOU	4.12	0.53	3.1	5.0
Work Efficiency Improvement	4.39	0.47	3.4	5.0
Behavioral Usage Intention	4.52	0.38	3.8	5.0

Note: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU)

The survey results presented in Table 8 show generally favorable technician perceptions of AI-supported service systems. Mean scores for PU, improvements in work efficiency, and behavioral intention are consistently high, while the relatively small standard deviations suggest a high level of agreement among respondents regarding these assessments.

Subgroup analysis conducted using Excel reveals differences linked to experience level. Senior technicians tend to report slightly higher perceptions of usefulness, whereas junior technicians exhibit greater variability in PEOU. This pattern is consistent with interview insights, which indicate that more experienced technicians adapt to the system more smoothly, while less experienced staff require a longer adjustment period.

From a statistical perspective, the low dispersion in responses indicates a shared view among technicians about the positive contribution of AI to after-sales service performance. Further subgroup examination reinforces this interpretation by showing that experience level shapes how the system is perceived, particularly in terms of usefulness and ease of use.

Taken together, the questionnaire findings offer quantitative support for technician acceptance of AI-supported systems and complement the performance-based evidence reported earlier.

Qualitative Findings and Effect Size Interpretation

Table 9. Joint Display Linking Qualitative Themes and KPI Effects

Qualitative Theme	Key Mechanism	Most Plausibly Affected KPI

Cognitive support	Improved diagnostic accuracy	Maintenance error rate ↓
Workflow simplification	Reduced procedural complexity	Average processing time ↓
Knowledge externalization	Reuse of accumulated repair knowledge	First-time fix rate ↑
Usability variation	Learning-curve differences	Technician idle rate (heterogeneous)

Table 9 presents effect sizes (Cohen's d) for improvements across key KPIs. Most indicators show medium-to-large or large effects, indicating that the performance changes observed after AI implementation are not only statistically detectable but also meaningful in day-to-day operations.

To address statistical uncertainty, paired comparisons between pre- and post-AI periods were conducted for all KPIs, with all differences reaching significance at the 1% level ($p < 0.01$). The accompanying standard errors and 95% confidence intervals suggest that these estimates are stable. Additional checks examined monthly KPI patterns to account for possible seasonal influences and compared results across service centers. The consistency in both direction and magnitude of the effects across these analyses indicates that the improvements are not attributable to seasonal variation or center-specific conditions.

Insights from the qualitative interviews help clarify why these effect sizes emerged. First, many technicians described AI as providing cognitive assistance during fault diagnosis, particularly by prompting relevant fault patterns and prior cases. This support reduces reliance on memory alone and is consistent with the large reduction observed in maintenance error rates. As one technician noted, "The AI system helps me diagnose problems faster by reminding me of similar past cases" (T12).

Second, interviewees emphasized that AI simplified service workflows by standardizing procedures and reducing unnecessary coordination. Clearer service steps shortened task sequences and limited repeated handoffs, which aligns with the substantial decrease in average processing time. One technician explained, "After AI was introduced, the service steps became clearer and easier to follow, which reduced unnecessary back-and-forth" (T27).

A third theme relates to the externalization of repair knowledge. Technicians frequently mentioned that experiential knowledge, previously held by individuals, is now embedded in the system and accessible to others. This sharing of accumulated experience offers a plausible explanation for the improvement in first-time fix rates, particularly among less-experienced staff. As stated by one respondent, "The system stores repair experience, so even less-experienced technicians can learn from previous cases" (T41).

Finally, interviews revealed differences in how easily technicians adapt to the system, often linked to digital literacy. While overall views were positive, this variation helps explain uneven reductions in technician idle time across individuals and service centers. As one technician observed, "Younger technicians adapt quickly, but some senior staff need more time to get used to the system" (T08).

DISCUSSION

Journal of the Community Development in Asia (JCDA)
Vol. 9 No. 1, pp.20-45, January, 2026
E-ISSN: 2654-7279 P-ISSN: 2685-8819
https://ejournal.aibpmjournals.com/index.php/JCDA/index

Interpreting AI-Enabled After-Sales Performance through Integrated Theoretical Lenses

This section interprets the empirical findings by integrating the RBV, S-D Logic, and the TAM. The Results section demonstrated consistent post-implementation improvements across multiple operational indicators, including reductions in average processing time, maintenance error rates, technician idle rates, and spare-part shortages, alongside an increase in first-time fix rates. Rather than treating these outcomes as isolated efficiency gains, the present discussion explains how they emerge from the interaction between technological capability, human acceptance, and organizational processes.

By adopting a multi-theoretical perspective, this study responds directly to gaps identified in the literature, particularly the lack of integrative frameworks that connect AI-enabled performance outcomes with both organizational strategy and employee behavior in emerging-market service contexts.

Interpretation through the RBV: AI as a Dynamic Capability

From an RBV perspective, the findings suggest that AI-enabled after-sales systems function as dynamic capabilities rather than as standalone technological assets. The sustained improvement observed across all key performance indicators (Table 7) indicates that AI contributes to ongoing operational reconfiguration rather than producing one-time efficiency effects.

Consistent with the dynamic capability framework, the AI platform enables continuous sensing, seizing, and reconfiguring of service resources. System-generated diagnostics and performance feedback enhance the firm's ability to sense operational inefficiencies, while algorithmic scheduling and inventory forecasting support timely resource reallocation. Over time, these mechanisms facilitate reconfiguration of workflows, technician deployment, and spare-part management, which is reflected in the stabilization and persistence of KPI improvements across multiple post-implementation months (Figures 3–7).

Importantly, the value of the AI system appears to depend on its organizational embeddedness. The platform draws on firm-specific historical service data, accumulated repair knowledge, and localized operational routines, rendering it imperfectly imitable. These characteristics align with RBV criteria for strategically valuable resources and suggest that AI-enabled after-sales systems may serve as potential sources of sustained competitive advantage when integrated with complementary human and managerial capabilities (Zdravković et al., 2022).

Interpretation through S-D Logic: AI as an Operant Resource

S-D Logic provides a complementary explanation for how AI contributes to value creation beyond efficiency metrics. Rather than acting as a passive automation tool, AI functions as an operant resource that integrates information, human expertise, and customer interaction into a coherent service system.

The observed reductions in processing time and error rates, together with rising first-time fix rates, reflect enhanced coordination among technicians, service managers, and customers. Qualitative evidence (Table 9) indicates that AI-supported diagnostics, workflow standardization, and knowledge externalization enable technicians to perform service tasks more effectively while reducing reliance on individual memory or ad hoc judgment.

From an S-D Logic perspective, these mechanisms facilitate value co-creation. Customers benefit from faster resolution, fewer repeat visits, and improved communication transparency, while technicians benefit from cognitive support and clearer service procedures (Dzreke, 2025). The AI platform thus mediates reciprocal interactions among actors, reinforcing service reliability and customer trust. This interpretation aligns with the study's finding by Schiavone et al. (2020) that performance improvements were not episodic but sustained over time, suggesting that value co-creation processes became embedded within routine service operations.

Interpretation through the TAM in Mandatory-Use Contexts
The survey results provide further insight into how human acceptance shapes the effectiveness of AI-enabled service systems. Consistent with TAM, technicians reported high levels of PU and PEOU (Table 8). However, the relative dominance of PU over PEOU refines TAM's explanatory power in mandatory organizational settings.

In this context, AI usage was institutionally required, limiting variability in adoption behavior. Under such conditions, PU appears to play a more decisive role in shaping how effectively the system is utilized, rather than whether it is used at all. The gradual improvement observed in first-time fix rates and technician idle time suggests a learning curve, where efficiency gains materialize as users increasingly recognize the system's instrumental value.

PEOU, while still relevant, functions primarily as a moderator of efficiency realization rather than as a determinant of adoption. Technicians who adapted more quickly to the system translated AI recommendations into performance gains sooner, whereas others required additional adjustment time. This finding extends TAM by demonstrating that, in mandatory-use environments, acceptance dimensions influence performance intensity and speed rather than adoption decisions (Fridkin et al., 2024).

Integrated Theory–Evidence Mapping and Cross-Level Interpretation
To strengthen theoretical grounding, Table 10 summarizes the alignment between empirical evidence and theoretical interpretations. Sustained KPI improvements support the RBV-based conceptualization of AI as a dynamic capability, while survey evidence highlights the role of PU emphasized by TAM. Interview-based findings illuminate S-D Logic mechanisms by revealing how AI facilitates knowledge sharing, workflow simplification, and relational value creation.

Table 10. Theory–Evidence Mapping Matrix Linking Excel-Based Results and Theoretical Frameworks

Theoretical Lens	Empirical Evidence	Excel Source
RBV	Sustained KPI improvement	KPI comparison tables
TAM	PU > PEOU dominance	Survey sheet
S-D Logic	Co-creation mechanisms	Interview coding matrix

Table 10 presents a theory–evidence mapping matrix that systematically links the empirical findings of this study to the three guiding theoretical frameworks: the RBV, S-D Logic, and the TAM. The purpose of this matrix is to demonstrate how each theoretical lens is empirically grounded in the study's quantitative and qualitative evidence, thereby strengthening the internal coherence of the Discussion.

From an RBV perspective, the sustained improvement observed across multiple operational KPIs, derived from Excel-based pre–post performance comparisons, supports the conceptualization of the AI-enabled after-sales system as a dynamic capability rather than a static IT investment. The consistency and persistence of KPI gains indicate that AI contributed to ongoing resource reconfiguration and capability development, aligning with RBV's emphasis on firm-specific, difficult-to-imitate resources.

In relation to TAM, the technician survey results reveal a stronger influence of PU compared to PEOU. As summarized in Table 10, this pattern suggests that in mandatory-use organizational contexts, acceptance dynamics shape the extent to which AI systems enhance performance rather than determining adoption itself. This finding refines conventional TAM assumptions and explains the gradual realization of efficiency gains observed in the Results section.

Finally, evidence drawn from the interview coding matrix illustrates S-D Logic mechanisms by highlighting how AI facilitates knowledge sharing, workflow standardization, and coordination among service actors. These qualitative insights explain how AI operates as an operant resource that enables value co-creation between technicians, customers, and the organization, thereby complementing the quantitative performance improvements.

Together, these perspectives form a multi-layer explanatory model. At the strategic level, AI enables dynamic capability development; at the service-system level, it operates as an integrative operant resource; and at the individual level, its effectiveness depends on user perceptions and learning processes. The downward linkages across these levels explain how individual acceptance translates into service-level value co-creation and, ultimately, into organizational performance outcomes.

Theoretical Contributions

This study contributes to the literature in three key ways. First, it extends the RBV by empirically illustrating how AI-enabled after-sales systems operate as dynamic capabilities grounded in firm-specific data and routines. Second, it operationalizes S-D Logic within an after-sales service context, demonstrating how AI mediates value co-creation among technicians, customers, and organizational systems. Third, it refines the TAM by showing that, in mandatory-use organizational environments, PU predominates, while PEOU conditions the realization of efficiency gains rather than adoption itself.

By integrating these perspectives, the study advances a cross-level theoretical framework that connects technology, human behavior, and operational performance, addressing long-standing calls for more holistic analyses of AI-enabled service transformation.

Managerial Implications and Performance Governance

Table 11. KPI Target Benchmarks

KPI	Current Level	Target Benchmark
Avg. Processing Time (Days)	2.41	≤ 2.20
First-Time Fix Rate (%)	91.5	≥ 93.0
Technician Idle Rate (%)	9.2	≤ 8.0
Spare-Part Shortage (Monthly)	6.8	≤ 6.0

Table 11 translates the empirical findings into concrete managerial benchmarks that can guide ongoing performance governance. The proposed target levels are deliberately incremental rather than aspirational, reflecting realistic improvements beyond current post-AI performance. By specifying measurable thresholds for processing time, first-time fix rates, technician idle rates, and spare-part shortages, the table operationalizes strategic recommendations into actionable control metrics. These benchmarks enable managers to monitor whether AI-driven improvements are sustained over time and to identify early deviations that may signal process drift or capability erosion. Importantly, the table reinforces the role of AI as part of a continuous improvement system rather than a one-time optimization initiative.

Operationalizing AI Governance through Managerial Analytics

Table 12. Excel Dashboard Structure

Dashboard Sheet	Core Metrics	Update Frequency	Managerial Purpose
AI Adoption	AI Suggestion Usage Rate	Weekly	Monitor system trust
Efficiency	Avg. Processing Time	Daily	Control service speed
Quality	First-Time Fix Rate	Weekly	Improve service accuracy
Resource	Idle Time & Overtime	Monthly	Optimize workforce
Knowledge	Case Contribution Count	Monthly	Encourage learning

Table 12 outlines an Excel-based managerial dashboard designed to operationalize AI-enabled governance in after-sales service. The dashboard structure links AI adoption, efficiency, quality, resource utilization, and organizational learning into a unified monitoring system. By specifying update frequency and managerial purpose for each dashboard component, the table illustrates how AI-generated outputs can be translated into transparent, auditable, and decision-relevant information. This structure emphasizes the complementary role of Excel as an interpretive interface that bridges advanced AI analytics and human judgment. As such, the dashboard supports data-driven decision-making while preserving managerial oversight, accountability, and organizational learning.

CONCLUSION

This study set out to examine how AI implementation reshapes after-sales service performance and organizational capability. By integrating operational performance data, technician perceptions, and qualitative insights, the study provides a comprehensive assessment of AI-enabled transformation within a service-intensive organizational context.

At the operational level, the findings demonstrate that AI-driven after-sales systems significantly enhance service efficiency, quality, and resource utilization. Substantial reductions in processing time, maintenance error rates, technician idle time, and spare-part shortages were observed alongside sustained improvements in first-time fix rates. These improvements were not transient but persisted over time, indicating that AI contributes to structural changes in service operations rather than isolated efficiency gains.

At the organizational level, the results reveal that AI generates value through identifiable and interpretable mechanisms. Cognitive support improves diagnostic accuracy, workflow standardization reduces coordination complexity, and knowledge externalization transforms individual expertise into shared organizational assets. Together, these mechanisms explain how AI-enabled systems translate technical functionality into reliable service outcomes and organizational learning.

At the strategic level, this study shows that AI-enabled after-sales service functions as a dynamic capability rather than a standalone technological investment. When embedded within organizational routines, managerial processes, and human expertise, AI supports continuous sensing, seizing, and reconfiguration of service resources. This positioning elevates after-sales service from a cost-oriented support function to a strategic capability that contributes to customer-centric differentiation and long-term competitive advantage.

From a theoretical perspective, the study makes three contributions. First, it extends the RBV by empirically demonstrating how AI-enabled service systems operate as dynamic capabilities grounded in firm-specific data and routines. Second, it operationalizes S-D Logic within an after-sales service context, illustrating how AI facilitates value co-creation among technicians, customers, and organizational systems. Third, it refines the TAM by showing that, in mandatory-use organizational settings, PU predominates, while PEOU conditions the speed and intensity with which performance gains are realized rather than adoption itself.

In conclusion, AI-driven after-sales service optimization represents a profound socio-technical transformation rather than a purely technological upgrade. Sustainable value creation depends on the strategic alignment of technology, people, and processes. Organizations that successfully integrate AI into after-sales service operations are better positioned to enhance service reliability, strengthen customer relationships, and build enduring competitive advantage in increasingly data-driven service ecosystems.

LIMITATION

Despite its contributions, this study has several limitations. First, the analysis is based on a single organizational case in an after-sales service context, which may constrain generalizability to other industries or institutional settings with different service complexity and digital maturity. Second, the empirical focus is primarily on operational and perceptual indicators; customer-level outcomes such as satisfaction or loyalty were not directly measured and are inferred indirectly from performance improvements. Third, the quantitative analysis relies on pre–post comparisons rather than causal modeling with counterfactual controls, limiting the ability to fully exclude unobserved external influences despite robustness checks. Finally, technician perceptions were captured at a single post-implementation point, restricting insight into longitudinal changes in acceptance, learning, and human–AI collaboration. Accordingly, the findings should be interpreted as context-specific rather than universally generalizable, while offering clear directions for future research to extend and validate AI-enabled service transformation mechanisms.

ACKNOWLEDGMENT

The author(s) thank the participating organization and respondents for their support.

DECLARATION OF CONFLICTING INTERESTS

The author(s) declare no conflicts of interest.

REFERENCES

Adam, M., Wessel, M., & Benlian, A. (2021). AI-based chatbots in customer service and their effects on user compliance. *Electronic Markets*, *31*(2), 427-445. https://doi.org/10.1007/s12525-020-00414-7

Andrade, I. M. D., & Tumelero, C. (2022). Increasing customer service efficiency through artificial intelligence chatbot. *Revista de Gestão*, *29*(3), 238-251. https://doi.org/10.1108/REGE-07-2021-0120

Barney, J., Wright, M., & Ketchen Jr, D. J. (2001). The resource-based view of the firm: Ten years after 1991. *Journal of Management*, *27*(6), 625-641. https://doi.org/10.1177/014920630102700601

Chang, J., Yu, D., Hu, Y., He, W., & Yu, H. (2022). Deep reinforcement learning for dynamic flexible job shop scheduling with random job arrival. *Processes*, *10*(4), 760. https://doi.org/10.3390/pr10040760

Davenport, T. (2019). *Is HR the most analytics-driven function?* Harvard Business Review. https://hbr.org/2019/04/is-hr-the-most-analytics-driven-function

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, *35*(8), 982-1003. https://doi.org/10.1287/mnsc.35.8.982

Dzreke, S. S. (2025). Developing holistic customer experience frameworks: Integrating journey management for enhanced service quality, satisfaction, and loyalty. *Frontiers in Research*, *2*(1), 90-115. https://doi.org/10.71350/30624533110

Fridkin, S., Greenstein, G., Cohen, A., & Damari, A. (2024). Perceived usefulness of a mandatory information system. *Applied Sciences*, *14*(16), 7413. https://doi.org/10.3390/app14167413

Gronroos, C. (2016). *Service Management and Marketing: Managing the Service Profit Logic*. John Wiley & Sons.

Husein, M., Rajagukguk, J. R., & Putranto, K. E. (2024). The role of artificial intelligence in improving the efficiency of the Company's supply chain. *International Journal of Engineering, Science and Information Technology*, *4*(4), 156-172.

Kilari, S. D. (2022). Optimizing manufacturing systems with AI: Reducing human errors and enhancing response times in MES and supply chain ordering systems. *International Journal of Engineering Technology Research & Management*, *6*(02), 221–230.

Koushik, P. (2024). *Supply Chain Synergy Integrating AI and ML for Optimal Order Management*. Xoffencer international book publication house.

Malik, A., Budhwar, P., & Kazmi, B. A. (2023). Artificial intelligence (AI)-assisted HRM: Towards an extended strategic framework. *Human Resource Management Review*, *33*(1), 100940. https://doi.org/10.1016/j.hrmr.2022.100940

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & management*, *58*(3), 103434. https://doi.org/10.1016/j.im.2021.103434

Prikshat, V., Islam, M., Patel, P., Malik, A., Budhwar, P., & Gupta, S. (2023). AI-Augmented HRM: Literature review and a proposed multilevel framework for future research. *Technological forecasting and social change*, *193*, 122645. https://doi.org/10.1016/j.techfore.2023.122645

Rainy, T. A., Rahman, M. A., & Mou, A. J. (2024). Customer relationship management and data-driven decision-making in modern enterprises: A systematic literature review. *American Journal of Advanced Technology and Engineering Solutions*, *4*(04), 57-82. https://doi.org/10.63125/jetvam38

Ranjith, P. V., Madan, S., Ang, W. J. D., Teoh, K. B., Singh, A. S., Ganatra, V., …, & Singh, P. (2021). Harnessing the power of artificial intelligence in the accounting industry: A case study of KPMG. *International Journal of Accounting Finance in Asia Pacific, 4*(2), 93–106. https://doi.org/10.32535/ijafap.v4i2.1117

Safarudin, M. S. (2025). The Integration of AI and IoT in Cyber-Physical Systems for Smart Manufacturing in Indonesia. *The Eastasouth Journal of Information System and Computer Science*. https://doi.org/10.58812/ESISCS.V2I03.530

Schiavone, F., Leone, D., Sorrentino, A., & Scaletti, A. (2020). Re-designing the service experience in the value co-creation process: An exploratory study of a healthcare network. *Business Process Management Journal*, *26*(4), 889-908. https://doi.org/10.1108/BPMJ-11-2019-0475

Song, Y., Qiu, X., & Liu, J. (2025). The impact of artificial intelligence adoption on organizational decision-making: An empirical study based on the technology acceptance model in business management. *Systems*, *13*(8), 683. https://doi.org/10.3390/systems13080683

Taschner, A., & Charifzadeh, M. (2023). Digitalization and Supply Chain Accounting. In *Management Accounting in Supply Chains* (pp. 281-324). Wiesbaden: Springer Fachmedien Wiesbaden.

Vargo, S. L., & Lusch, R. F. (2014). Evolving to a new dominant logic for marketing. In *The Service-Dominant Logic of Marketing* (pp. 3-28). Routledge.
Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A., & Trichina, E. (2023). Artificial intelligence, robotics, advanced technologies and human resource management: a systematic review. *Artificial Intelligence and International HRM*, 172-201. https://doi.org/10.1080/09585192.2020.1871398
Wang, X., Zhang, L., Wang, L., Zuñiga, E. R., Wang, X. V., & Flores-García, E. (2025). Dynamic multi-tour order picking in an automotive-part warehouse based on attention-aware deep reinforcement learning. *Robotics and Computer-Integrated Manufacturing*, *94*, 102959. https://doi.org/10.1016/j.rcim.2025.102959
XiaoFeng, H., & Cott, W. W. A. (2025). Examining the impact of generative AI content on impulse buying behavior in social commerce. *International Journal of Applied Business and International Management,* *10*(3), 554–573. https://doi.org/10.32535/ijabim.v10i3.4292
Zdravković, M., Panetto, H., & Weichhart, G. (2022). AI-enabled enterprise information systems for manufacturing. *Enterprise Information Systems*, *16*(4), 668-720. https://doi.org/10.1080/17517575.2021.1941275

ABOUT THE AUTHOR(S)

1st Author
Xubin is currently doctoral student at President University, Indonesia.