p-ISSN: 2963-7856| e-ISSN: 2961-98901
Available online at jerkin.org/index.php/jerkin
Jurnal Pengabdian Masyarakat dan Riset Pendidikan
Volume 5 No. 1 Juli-September 2026, 3095- 3112

Diagnostik Sepeda Motor Berbasis Android Mentransformasi Troubleshooting dan Produktivitas Bengkel Komunitas

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https://doi.org/10.31004/jerkin.v5i1.7565

ARTICLE INFO

Article history
Received: 10 Aug 2026
Revised: 13 Aug 2026
Accepted: 18 Aug 2026

Kata Kunci:
diagnostik Android; electronic fuel injection; bengkel sepeda motor; efisiensi troubleshooting; produktivitas usaha kecil

Kata kunci
Android diagnostics; electronic fuel injection; motorcycle workshop; troubleshooting efficiency; small-business productivity

ABSTRACT

Perkembangan sistem electronic fuel injection meningkatkan kebutuhan diagnosis berbasis data pada bengkel sepeda motor skala kecil. Penelitian ini mengevaluasi penerapan sistem diagnostik sepeda motor berbasis Android yang dipadukan dengan pelatihan mekanik dan prosedur operasi standar pada 24 mekanik di 12 bengkel PPBMR, Malang Raya. Studi prospektif sebelum–sesudah selama enam bulan membandingkan 120 kasus diagnosis sebelum dan 120 kasus setelah intervensi. Waktu diagnosis rata-rata menurun dari 42 menjadi 27 menit per kasus, ketepatan diagnosis pertama meningkat dari 81,67% menjadi 92,50%, dan salah diagnosis/pemeriksaan ulang turun dari 18,33% menjadi 7,50%. Produktivitas meningkat 25%, pendapatan kotor harian 18%, kepuasan pelanggan dari 3,62 menjadi 4,38/5, dan adopsi aktif mencapai 91,67% bengkel. Temuan menunjukkan bahwa diagnostik mobile menciptakan nilai ketika dipadukan dengan kompetensi mekanik dan standardisasi kerja.

Small motorcycle workshops increasingly need data-supported diagnosis for electronic fuel-injection faults. This study evaluated an affordable Android-based motorcycle diagnostic system combined with mechanic training and a standardized operating procedure in 24 mechanics from 12 PPBMR workshops in Malang Raya, Indonesia. A six-month prospective before–after study compared 120 diagnostic cases before and 120 after implementation. Mean diagnostic time decreased from 42 to 27 min/case, first-pass accuracy increased from 81.67% to 92.50%, and misdiagnosis/re-examination declined from 18.33% to 7.50%. Daily service productivity increased by 25%, gross daily revenue by 18%, customer satisfaction from 3.62 to 4.38/5, and active technology adoption reached 91.67% of workshops. These findings show that mobile diagnostics create operational value when embedded in mechanic capability development and standardized diagnostic routines.

How to Cite Eddy Rudiyanto et al (2026). Diagnostik Sepeda Motor Berbasis Android Mentransformasi Troubleshooting dan Produktivitas Bengkel Komunitas 5(1). https://doi.org/10.31004/jerkin.v5i1.7565

INTRODUCTION

Electronic fuel injection (EFI) has shifted motorcycle maintenance from a predominantly mechanical activity toward a hybrid mechanical–electronic service process. Engine performance is now governed by interactions among sensors, actuators, electrical circuits, the electronic control unit (ECU), and software-based control logic, so a visible symptom may reflect several possible electronic or mechanical causes. Contemporary diagnostic practice increasingly relies on diagnostic trouble codes (DTCs), live sensor values, actuator status, and communication with the ECU to narrow the search space before physical verification. Reviews of OBD-II maintenance technologies emphasize that standardized communication enables access to service codes and sensor information, while also noting that generic codes may not always reveal the physical cause of a malfunction (Cumin et al., 2024). Work on online and off-board diagnosis similarly describes a transition toward more connected and pervasive vehicle monitoring (Nagy & Lakatos, 2023; Siegel et al., 2021; Subke & Mayer, 2022). This transition changes the informational requirements of workshop practice: mechanic judgement remains essential, but it is increasingly exercised in relation to digital evidence rather than solely through symptoms and sequential component checks.

The technological trajectory is reinforced by the rapid expansion of mobile and wireless diagnostic architectures. Bluetooth-enabled OBD-II systems can stream ECU data to Android devices, while smartphone applications provide an accessible interface for visualization, logging, and communication. Bulut Ibrahim and Ilhan (2021), for example, demonstrated an Android-linked OBD-II architecture for collecting real-time ECU data, whereas Rajput and Parekh (2020) used an Android application and ELM327 scanner to support remote OBD-based testing with limited infrastructure. Giron et al. (2023) likewise showed that an Android-based interface can capture, log, and visualize real-time vehicle parameters for maintenance, and Alvear et al. (2014) developed a wireless ECU emulation environment supporting OBD-II communication. Other studies have extended this logic toward remote diagnostics, OTA-supported prognostics, cloud connectivity, and continuous vehicle-data collection (Rocha et al., 2023; Subke et al., 2020). Collectively, these studies establish the technical feasibility of mobile diagnostic ecosystems, but technical feasibility alone does not establish whether such systems improve the performance of small service businesses.

This distinction is particularly important for micro- and small-scale repair workshops. Professional multi-brand scanners, proprietary diagnostic platforms, and specialized test equipment can be difficult to justify where capital is constrained and service volumes are modest. Babela et al. (2023) explicitly framed easy-to-use diagnostic access as a way to reduce maintenance burden, while David Cruz Ramírez (2025) described how lack of specialized tools can contribute to inaccurate diagnosis and ineffective repair in resource-constrained workshop environments. Smartphone and tablet platforms are attractive because they provide a comparatively cost-effective computing and display ecosystem, although usability, ergonomics, and compatibility remain practical concerns (Krishnamurthy, 2022). Mobile applications can also integrate multiple forms of diagnostic information; Cunanan et al. (2025), for example, combined OBD-II data retrieval with image recognition in a vehicle-inspection application.

The baseline conditions of the Perkumpulan Praktisi Bengkel Malang Raya (PPBMR) illustrate this implementation gap. Before the intervention, only 3 of 12 participating workshops had used a scanner, and even those workshops used it selectively; 9 workshops did not employ digital diagnostic tools routinely. Troubleshooting was dominated by visual inspection, mechanic experience, and sequential trial-and-error testing. Diagnosis records were not standardized, and DTCs or live sensor values were not consistently incorporated into repair decisions. These conditions produced a strongly person-dependent service process. The baseline mean diagnostic time was 42 min/case; first-pass diagnosis was correct in 98 of 120 cases (81.67%); 22 cases (18.33%) required re-examination or represented misdiagnosis; and repeat repair occurred in 16 cases (13.33%). The average workshop handled five relevant service units per day and generated IDR 1.25 million in gross daily revenue. Customer satisfaction averaged 3.62 on a five-point scale. Thus, the technology gap was simultaneously technical, operational, and economic.

Existing research suggests several reasons why digital diagnostics could alter this pattern. Real-time ECU and sensor data can support faster fault localization and more structured decision-making. El Mahri et al. (2023) showed how ECU interrogation can provide maintenance personnel with diagnostic information needed to identify faults accurately, while Hnatov et al. (2026) emphasized sequential interrogation of electronic control units, analysis of live data streams, and cross-verification as a structured service methodology. Siswanto et al. (2024) demonstrated that OBD-II data can support real-time maintenance decision systems, and Hawari et al. (2025) showed the feasibility of continuous OBD-II-based monitoring for operational decision support. At a more advanced level, AI-driven diagnostic approaches have been developed to improve fault detection and interpretability. Akbalık et al. (2024) achieved high classification performance using acoustic features and machine learning, Sasikala et al. (2024) proposed AI-based assistance to address time-consuming and inconsistent conventional diagnostics, and Pandey et al. (2026) reported substantial reductions in troubleshooting time in an LLM-supported diagnostic framework. These systems differ from the present intervention, but they converge on the proposition that better information can reduce diagnostic uncertainty.

At the same time, the literature also cautions against treating digital codes as complete substitutes for mechanic reasoning. Cumin et al. (2024) noted that common OBD-II error codes may not identify

ISSN 2963-7856 (print), ISSN 2961-9890 (online)

the physical cause of a malfunction, and Akilan et al. (2026) explicitly observed that conventional OBD tools may fail to recognize some mechanical engine problems. Advanced fault-detection methods also have operating limits: Zhang et al. (2021), for instance, reported strong misfire-detection performance under defined conditions but deterioration outside the model's effective operating range. These findings support a human–technology complementarity perspective. Digital tools can narrow the search space and identify abnormal signals, whereas the mechanic must interpret those signals in context and confirm them through electrical, fuel-system, or mechanical testing when necessary. Accordingly, the quality of implementation should depend not only on access to a scanner but also on mechanic capability, procedural standardization, and opportunities to practice interpretation.

Training is therefore a central component rather than an ancillary activity. The growing complexity and data intensity of contemporary vehicle systems create new skill requirements for technicians. Guptha et al. (2025) argued that conventional static training is increasingly inadequate for complex diagnostic environments and proposed adaptive training linked to diagnostic data. Obe et al. (2023) likewise reported differences in auto-diagnostic skills when modern OBD-II practice was incorporated into work-integrated learning. In the Indonesian context, Abdi (2023) addressed Android-based learning for vehicle-maintenance practice. These studies are consistent with the premise that adoption requires both technical access and skill development. A diagnostic device that is easy to connect but difficult to interpret may simply shift the bottleneck from fault detection to data interpretation.

Technology acceptance is another important layer. In a study of auto mechanics in Ghana, Turkson et al. (2023) found that facilitating conditions were strong predictors of intention to use and actual use of electronic vehicle diagnostic technology. This is especially relevant to small workshops, where a nominally low-cost tool may still fail if the smartphone is incompatible, connectors are unavailable, wireless communication is unstable, or no technical support exists. Readiness research in automotive SMEs similarly indicates that digital transformation depends on organizational and resource conditions rather than on technology availability alone (Dwivedy et al., 2025). The PPBMR intervention therefore combined hardware provision with training, an explicit diagnostic SOP, field mentoring, and performance monitoring, thereby treating adoption as a socio-technical process rather than a device-distribution exercise.

The most important unresolved question concerns the downstream economic value of diagnostic digitalization. Much of the supplied literature focuses on architectures, communication, detection accuracy, remote access, predictive maintenance, or data collection (Biewer et al., 2021; Dorokhov et al., 2022; Silva et al., 2021; Yassin et al., 2023). Studies also suggest that connected vehicle data can create new service and monetization opportunities (Kumar et al., 2023), while digital monitoring can support equipment availability and enterprise efficiency (Sivakov et al., 2024). Yet direct empirical evidence linking Android-based motorcycle diagnostics to workshop throughput, gross revenue, and customer experience in small community repair businesses remains limited in the literature assembled for this study. This gap matters because technical success does not necessarily create business value: a tool can retrieve DTCs correctly and still fail to improve workshop performance if it does not shorten service cycles, reduce rework, or increase completed jobs.

The customer interface provides an additional reason to examine business outcomes. Repair services are information-asymmetric: customers generally cannot independently verify the fault source or the necessity of a recommended repair. Research on diagnosis-and-cure markets highlights the importance of information in consumer evaluation of service providers (Lee & Ma, 2021). Digital diagnostics may therefore have a signaling function as well as a technical one. When mechanics can explain a fault with reference to a DTC or abnormal sensor reading, the recommendation may become more transparent. Mobile diagnostic services have already been proposed as a service model in other automotive contexts (Siegel et al., 2018), while smart and remote maintenance technologies increasingly position diagnostic information as part of the service interaction (Šimon et al., 2023; Ťapák et al., 2023). Whether such transparency is accompanied by measurable gains in customer satisfaction is therefore relevant to the value proposition of small workshops.

Against this background, the present study conceptualized Android-based diagnostics as a productivity-enabling intervention embedded in a workshop service system. The proposed mechanism was sequential: technology access plus training and a standardized operating procedure would improve mechanic capability and access to actionable information; better information would reduce undirected checking, increase first-pass diagnostic accuracy, and shorten diagnostic time; lower cycle time and less rework would release service capacity; and greater realized capacity, together with clearer customer communication, would be associated with higher gross revenue and satisfaction. Figure 1 summarizes this technology-to-performance pathway. This framing shifts the unit of interest from the diagnostic device itself to the organizational process through which information is converted into operational and economic value.

The study therefore aimed to evaluate the technical, operational, economic, and service effects of implementing Android-based motorcycle diagnostic technology in PPBMR workshops. The primary outcomes were diagnostic time and first-pass diagnostic accuracy. Secondary outcomes included mechanic competence, misdiagnosis/re-examination, repeat repair, daily service productivity, gross workshop revenue, customer satisfaction, SOP compliance, documentation completeness, and active technology adoption. We hypothesized that implementation would be associated with faster and more accurate troubleshooting and that these technical improvements would be accompanied by higher service capacity, greater gross revenue, and better customer experience. The intended contribution is an empirically grounded account of how affordable mobile diagnostics can support the transition from experience-dominated troubleshooting to data-supported operations in community-scale automotive service enterprises.

The study's novelty therefore lies in evaluating the full conversion pathway from diagnostic access and mechanic capability to diagnostic quality, realized service throughput, gross revenue, and customer experience within the same community-workshop implementation.

Figure 1. Proposed technology-to-performance pathway linking mechanic capability and Android-based diagnostics to troubleshooting quality, workshop service capacity, revenue, and customer experience.

METHOD

Study design and setting

A prospective before–after implementation study was embedded in a six-month community technology-transfer program involving the Perkumpulan Praktisi Bengkel Malang Raya (PPBMR) in Malang Raya, Indonesia. PPBMR is a community of motorcycle repair practitioners whose member workshops provide routine maintenance and repair services, including EFI troubleshooting, to local customers. The intervention was designed as a real-world implementation rather than a laboratory experiment. It combined technology provision, mechanic training, standardization of the diagnostic process, field mentoring, and performance monitoring. The unit of implementation was the workshop, while several outcomes were measured at the mechanic, diagnostic-case, customer, and workshop levels.

The program involved 12 workshops and 24 mechanics. Implementation followed sequential phases: baseline identification and socialization, two training sessions, technology deployment, three field mentoring/monitoring visits, and a final evaluation/dissemination session. Across the six-month period, the implementation team completed eight structured activities or field visits. Each workshop received access to one Android-compatible scanner, allowing the diagnostic system to be used on actual customer vehicles during normal workshop operations. The design preserved the practical constraints of small workshops and therefore offers implementation evidence under routine service conditions.

ISSN 2963-7856 (print), ISSN 2961-9890 (online)

Participants, diagnostic cases, and comparison periods

All 24 participating mechanics were included in the training and competency assessment. Baseline workshop conditions were assessed through observation, interviews, equipment review, competence testing, and service-performance records. For case-level diagnostic outcomes, the compiled dataset contained 120 cases observed before implementation and 120 cases observed after implementation. The report describes the pre- and post-intervention case sets as relatively comparable in fault characteristics; they were not the same vehicles and were therefore treated as independent case samples for proportion-based analyses. Post-intervention cases were distributed across the 12 workshops, averaging ten cases per workshop during the implementation-monitoring period.

Customer satisfaction was measured in 120 customers before and 120 customers after implementation, corresponding to the case-monitoring periods. Workshop-level productivity and revenue were available for each of the 12 workshops before and after implementation, permitting paired analysis. Individual pre/post mechanic score distributions were not retained in the compiled dataset beyond the reported mean scores and competence-category counts. Similarly, case-level diagnostic-time values were summarized as an overall mean and post-intervention time categories. These data-availability constraints were respected in the statistical analysis; no individual-level values were reconstructed or imputed.

Android-based diagnostic technology

The technology consisted of a compact diagnostic scanner connected to the motorcycle's DLC through an appropriate cable or connector and linked wirelessly to an Android smartphone via Bluetooth or Wi-Fi. The scanner was approximately 8–10 cm in size and was designed to support DTC reading, real-time sensor data, and fault-reset functions. The Android application was specified for Android version 8 or later, incorporated a multi-brand selection interface, and supported data logging. The effective wireless range was approximately 10–15 m under the implementation conditions.

Operationally, the application provided access to parameters used in EFI troubleshooting, including engine speed, engine temperature, throttle position, battery voltage, fuel/injection-related information, oxygen-sensor behavior, and other sensor or system-status indicators available through the connected ECU. The smartphone served as the principal display and interaction terminal. This architecture was selected because it combined portability with a lower equipment burden than a dedicated professional diagnostic console. The intervention did not assume that DTC output was synonymous with root-cause identification. Mechanics were instructed to use the scanner as a decision-support tool within a broader verification process.

Training, SOP standardization, and mentoring

Training was delivered in two face-to-face sessions using a blended practice-oriented model that combined conceptual explanation, demonstration, digital learning material, and direct vehicle practice. Topics included EFI operating principles; the relationship among sensors, actuators, and the ECU; scanner installation; Bluetooth/Wi-Fi connection; DTC reading; interpretation of real-time sensor data; fault-code clearing; and post-repair verification. Practice involved 24 EFI motorcycles with different brands, types, symptoms, and fault-code profiles, providing exposure to varied service situations.

A 12-step diagnostic SOP was developed to standardize the sequence from complaint recording through diagnosis, verification, and documentation. Although the compiled report does not reproduce all 12 steps as a numbered list, it states that the workflow began with recording the customer complaint and vehicle information, incorporated scanner and supporting physical measurements, and ended with post-repair verification and documentation. The SOP was intended to reduce variation in mechanic behavior and to prevent a return to unguided trial-and-error checking. During field implementation, mentoring focused on connection problems, interpretation of ambiguous sensor data, integration of scanner results with electrical/mechanical tests, and consistent completion of diagnostic records.

Outcome definitions and data collection

Diagnostic time was defined as the interval from receipt and recording of the customer complaint until the likely fault source and repair decision were established. Repair or component-replacement time was excluded because it depended on fault type and parts availability. First-pass diagnostic accuracy was defined as identification of the correct fault source at the first diagnostic assessment, confirmed by component testing and vehicle performance after repair. Cases requiring a second diagnostic assessment were classified as misdiagnosis/re-examination. Repeat repair represented vehicles requiring additional corrective work after the initial service decision. Repair success was defined as restoration of normal vehicle function following repair and final verification.

Mechanic competence was assessed on a 0–100 scale combining knowledge and practical performance. The assessment covered EFI understanding, scanner connection, DTC reading, sensor-data reading, fault-source determination, and DTC clearing/verification. A score of at least 75 was used as the competence threshold. Workshop productivity was defined as the number of vehicles completing diagnosis, repair, and final verification within a working day. Workshop revenue was gross daily income from diagnosis, service/repair labor, and associated component sales; it did not represent net profit after operating costs, labor, parts procurement, or equipment maintenance.

Customer satisfaction was measured on a five-point Likert scale across six domains: service speed, diagnostic accuracy, clarity of fault information, service transparency, satisfaction with repair results, and intention to reuse the workshop. The average of the domain scores was used as the overall satisfaction indicator. Adoption was assessed by observation, diagnostic records, mechanic interviews, and case logs. A workshop was classified as an active user if it used the diagnostic system at least three days per week or on most EFI fault cases. SOP compliance and documentation completeness were assessed from the 120 post-intervention case records.

Statistical analysis

Descriptive analyses summarized counts, percentages, means, absolute changes, percentage-point changes, and relative percentage changes. Percentage change was calculated as (post – pre)/pre × 100%; for outcomes in which a decrease represented improvement, the reduction was reported as (pre – post)/pre × 100%. Because workshop-level paired observations were available for productivity and revenue, these outcomes were analyzed with an exact two-sided Wilcoxon signed-rank test, appropriate to the small sample of 12 workshops and the discrete/skewed pattern of paired differences. Mean and median paired changes were also reported.

For diagnostic accuracy, misdiagnosis/re-examination, and repeat repair, the 120 pre-intervention and 120 post-intervention case samples were treated as independent case groups. Two-sample tests of proportions were used, with risk ratios and 95% confidence intervals reported for the principal binary outcomes. Repair success, which reached 100% in the post-intervention sample, was compared using Fisher's exact test because of the zero failure cell. Changes in the distribution of customer-satisfaction categories were evaluated using a chi-square test of independence after excluding the category that had zero observations in both periods; Cramér's V was used as an effect-size measure. Two-sided $p<0.05$ was considered statistically significant.

Formal hypothesis tests were not calculated for mean diagnostic time, mean competence score, or overall mean satisfaction because the compiled dataset did not retain the individual-level or dispersion information needed for defensible inference on those means. Those outcomes were therefore treated descriptively, while related complete categorical data were tested where possible. This conservative strategy avoids pseudo-replication and prevents artificial precision from being introduced into the analysis.

Table 1. Study design, intervention components, and outcome framework

Element	Specification
Design	Prospective before–after implementation study embedded in a six-month community technology-transfer program.
Setting	12 PPBMR community motorcycle repair workshops in Malang Raya, Indonesia.
Participants	24 mechanics; 12 workshops.
Case samples	120 diagnostic cases before implementation and 120 relatively comparable cases after implementation.
Customer samples	120 customers before and 120 customers after implementation.

ISSN 2963-7856 (print), ISSN 2961-9890 (online)

Element	Specification
Technology	Android-compatible motorcycle scanner linked to DLC/ECU via cable and Bluetooth/Wi-Fi; Android 8+ interface with DTC, real-time data, logging, and fault-reset functions.
Implementation package	Two training sessions, 12 scanners, 12-step SOP, three field mentoring visits, monitoring and final evaluation.
Primary outcomes	Diagnostic time; first-pass diagnostic accuracy; misdiagnosis/re-examination.
Secondary outcomes	Mechanic competence; repeat repair; repair success; daily service productivity; gross daily revenue; customer satisfaction; active adoption; SOP compliance; documentation completeness.

RESULTS AND DISCUSSION

Program implementation and technology adoption

All 24 mechanics from the 12 participating workshops completed the core training program. Twelve scanner units were deployed, one per workshop, and post-training practice was integrated into routine workshop cases. At the end of the training phase, all participants were able to establish a basic connection between the scanner and the Android application; 21 of 24 mechanics could read and interpret diagnostic information without intensive assistance. During implementation, the technology was used in all 120 monitored post-intervention cases. Eleven of 12 workshops (91.67%) met the program definition of active use, compared with 3 of 12 workshops (25%) that had used a scanner before the intervention. One workshop remained a limited user because the available smartphone did not maintain a stable Bluetooth connection.

The depth of adoption extended beyond device use. Of the 120 post-intervention cases, 110 (91.67%) followed all major SOP stages, while 108 (90.00%) had complete diagnostic documentation. Eighty-three cases (69.17%) used the scanner as the main diagnostic tool from the beginning of the assessment, 28 cases (23.33%) combined scanner data with electrical or fuel-system measurements, and 9 cases (7.50%) required more extensive follow-up because of intermittent or multi-component faults. This distribution is important because it demonstrates that the intervention did not eliminate conventional testing; rather, scanner information was integrated with supporting measurements according to case complexity.

Mechanic competence

Mean mechanic competence increased from 61.25 before training to 86.50 after training, an absolute increase of 25.25 points and a relative increase of 41.22%. The proportion meeting the predefined competence threshold (≥75) rose from 5 of 24 mechanics (20.83%) to 21 of 24 (87.50%). The largest domain increase was observed in DTC reading, from 58 to 86 (+48.28% relative to baseline). Scanner-connection skill increased from 60 to 87 (+45.00%), sensor-data reading from 59 to 84 (+42.37%), fault-source determination from 62 to 85 (+37.10%), and DTC clearing/verification from 62.5 to 89 (+42.40%). EFI-system understanding increased from 66 to 88 (+33.33%).

The post-training pattern suggests that procedural interaction with the device was learned somewhat faster than higher-order interpretation. Sensor-data reading had the lowest final domain score (84), and three mechanics still required mentoring when a case involved ambiguous sensor behavior or when the displayed DTC did not map directly to a single component failure. These mechanics were nevertheless able to connect the scanner and retrieve basic information. Thus, the intervention markedly increased operational competence while also identifying interpretation of complex data as the main residual training need.

Troubleshooting speed, accuracy, and repeat work

Mean diagnostic time decreased from 42 min/case before the intervention to 27 min/case after implementation, saving 15 min/case and representing a 35.71% reduction. This exceeded the program target of a ≥30% reduction. In the post-intervention sample, 83 of 120 cases (69.17%) were diagnosed within 30 min, 28 cases (23.33%) required 31–40 min, and 9 cases (7.50%) required more than 40 min.

The nine longest cases were the same set requiring additional diagnostic work because of intermittent connections, combined faults, or the need for extended mechanical testing. Because case-level pre-intervention times and variances were not available, this reduction is reported descriptively rather than with a p value.

First-pass diagnostic accuracy increased from 98 of 120 cases (81.67%) to 111 of 120 cases (92.50%), an absolute increase of 10.83 percentage points. The post-intervention probability of a correct first-pass diagnosis was 1.13 times the pre-intervention probability (RR 1.13, 95% CI 1.03–1.25; p=0.012). Conversely, misdiagnosis/re-examination fell from 22 of 120 cases (18.33%) to 9 of 120 (7.50%), corresponding to a risk ratio of 0.41 (95% CI 0.20–0.85; p=0.012) and a relative reduction of 59.08%. Repeat repair decreased from 16 cases (13.33%) to 5 cases (4.17%), RR 0.31 (95% CI 0.12–0.83; p=0.012).

Repair completion also improved. Before implementation, 104 of 120 cases (86.67%) were reported as successfully resolved without further complaint during the monitoring period. After implementation, all 120 cases reached successful final verification, including the nine that required additional diagnostic steps. The difference in success proportions was significant by Fisher's exact test (p<0.001). The diagnostic technology therefore appears to have improved both the speed with which mechanics narrowed a fault and the probability that the first diagnostic direction was correct, while preserving the need for confirmatory measurement in difficult cases.

Fault profile in post-intervention cases

The 120 post-intervention cases covered a broad range of EFI-related faults. Sensor and ECU input-circuit problems accounted for 47 cases (39.17%), fuel-system and injector problems for 28 (23.33%), ignition-system problems for 19 (15.83%), battery/electrical-system problems for 14 (11.67%), and actuator, connector, or communication problems for 12 (10.00%). The most common diagnostic parameters included engine speed, engine temperature, throttle position, intake-pressure-related values, battery voltage, injection information, and oxygen-sensor behavior.

The nine cases requiring repeat or extended diagnosis illustrate the boundaries of scanner-only reasoning. Five involved intermittent connectors or wiring, two involved combined sensor and fuel-system problems, and two required further mechanical testing. In these cases, the final diagnosis depended on combining the scanner result with voltage, resistance, fuel-pressure, or mechanical-condition checks. This case pattern supports the intervention logic: digital data are most valuable when they reduce the search space and guide verification, not when they are treated as a substitute for physical diagnosis.

Workshop productivity and revenue

Workshop productivity increased in every participating workshop. Mean daily service capacity rose from 5.00 to 6.25 vehicles per workshop, an absolute increase of 1.25 vehicles/day and a relative increase of 25%. Across all 12 workshops, capacity rose from 60 to 75 vehicles/day. Ten workshops gained one additional vehicle per day; Workshop 11 increased from four to seven vehicles/day, and Workshop 12 from four to six. The median paired increase was 1 vehicle/day (interquartile range 1–1). The exact Wilcoxon signed-rank test showed a significant paired improvement (p=0.00049). Figure 2 displays the workshop-level trajectories.

Gross daily workshop revenue increased in all 12 workshops. Mean revenue rose from IDR 1,250,000/day to IDR 1,475,000/day, a mean gain of IDR 225,000/day or 18%. Combined daily revenue across the 12 workshops rose from IDR 15.0 million to IDR 17.7 million. The median paired gain was IDR 220,000/day (interquartile range IDR 215,000–222,500), and the exact Wilcoxon signed-rank test was significant (p=0.00049). The increase was heterogeneous: Workshop 11 had the largest nominal gain (IDR 350,000/day), whereas Workshop 12 gained IDR 170,000/day despite a two-unit increase in daily service volume. This difference reinforces that revenue growth depends not only on the number of vehicles served but also on service mix, repair complexity, labor charges, and associated component sales.

The productivity gain was larger in relative terms than the revenue gain (25% vs 18%), consistent with variation in transaction value across jobs. Nevertheless, the fact that every workshop showed a positive revenue change and every workshop increased service capacity supports the operational pathway proposed in Figure 1. The intervention did not create customer demand directly; instead, it

ISSN 2963-7856 (print), ISSN 2961-9890 (online)

increased the workshop's ability to complete more work within existing operating time while reducing the burden of repeat diagnosis.

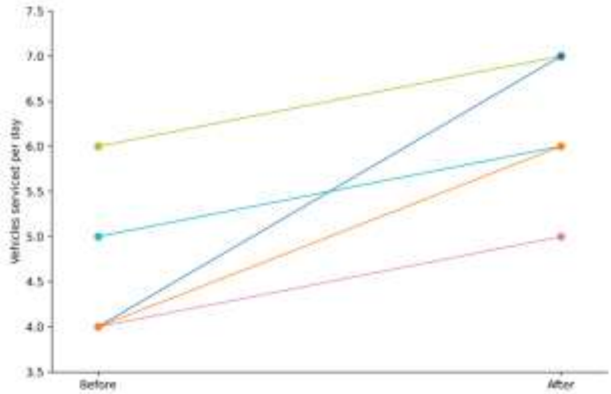

Figure 2. Workshop-level change in daily service productivity. Each line represents one of the 12 participating workshops.

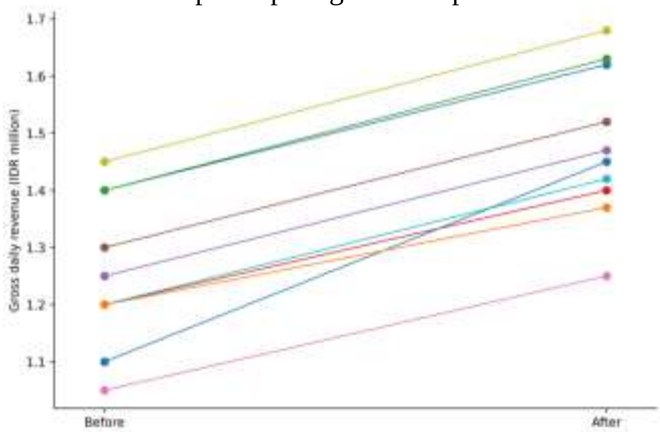

Figure 3. Workshop-level change in gross daily revenue. Each line represents one of the 12 participating workshops.

Customer satisfaction and service experience

Overall customer satisfaction increased from 3.62 to 4.38 on a five-point scale (+0.76 points; +20.99% relative to baseline). All six dimensions improved. Service speed rose from 3.45 to 4.30, diagnostic accuracy from 3.55 to 4.45, clarity of fault information from 3.60 to 4.35, service transparency from 3.58 to 4.28, satisfaction with repair results from 3.70 to 4.45, and intention to reuse the workshop from 3.84 to 4.45. The largest absolute improvement was in perceived diagnostic accuracy (+0.90), followed by service speed (+0.85).

The categorical distribution shifted strongly toward higher satisfaction. Before implementation, 24 customers (20.00%) were very satisfied, 62 (51.67%) satisfied, 27 (22.50%) moderately satisfied, and 7 (5.83%) dissatisfied. After implementation, 68 customers (56.67%) were very satisfied, 45 (37.50%) satisfied, 7 (5.83%) moderately satisfied, and none dissatisfied. The overall distributional change was significant ($\chi^2=42.51$, df=3, $p<0.001$), with Cramér's V=0.421, indicating a substantial association between implementation period and satisfaction category. The proportion in the combined satisfied/very satisfied categories increased from 71.67% to 94.17%.

Mechanics reported using scanner outputs as part of customer explanation, for example by showing a DTC or abnormal sensor value before describing the recommended repair. Although the dataset does not isolate the causal contribution of this communication behavior, the simultaneous improvement in clarity, transparency, accuracy, and reuse intention suggests that diagnostic data became part of the service encounter rather than remaining solely an internal technical resource.

Integrated outcome pattern

Figure 4 summarizes the direction and magnitude of the principal relative changes. Mechanic competence increased by 41.22%, diagnostic time decreased by 35.71%, misdiagnosis/re-examination decreased by 59.08%, productivity increased by 25.00%, gross daily revenue increased by 18.00%, and customer satisfaction increased by 20.99%. The most pronounced improvement was the reduction in diagnostic error, followed by the increase in mechanic competence and reduction in diagnostic time.

Taken together, the results show a coherent chain rather than an isolated device effect. Training improved the ability to use and interpret the technology; active use reached 91.67% of workshops; the diagnostic process became faster and more accurate; workshop throughput increased; revenue rose; and customer experience improved. Because the study did not include a concurrent control group, this sequence should not be interpreted as definitive proof of causality. It does, however, provide internally consistent real-world evidence that the technical and economic outcomes changed in the direction predicted by the intervention model.

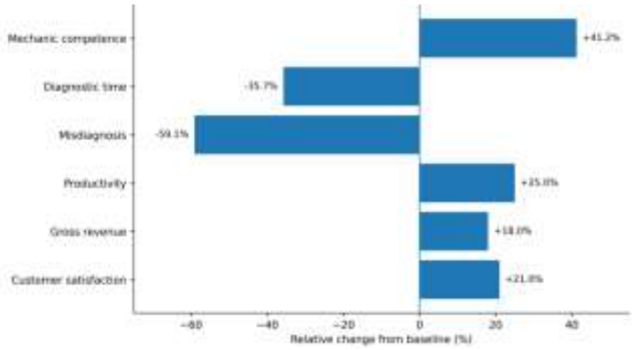

Figure 4. Relative change in principal study outcomes after implementation. Negative values represent desirable reductions in diagnostic time and misdiagnosis; positive values represent increases in competence, productivity, gross revenue, and customer satisfaction.

Table 2. Pre–post outcomes and statistical analyses

Outcome	Before	After	Change	Statistical result
Diagnostic time	42 min/case	27 min/case	−15 min; −35.71%	Descriptive only; case-level pre variance unavailable
First-pass accuracy	98/120 (81.67%)	111/120 (92.50%)	+10.83 percentage points	RR 1.13 (95% CI 1.03–1.25); p=0.012
Misdiagnosis/re-examination	22/120 (18.33%)	9/120 (7.50%)	−59.08% relative	RR 0.41 (95% CI 0.20–0.85); p=0.012
Repeat repair	16/120 (13.33%)	5/120 (4.17%)	−68.72% relative	RR 0.31 (95% CI 0.12–0.83); p=0.012
Repair success	104/120 (86.67%)	120/120 (100%)	+13.33 percentage points	Fisher exact p<0.001
Mechanic competence	61.25	86.50	+25.25 points; +41.22%	Descriptive mean; individual-level variance unavailable
Productivity	5.00 vehicles/day	6.25 vehicles/day	+1.25; +25.00%	Exact paired Wilcoxon p=0.00049
Gross daily revenue	IDR 1.250 million	IDR 1.475 million	+IDR 0.225 million; +18.00%	Exact paired Wilcoxon p=0.00049

ISSN 2963-7856 (print), ISSN 2961-9890 (online)

Outcome	Before	After	Change	Statistical result
Customer satisfaction	3.62/5	4.38/5	+0.76; +20.99%	Category shift: χ^2=42.51, df=3, p<0.001; Cramér's V=0.421
Active workshop use	3/12 (25.00%)	11/12 (91.67%)	+66.67 percentage points	Descriptive; transition matrix not retained

Notes: RR, risk ratio; CI, confidence interval. Proportion tests compare the 120-case pre-intervention sample with the 120-case post-intervention sample. Workshop productivity and revenue were analyzed as paired observations across 12 workshops. Statistical inference was intentionally restricted to outcomes for which the compiled dataset retained appropriate observations.

Principal findings

This study evaluated Android-based motorcycle diagnostics as an intervention in a real community workshop system rather than as a stand-alone device test. Four connected domains changed after implementation: mechanic capability, diagnostic performance, workshop operations, and business/service outcomes. Mechanic competence increased from 61.25 to 86.50; 91.67% of workshops became active users; mean diagnostic time fell by 35.71%; first-pass accuracy rose from 81.67% to 92.50%; daily workshop throughput increased by 25%; gross daily revenue increased by 18%; and customer satisfaction rose from 3.62 to 4.38/5. These results support the central proposition that mobile diagnostics can function as productivity-enabling infrastructure when embedded in training, standardized work, and follow-up support.

The contribution is not that Android, Bluetooth, or OBD-based diagnosis is technically new. Prior studies have already demonstrated smartphone-linked vehicle communication, mobile expert systems, real-time data visualization, wireless ECU access, and mobile maintenance support (Alvear et al., 2014; Bulut Ibrahim & Ilhan, 2021; Giron et al., 2023; Naryanto et al., 2022; Rajput & Parekh, 2020; Syahidi, 2024). The stronger contribution is the empirical linkage of technical improvement to workshop-level service capacity and gross revenue in a small community enterprise setting. The intervention therefore addresses a different question from device-centered studies: not simply whether the technology retrieves information, but whether the information changes how work is performed and whether that altered work process creates measurable service and economic value.

From experience-dominated troubleshooting to data-supported decisions

Before implementation, diagnosis in most PPBMR workshops was strongly experience-dependent. Mechanics typically moved from symptom recognition to visual inspection and successive component checks, with limited use of DTCs or live data. Such practice is increasingly difficult to sustain as EFI systems become more electronically interconnected. The literature on OBD-II, online diagnosis, and smart maintenance describes a service environment in which vehicle-state information is available through scan-tool communication and can be used to focus subsequent inspection (Cumin et al., 2024; Nagy & Lakatos, 2023; Subke & Mayer, 2022). Hnatov et al. (2026) similarly emphasized sequential ECU interrogation and cross-verification of live data in structured service diagnostics. The PPBMR findings show how this informational shift operates in a resource-constrained workshop context.

The 15-min reduction in mean diagnostic time is consistent with a narrowing of the diagnostic search. A mechanic who retrieves a relevant DTC or recognizes an abnormal live parameter can prioritize a smaller set of circuits or components instead of testing many possibilities in sequence. Similar logic motivates AI-assisted diagnosis, where the purpose is to interpret fault information and reduce time spent on root-cause analysis; Pandey et al. (2026) reported a 50–70% reduction in troubleshooting time in their LLM-based framework, while Sasikala et al. (2024) framed AI assistance as a response to time-consuming and inconsistent conventional diagnosis. The present intervention was much simpler technologically, yet the mechanism is comparable: structured information reduces search uncertainty. In a small workshop, this matters because diagnostic minutes are scarce production time.

Importantly, speed improved together with accuracy. First-pass accuracy increased by 10.83 percentage points, misdiagnosis/re-examination fell by 59.08% relatively, and repeat repair fell from 13.33% to 4.17%. This pattern argues against an interpretation in which mechanics merely worked faster. It suggests that the diagnostic direction itself improved. Real-time decision-support systems in vehicle maintenance have been developed around the same premise that timely sensor information can improve maintenance recommendations and operational decisions (Hawari et al., 2025; Siswanto et al., 2024). The PPBMR results extend this logic to motorcycle workshop operations by showing that better diagnostic direction can simultaneously reduce cycle time and avoidable rework.

Human–technology complementarity

The post-intervention cases also make clear that the scanner did not replace mechanic expertise. Nine cases required extended investigation, including intermittent wiring, connector faults, combined sensor/fuel-system problems, and conditions requiring further mechanical tests. This is consistent with Cumin et al. (2024), who noted that common OBD-II codes may not reveal the physical cause of a fault, and with Akilan et al. (2026), who observed that OBD tools may miss some mechanical engine problems. Even highly sophisticated fault-detection methods operate within defined conditions: Zhang et al. (2021) demonstrated strong CNN-based misfire detection but also identified performance limits outside effective operating ranges. A DTC is therefore best treated as evidence that directs inspection, not as an automatic instruction to replace a component.

This complementarity explains why training was integral to the intervention. The mean competence gain of 25.25 points was accompanied by a shift from 20.83% to 87.50% of mechanics meeting the competence threshold. The remaining difficulty was not basic scanner connection but interpretation of ambiguous sensor behavior. This pattern parallels wider concerns about technician capability in data-intensive vehicle environments. Guptha et al. (2025) argued that rapidly changing diagnostic requirements create knowledge gaps that conventional static training may not address adequately, and Obe et al. (2023) emphasized practical exposure to modern OBD-II tools in developing diagnostic skills. Android-based learning has also been proposed for vehicle-maintenance practice (Abdi, 2023). Together, these studies support the view that digitalization shifts the competence requirement toward interpretation, verification, and integration of multiple evidence sources.

The standardized SOP provided the organizational bridge between the tool and the mechanic. After implementation, 91.67% of monitored cases followed all major SOP stages and 90% had complete documentation. Standardization matters because small workshops often rely on tacit knowledge that is difficult to transfer. Codifying the sequence from complaint intake to DTC/live-data review, supporting measurement, repair, and final verification creates a shared diagnostic grammar. That shared process can reduce variability among mechanics and can make mentoring more scalable. The finding therefore suggests that the effective intervention was not “scanner versus no scanner” but a package of scanner, competence, workflow, and feedback.

Converting diagnostic efficiency into workshop productivity

The paired workshop data provide the clearest evidence that technical improvement translated into operations. All 12 workshops increased daily service volume, and mean throughput rose from 5.00 to 6.25 vehicles/day. For a small workshop, diagnostic time is a direct consumer of mechanic capacity; reducing it releases productive minutes. At the observed baseline workload, a 15-min saving across five diagnostic cases corresponds to approximately 75 min that can be redirected to another vehicle, preventive work, documentation, or customer explanation. In parallel, fewer repeat repairs protect capacity that would otherwise be absorbed by rework.

The result is conceptually consistent with digital-maintenance research that links vehicle-data availability to improved maintenance planning and operational reliability. Silva et al. (2021) described OBD-II data as an input to customized maintenance within an Industry 4.0 context, while Sivakov et al. (2024) connected service-maintenance improvement and digital monitoring to enterprise economic efficiency. Connected diagnostic infrastructures are similarly intended to support timely intervention and better utilization of equipment (Dorokhov et al., 2022; Yassin et al., 2023). The present findings add a service-operations perspective: at workshop scale, the value of diagnostic information can be expressed as additional completed jobs rather than only as improved machine availability.

The productivity result should nevertheless be interpreted as realized service volume, not as an unconstrained capacity estimate. Customer arrivals, job complexity, parts availability, staffing, and opening hours still determine the number of vehicles that can actually be completed. What it appears to do is reduce an internal processing constraint. The larger proportional gains in workshops with lower

ISSN 2963-7856 (print), ISSN 2961-9890 (online)

baseline throughput are consistent with this interpretation, but a controlled design with arrival-rate and job-mix data would be needed to estimate the causal capacity effect more precisely.

From productivity to workshop income

Gross daily revenue increased in every participating workshop, from a mean of IDR 1.25 million to IDR 1.475 million. The 18% increase was smaller than the 25% increase in service volume, which is expected because transaction value varies by service type and repair complexity. The relationship is therefore not a fixed revenue-per-vehicle conversion. Instead, diagnostic efficiency appears to expand the opportunity set: more jobs can be completed within the existing day, and realized revenue depends on the mix of those jobs.

This finding is important because the economic value of diagnostic technology is often assumed rather than measured. Connected-vehicle research has identified opportunities for data-driven services and monetization (Kumar et al., 2023), and broader digital maintenance studies emphasize value creation over the equipment lifecycle (Silva et al., 2021). In PPBMR, that value pathway was observable at the microenterprise level. Faster diagnosis reduced time spent on non-productive search, higher first-pass accuracy reduced avoidable rework, and both effects were followed by greater realized throughput and revenue. The sequence is internally consistent with the proposed technology-to-performance pathway.

However, the revenue metric is gross income, not profit. The analysis does not deduct labor, parts procurement, electricity, smartphone replacement, scanner maintenance, software costs, or other operating expenses. The study therefore supports an association with higher gross revenue but cannot claim an 18% increase in profitability. Future studies should incorporate contribution margin, scanner and smartphone total cost of ownership, payback period, and return on investment. Such analysis would directly test whether the affordability advantage suggested for smartphone-based systems (Babela et al., 2023; Krishnamurthy, 2022) persists after compatibility and maintenance costs are included.

Customer value and competitive differentiation

Customer satisfaction improved in parallel with technical performance. The largest domain improvements were perceived diagnostic accuracy and service speed, corresponding directly to the strongest operational changes. Clarity of fault information and transparency also increased. These dimensions are consequential in repair markets because customers face substantial information asymmetry: they typically cannot directly observe the fault or evaluate whether a proposed repair is necessary. Research on diagnosis-and-cure markets highlights the importance of information in consumer decision processes (Lee & Ma, 2021).

Mobile diagnostic evidence can partially reduce this asymmetry by making the basis of a recommendation more legible. Mechanics in the program used DTCs or abnormal sensor readings as part of customer explanations. The technology therefore had a signaling role in addition to its technical role. This is consistent with the broader evolution of diagnostics as a service, in which mobile platforms are used to deliver interpretable vehicle-condition information to users (Siegel et al., 2018). Remote and augmented maintenance approaches likewise aim to present diagnostic information in ways that support decisions and reduce cognitive burden (Krishnamurthy, 2022; Šimon et al., 2023). The increase from 71.67% to 94.17% of customers being satisfied or very satisfied suggests that customers noticed the service change, although the design cannot isolate which component—speed, accuracy, explanation, or other factors—accounted for the change.

For community workshops, this may create a feasible differentiation strategy. Authorized service networks often possess stronger brand infrastructure, whereas independent workshops may compete through accessibility, responsiveness, personal relationships, and price. Data-supported explanation adds a further dimension: professional credibility based on visible evidence. David Cruz Ramírez (2025) linked better diagnostic capability with service quality and reduced vehicle downtime, while Cunanan et al. (2025) showed that mobile diagnostic interfaces can be evaluated positively for data retrieval and usability. The PPBMR findings suggest that when digital evidence is incorporated into the customer encounter, diagnostic modernization can improve both technical confidence and perceived service quality.

Adoption and sustainability in a community workshop ecosystem

A common weakness of technology-transfer programs is the gap between training attendance and sustained use. PPBMR achieved active use in 11 of 12 workshops and independent operation in 21 of 24 mechanics. This level of adoption is consistent with a socio-technical interpretation of technology acceptance. Turkson et al. (2023) found that facilitating conditions strongly predicted intention to use and actual use of electronic vehicle diagnostic technology among mechanics. The PPBMR intervention deliberately created such conditions by supplying one scanner per workshop, using real motorcycles in training, providing mentoring, and embedding the tool in a shared SOP.

The one limited-adoption workshop is analytically useful because its barrier was smartphone compatibility and Bluetooth stability rather than rejection of the diagnostic concept. Low-cost mobile systems do not eliminate infrastructure dependency; they relocate part of that dependency to the consumer-device ecosystem. Android versions, wireless performance, application updates, vehicle-brand support, and connector availability can all affect routine use. Research on mobile and connected diagnostic architectures similarly emphasizes communication and platform integration (Bulut Ibrahim & Ilhan, 2021; Rocha et al., 2023; Subke et al., 2020). Thus, long-term sustainability requires maintenance of both human competence and the hardware/software stack.

The planned internal-trainer model could strengthen sustainability. Six independent mechanics were identified as potential internal trainers, supported by refresher sessions, case discussions, and continuing KPI monitoring. Such peer learning is especially relevant for uncommon or intermittent faults that are difficult to cover in one-off training. A shared case bank can convert distributed mechanic experience into a community knowledge asset. This organizational dimension is important because SME digital readiness depends on capabilities and supporting structures, not simply technology acquisition (Dwivedy et al., 2025).

Implications for diagnostic-technology research and practice

For research, the findings support a multi-level framework for evaluating automotive diagnostic technologies. Device-level outcomes such as connectivity, code retrieval, response latency, or classification accuracy are necessary but insufficient when technology is intended for service enterprises. Advanced systems have demonstrated capabilities ranging from acoustic fault classification and AI-supported problem solving to real-time maintenance recommendations (Akbalık et al., 2024; Sasikala et al., 2024; Siswanto et al., 2024). The next evaluative step is to determine whether those capabilities improve decisions, workflow, rework, throughput, revenue, and customer experience.

For practice, the results argue against hardware-only deployment. Effective implementation requires compatible hardware, training, structured verification, documentation, technical support, and outcome monitoring. This is consistent with the rationale for accessible diagnostic tools and mobile real-time vehicle data (Babela et al., 2023; Giron et al., 2023; Rajput & Parekh, 2020). For vocational programs, digital upskilling should likewise be evaluated beyond test scores: applied diagnostic competence matters because it changes the quality and speed of income-generating work (Guptha et al., 2025; Obe et al., 2023).

Conceptually, these findings position diagnostic capability as a conversion mechanism rather than an endpoint: digital information becomes economically consequential only when mechanics can interpret it, embed it in a repeatable workflow, and translate saved diagnostic time into completed service work.

Limitations and future research

Several limitations constrain causal interpretation. First, the study used a before–after design without a concurrent control group. Improvements may partly reflect mechanic learning, temporal demand variation, changes in case mix, or other conditions during the six-month program. The coherent direction of technical and business outcomes supports the proposed mechanism but does not establish that the intervention was the sole cause. Second, the sample comprised 12 workshops within one professional community in Malang Raya. PPBMR may have stronger peer interaction or leadership support than unaffiliated workshops, limiting external generalizability.

Third, the pre- and post-intervention diagnostic cases were described as relatively comparable but were not the same vehicles and were not randomized. Differences in fault complexity could influence time and accuracy. Fourth, some variables were retained only as aggregate means rather than individual observations, limiting formal inferential analysis for diagnostic time, mechanic competence, and average satisfaction. Fifth, the satisfaction comparison used different customer samples before and after implementation, so the significant distributional shift should be interpreted as an association with implementation period rather than within-person change. Sixth, gross revenue does not represent profit and cannot establish a return on investment.

ISSN 2963-7856 (print), ISSN 2961-9890 (online)

Future studies should use multi-site designs with matched or randomized comparison groups where feasible, retain case-level timestamps and fault complexity measures, collect individual mechanic trajectories, and distinguish labor revenue, parts revenue, and net contribution margin. Longitudinal follow-up is needed to test whether adoption, diagnostic speed, and accuracy persist after external mentoring ends. Mediation analysis could then evaluate whether competence and reduced diagnostic cycle time statistically explain the relationship between technology adoption and workshop economic outcomes. Finally, future systems should explicitly assess the limits of electronic diagnosis for mechanical faults, reflecting evidence that OBD-based tools and even advanced algorithms may not detect every failure mode (Akilan et al., 2026; Zhang et al., 2021).

CONCLUSION

Implementation of Android-based motorcycle diagnostic technology in 12 PPBMR community workshops was associated with broad improvements in technical, operational, economic, and customer-service outcomes. Mechanic competence increased from 61.25 to 86.50, mean diagnostic time decreased from 42 to 27 min/case, and first-pass diagnostic accuracy increased from 81.67% to 92.50%. Misdiagnosis/re-examination fell from 18.33% to 7.50%. These technical changes were accompanied by a 25% increase in daily service productivity, an 18% increase in gross daily workshop revenue, and an increase in customer satisfaction from 3.62 to 4.38/5. Active technology use reached 91.67% of participating workshops.

The findings support a service-system interpretation of mobile diagnostics. The technology created value not merely by displaying fault information but by restructuring troubleshooting around digital evidence, mechanic judgement, standardized verification, and documented work. Faster diagnosis and fewer incorrect diagnostic paths released workshop capacity, while visible diagnostic information supported clearer customer communication. Complex and intermittent faults still required physical measurement and expert interpretation, confirming that digital tools complement rather than replace mechanic expertise. Although the uncontrolled before–after design limits causal claims, the coherent outcome pattern provides a strong basis for controlled, multi-site evaluation of mobile diagnostics as a pathway for digital transformation and productivity growth in small automotive service enterprises.

The practical implication is that affordable diagnostics should be deployed as a socio-technical service package—technology, training, verification routines, and performance monitoring—rather than as hardware alone.

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ISSN 2963-7856 (print), ISSN 2961-9890 (online)