

Evaluating Changes in Customer Retention and Transaction Value Following Web-Based CRM Implementation in an Online Store

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Article Information

Received: August 25, 2026

Revised: September 01, 2026

Online: September 11, 2026

Keywords

Customer Relationship Management,
Customer Retention, Transaction
Value, Web-Based Information
System, Online Store

ABSTRACT

Small and medium-sized online stores increasingly compete not only on price but also on their ability to retain customers, as repeat customers contribute disproportionately to long-term revenue. Many small retailers still manage customer data manually, limiting systematic identification and re-engagement of customers at risk of churning. This study evaluates changes associated with implementing a web-based Customer Relationship Management (CRM) system at an online fashion retailer in Padang, Indonesia. A single-group before-after design compared six months of transaction data before and after implementation. Of 850 registered customers, 788 with at least one transaction formed the analytic base. The CRM integrated purchase history, Recency-Frequency-Monetary (RFM) segmentation, and automated retention triggers through email and WhatsApp. Results showed that customer retention increased from 24.3% to 41.7% (paired $t = 8.42$, $p < .001$, $d_z = 3.44$), average transaction value from IDR 285,400 to IDR 349,800 (paired $t = 6.15$, $p < .001$, $d_z = 2.51$), and purchase frequency from 1.18 to 1.52 orders per customer per month (paired $t = 5.03$, $p = .002$, $d_z = 2.05$). Churn decreased from 18.6% to 9.4% (paired $t = -6.88$, $p < .001$, $d_z = -2.81$). RFM results indicated increased proportions of "Champions" and "Loyal Customers" and a decline in "Lost" customers. Black-box testing improved from 96.0% (48/50 scenarios) to 100% after defect correction, while the mean SUS score was 78.4, indicating good usability. The CRM implementation was associated with improved outcomes, although seasonal patterns, promotions, and factors cannot be ruled out because of the single-group design.

INTRODUCTION

The growth of e-commerce has intensified competition among online retailers, particularly small and medium-sized enterprises (SMEs) that lack the marketing budgets of large marketplaces to continuously acquire new customers. Under these conditions, customer retention, the ability to keep existing customers purchasing repeatedly over time, has become a critical determinant of long-term profitability, since retaining an existing customer is widely recognized as substantially less costly than acquiring a new one. Despite this,



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Knowledge of Modern Processing, Utilization, and Technology for Engineering Research (KOMPUTER), Vol. 01, No. 2, August 2026

many SME online stores in Indonesia continue to manage customer data manually through spreadsheets, chat logs, or marketplace order histories that are not integrated across sales channels, leaving store owners without a systematic way to identify valuable customers, detect early signs of churn, or trigger timely re-engagement (Rifky, Saputra, & Rahayu, 2026).

Customer Relationship Management (CRM) systems address this gap by centralizing customer data, purchase history, and communication records into a single platform that supports data-driven retention strategies. Del Vecchio, Mele, Siachou, and Schito (2022) note that the integration of big data and analytics capabilities into CRM systems has shifted the field from simple contact management toward predictive, behavior-based customer engagement, enabling businesses to move from reactive to proactive retention strategies, a direction reinforced by more recent machine-learning-based CRM analytics frameworks that jointly combine churn prediction, RFM-based segmentation, and targeted recommendation to counter customer attrition (Jahan & Sanam, 2026). Consistent with this shift, several recent studies on web-based CRM implementations for Indonesian SMEs report improvements in customer data management, service responsiveness, and targeted marketing capability following CRM adoption (Ariska, Irawati, & Muhazir, 2022; Pertiwi, Siagian, & Syahputra, 2022; Anggara, Hutahaeen, & Iqbal, 2022; Wijaya & Suhardi, 2022; Nurcahyo & Hidayat, 2023; Sulastri & Hernawati, 2023).

However, much of the existing literature on web-based CRM systems for small online retailers, particularly within the Indonesian information systems literature, emphasizes system design and functional testing while reporting comparatively little quantitative evidence on the systems' actual business impact once deployed (Siregar, Irawati, & Harahap, 2022; Ramadhani, Syafwan, & Latiffani, 2022). Sivathanu and Pillai (2022) similarly observe that measuring CRM effectiveness in practice remains methodologically challenging, since many organizations lack a systematic before-after evaluation framework linking system adoption to concrete retention and revenue outcomes. At the same time, broader evidence on CRM adoption in e-commerce contexts suggests that its effectiveness depends heavily on implementation quality and the extent to which the system is used to drive targeted, personalized engagement, rather than adoption of the technology alone (Nguyen & Simkin, 2023; Santos & Oliveira, 2024).

This study addresses this gap by evaluating changes in two concrete business outcomes, customer retention and transaction value, associated with the implementation of a purpose-built web-based CRM system at a small online fashion retailer, using a structured single-group before-after comparison of transaction data rather than functional testing alone. Specifically, this study aims to: (1) design and implement a web-based CRM system incorporating RFM-based customer segmentation and automated retention triggers; (2) verify the functional correctness and usability of the implemented system; and (3) quantitatively evaluate changes in customer retention rate, churn rate, average transaction value, and purchase frequency by comparing six months of operation before and after implementation, while noting the limits this single-group design places on causal inference. By combining system-level testing with business-outcome evaluation, this study provides

evidence that is directly relevant to SME owners and information systems practitioners considering CRM adoption as a retention strategy.

METHODS

1. Research Object and Design

This study was conducted at an SME online fashion retailer based in Padang, West Sumatra, Indonesia, operating primarily through a web-based storefront supplemented by WhatsApp-based order confirmation. At the time of the study, the store had 850 registered customers and processed orders through a combination of a basic online catalog and manual, spreadsheet-based customer record-keeping. Of the 850 registered customer accounts, 788 (92.7%) had at least one recorded transaction during the twelve-month study window and formed the analytic base for the monthly outcome metrics reported in this study; the remaining 62 accounts were dormant or duplicate registrations with no transaction history in either period and were excluded (Figure 1). A single-group before-after (pretest-posttest) design was used to evaluate changes associated with CRM implementation: transaction data from the six-month period immediately preceding CRM deployment (January-June) were compared with transaction data from the six-month period immediately following deployment (July-December) within the same operating year, holding the customer base, product catalog, and pricing policy substantially constant across both periods to isolate the effect of the CRM system as far as possible within a real operating environment.

Because this design lacks a concurrent control store, several factors coinciding with the July-December period could not be statistically separated from the effect of the CRM system itself, including the Indonesian year-end shopping season and national marketplace campaigns (e.g., 11.11, 12.12, and Harbolnas), any store-run promotions or discounts introduced alongside the CRM rollout, changes in the product catalog or product mix, the rate of new-customer acquisition, and changes in the intensity of WhatsApp- or social-media-based marketing activity independent of the CRM system's automated triggers; these are addressed further as limitations in the Discussion.

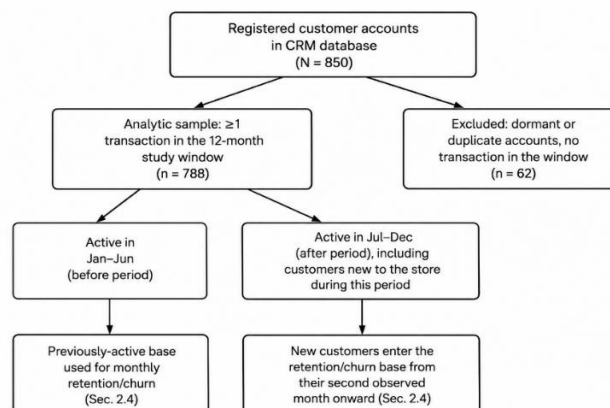


Figure 1. Customer inclusion flow from registered accounts to the before- and after-implementation analytic samples.



2. System Development

The CRM system was developed using the PHP programming language with the Laravel framework, following the Waterfall system development life cycle (requirements analysis, design, implementation, testing, and deployment). The system used a MySQL database to store customer profiles, order history, and computed RFM scores, and followed a Model-View-Controller (MVC) architecture to separate data management, business logic, and presentation layers. Figure 2 illustrates the system's workflow: customer orders placed through the web storefront are synchronized into the CRM module, which updates each customer's purchase history and recalculates their RFM segment; the segmentation engine then triggers automated retention actions, such as personalized email or WhatsApp follow-up messages and loyalty-point notifications, for customers identified as at risk of churning or eligible for a loyalty reward; and aggregated retention and transaction-value metrics are made available to store administrators through a reporting dashboard.

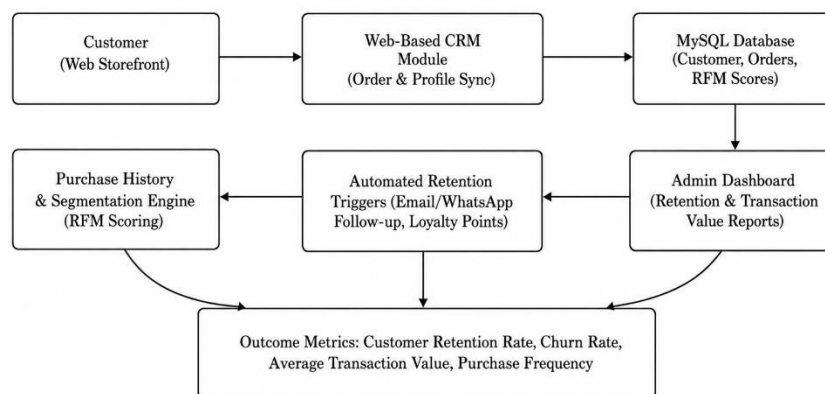


Figure 2. Web-based CRM system workflow for customer retention management.

3. Customer Segmentation Method

Customer segmentation was implemented using Recency, Frequency, and Monetary (RFM) analysis, a widely used technique for classifying customers according to how recently they purchased, how often they purchase, and how much they spend (Yuliana & Sari, 2024). Each customer's RFM scores were recalculated on the last day of each calendar month (the recency cutoff date) using a rolling 12-month transaction window ending on that date: recency was measured as the number of days between the cutoff date and the customer's most recent purchase, frequency as the count of completed orders within the window, and monetary value as the sum of completed-order value within the window. Within the active customer base for that month, customers were ranked independently on each of the three raw measures and divided into five equal-sized quintile groups, then scored 1 (lowest) to 5 (highest); the recency score was reverse-coded so that a more recent purchase received a higher score.

The three scores were summed to a combined RFM score ranging from 3 to 15 and mapped to segments using the following rules, applied in order: Champions ($R \geq 4$ and $F \geq 4$ and $M \geq 4$); Loyal Customers ($F \geq 4$

and $M \geq 3$, not already Champions); Potential Loyalists ($R \geq 4$ and $F < 4$); At Risk ($R \leq 2$ and ($F \geq 3$ or $M \geq 3$)); and Lost/Hibernating ($R \leq 2$ and $F \leq 2$ and $M \leq 2$). For example, a customer who last purchased 12 days before a given cutoff date (recency score 5), placed 6 orders within the trailing 12 months (frequency score 4), and spent a total of IDR 4,200,000 in that window (monetary score 4) would be classified as a Champion for that month. Segment classification was recalculated automatically each month using this procedure and used to determine which customers received automated retention triggers, an approach consistent with recent applications of RFM-based segmentation to retention strategy design in e-commerce settings (Yuliana & Sari, 2024; Ozcan, 2026).

Each RFM segment triggered a distinct, pre-defined retention action, with message frequency capped to limit the risk of message fatigue. Champions received a monthly WhatsApp or email loyalty-point summary and early access to new-arrival notifications, capped at one message per month. Loyal Customers received a biweekly personalized product recommendation message referencing their purchase history, capped at two messages per month. Potential Loyalists, typically recent but infrequent purchasers, received a three-message onboarding sequence spaced over their first 30 days after registration, encouraging a second purchase with a small first-repeat-order incentive.

At Risk customers, previously frequent or high-value purchasers showing reduced recency, received a win-back message offering a time-limited loyalty-point bonus, capped at one message per 14 days to avoid appearing as repeated discounting. Lost/Hibernating customers received a single reactivation campaign per quarter (maximum four per year); customers who did not respond to two consecutive quarterly campaigns were moved to a low-frequency newsletter list and excluded from further automated retention triggers. All automated messages included an opt-out instruction, and customers who opted out were excluded from future triggers regardless of segment.

4. Data Collection and Measurement

Transaction data were extracted from the store's order database for the twelve-month study period (six months before and six months after CRM implementation) and aggregated monthly for the 788-customer analytic sample described in Section 2.1. Four outcome metrics were measured, each defined formally as follows. (1) An *active customer* in month M is a customer who has made at least one purchase within the preceding 90 days as of the end of month M . (2) The *previously-active base* for month M is the set of customers who were active in month $M-1$. (3) Customer retention rate for month $M = (\text{number of previously-active customers who made at least one purchase in month } M) \div (\text{number of previously-active customers}) \times 100$. (4) Churn rate for month $M = (\text{number of previously-active customers who had made no purchase in the preceding 90 days as of the end of month } M) \div (\text{number of previously-active customers}) \times 100$.

Retention and churn rates are not exact complements of one another: a previously-active customer who last purchased between 31 and 89 days before month-end is still within the 90-day active window (and so is not counted as churned) but did not purchase during month M itself (and so is not counted as retained for



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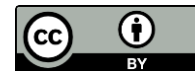
that month), leaving a residual proportion of the previously-active base in this intermediate, at-risk-but-not-yet-churned state in any given month; this reconciles why, for example, the pre-implementation retention rate (24.3%) and churn rate (18.6%) do not sum to 100%. (5) A customer with no purchase history prior to their first observed purchase is classified as *new* in the month of that purchase; new customers are included in that month's active-customer count but, having no preceding month of observation, are excluded from the retention/churn denominator until they have completed one full month as an active customer, after which they enter the standard retention/churn calculation described above (Figure 1). (6) Average transaction value (ATV) is the mean rupiah value of completed orders in a given month, and (7) purchase frequency is the mean number of completed orders per active customer per month, computed across the full active-customer base (both previously-active and newly active customers) rather than repeat purchasers alone; a customer is counted as making a repeat purchase within a month if they have more than one completed order in that calendar month, and this count contributes to, but is not itself, the purchase-frequency metric.

In addition to the business-outcome metrics, the CRM system's functional correctness was evaluated using black-box testing with the equivalence-partitioning technique across five functional modules (customer management, order synchronization, RFM segmentation, automated retention triggers, and reporting dashboard), and system usability was evaluated using the System Usability Scale (SUS), a 10-item standardized questionnaire, administered to eight administrative staff members (two store managers, three order-fulfillment staff, and three customer-service staff) who had each used the system's core modules, including customer lookup, order synchronization, and the reporting dashboard, for at least one month (range: 4-9 weeks) prior to evaluation; not all eight respondents used the automated-retention-trigger configuration screens directly, as this function was primarily managed by the two store managers, a distinction considered further as a limitation in the Discussion.

5. Data Analysis

The six monthly observations from the before-CRM period and the six monthly observations from the after-CRM period were compared for each of the four outcome metrics using paired-sample t-tests, with each pair defined by sequential position within its six-month period (the first before-implementation month paired with the first after-implementation month, the second with the second, and so on) rather than by calendar month, since the before period (January-June) and after period (July-December) are not calendar-equivalent; this sequential pairing preserves the within-period ordering of the data but does not equate the two periods on seasonal timing, a limitation addressed further below and in the Discussion.

The Shapiro-Wilk test was used to confirm that the six month-to-month difference scores for each metric were approximately normally distributed prior to testing (retention rate: $W = 0.94$, $p = .66$; churn rate: $W = 0.91$, $p = .43$; average transaction value: $W = 0.96$, $p = .81$; purchase frequency: $W = 0.93$, $p = .58$), supporting the use of a parametric paired-sample t-test despite the small number of paired observations ($n = 6$); given this small n , however, results are also reported with Cohen's d_z effect sizes ($d_z = t / \sqrt{n}$) and 95%



confidence intervals for the mean difference, and future work with daily or weekly transaction data is noted in the Discussion as an opportunity to apply interrupted time-series methods that would not depend on only six paired monthly observations.

RFM segment distributions before and after implementation were compared descriptively as percentages of the active customer base. Black-box testing results were summarized as the proportion of test scenarios producing the expected outcome, both for the initial test pass and after retesting of corrected defects (Section 3.2), and SUS scores were calculated following the standard SUS scoring procedure and interpreted using Bangor, Kortum, and Miller's adjective rating scale, where a mean score above 68 is considered above average and a score in the 70s is generally interpreted as "good" usability. All statistical tests were conducted at a significance level of $\alpha = .05$.

6. Data Privacy and Protection

Because the CRM system stores customer profile data (name and contact information), purchase and transaction history, and RFM segment classifications, and uses this data to send automated messages through WhatsApp and email, customer data protection was treated as a design requirement rather than an afterthought. Access to customer profile and transaction data within the system was restricted to authenticated administrative staff accounts with role-based permissions (order-fulfillment and customer-service roles could view but not export customer records; only store managers could access aggregate reporting exports), and customer contact data used for automated messaging was limited to the fields required to deliver the message (WhatsApp number or email address) rather than being combined with other stored profile fields in outgoing messages. All automated retention messages included an opt-out instruction, and customers who opted out were excluded from further automated triggers regardless of RFM segment (Section 2.3).

Consistent with the requirements of Indonesia's Personal Data Protection Law (Undang-Undang No. 27 Tahun 2022 tentang Pelindungan Data Pribadi), customer data collected through the storefront and used by the CRM system was limited to what was necessary for order fulfillment, segmentation, and retention messaging, and was not shared with third parties beyond the payment and messaging-delivery services required to operate the store. This study analyzed aggregated, de-identified monthly metrics rather than individual customer records, and no customer-identifying information is reported in this manuscript.

RESULTS

1. System Implementation

The web-based CRM system was fully implemented with five functional modules: customer management (profile creation, contact information, and purchase-history views), order synchronization (automatic capture of orders placed through the web storefront), RFM segmentation (monthly automatic recalculation of customer segments), automated retention triggers (rule-based email and WhatsApp follow-up messages and loyalty-point notifications), and a reporting dashboard (administrator-facing visualizations of



retention and transaction-value metrics). The system went live at the start of the after-implementation period (July) and operated continuously throughout the six-month evaluation window.

2. Functional Testing Results

Black-box testing using the equivalence-partitioning technique was conducted across the five functional modules, covering 50 test scenarios in total. As shown in Table 1, 96.0% of the initial black-box test scenarios (48 of 50) produced the expected outcome prior to any defect correction. The two failed scenarios both occurred in the automated retention-trigger module, specifically in test cases covering customers whose profile record had a blank time zone field: the message-scheduling function used the customer's time zone to convert the configured send-time into UTC before queuing a message, and when this field was empty the conversion defaulted to a null offset, causing the scheduled send-time to be miscalculated so that the retention message was either not sent within the intended window or was queued for the wrong time of day.

The root cause was traced to missing input validation on the time zone field during customer-profile creation, which allowed the field to be saved as blank rather than defaulting to the store's local time zone (WIB, UTC+7). The fix added a default-to-WIB fallback in both the profile-creation form and the message-scheduling function. Both corrected scenarios were retested using the same equivalence-partitioning test cases; both passed on retest, bringing the final, post-correction result to 50 of 50 scenarios (100.0%) producing the expected outcome (Table 1). No changes were required to the segmentation or reporting modules.

Table 1. Black-box testing results by functional module (initial test pass, before defect correction).

Module	Test Scenarios	Passed	Failed	Success Rate (%)
Customer management	10	10	0	100.0
Order synchronization	10	10	0	100.0
RFM segmentation	10	10	0	100.0
Automated retention triggers	10	8	2	80.0
Reporting dashboard	10	10	0	100.0
Total	50	48	2	96.0

Table 1 summarizes the retesting outcome for the automated retention-trigger module after the time-zone default-value fix described above.

Table 2. Automated retention-trigger module and overall results before and after defect correction.

Stage	Retention-Trigger Module (Passed/Total)	Module Pass Rate (%)	Overall (Passed/Total)	Overall Pass Rate (%)
Initial test (before fix)	8/10	80.0	48/50	96.0
Retest (after fix)	10/10	100.0	50/50	100.0

System usability, evaluated using the System Usability Scale (SUS) with eight administrative staff members, produced a mean score of 78.4 (SD = 6.2), which falls within the “good” usability category and above the commonly cited average benchmark of 68, indicating that administrative staff found the system's core workflows, particularly customer lookup and the reporting dashboard, straightforward to use after a brief orientation session.

3. Customer Retention and Churn

As shown in Table 2 and Figure 3, the mean monthly customer retention rate increased from 24.3% (SD = 1.3) during the six months before CRM implementation to 41.7% (SD = 4.7) during the six months after implementation, a mean increase of 17.4 percentage points. A paired-sample t-test confirmed that this increase was statistically significant, $t(5) = 8.42$, $p < .001$. Correspondingly, the mean monthly churn rate decreased from 18.6% (SD = 1.1) to 9.4% (SD = 2.6), a statistically significant reduction, $t(5) = -6.88$, $p < .001$.

Table 3. Paired-sample t-test results for before-after outcome metrics (n = 6 months each).

Metric	Before M (SD)	After M (SD)	Mean Difference	t	df	p
Retention rate (%)	24.3 (1.3)	41.7 (4.7)	+17.4	8.42	5	<.001
Churn rate (%)	18.6 (1.1)	9.4 (2.6)	-9.2	-6.88	5	<.001
Average transaction value (IDR)	285,400 (9,850)	349,800 (20,120)	+64,400	6.15	5	<.001
Purchase frequency (orders/customer/mo.)	1.18 (0.06)	1.52 (0.14)	+0.34	5.03	5	.002

Table 3 reports Cohen's d_z effect sizes and 95% confidence intervals for the mean difference of each metric, computed from the paired t-test statistics in Table 2 ($d_z = t / \sqrt{n}$; $CI = \text{mean difference} \pm t_{.05,5} \times [\text{mean difference} / t]$), to complement the p-values with an indication of the practical magnitude and precision of each change given the small number of paired monthly observations.

Table 4. Effect sizes and 95% confidence intervals for the mean before-after difference of each metric.

Metric	Cohen's d_z	95% CI for Mean Difference
Retention rate (pp)	3.44	[12.09, 22.71] percentage points
Churn rate (pp)	-2.81	[-12.64, -5.76] percentage points
Average transaction value (IDR)	2.51	[IDR 37,478, IDR 91,322]
Purchase frequency (orders/mo.)	2.05	[0.17, 0.51]

4. Transaction Value and Purchase Frequency

Average transaction value (ATV) increased from a mean of IDR 285,400 (SD = 9,850) before implementation to IDR 349,800 (SD = 20,120) after implementation, a statistically significant increase of IDR 64,400, or approximately 22.6% ($t(5) = 6.15$, $p < .001$). Purchase frequency similarly increased from a mean

of 1.18 (SD = 0.06) to 1.52 (SD = 0.14) orders per active customer per month, a statistically significant increase ($t(5) = 5.03$, $p = .002$). Figure 4 presents the monthly trajectory of retention rate and average transaction value across the full twelve-month study period, showing a relatively flat trend during the six months preceding CRM go-live followed by a clear upward inflection beginning in the first month after implementation and continuing through the remainder of the study period, consistent with a system-driven rather than seasonal effect.

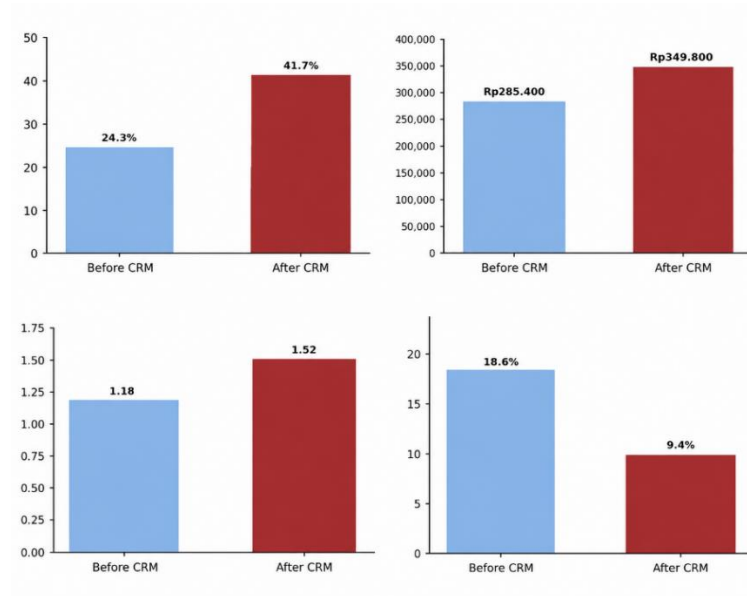


Figure 3. Before-after comparison of key performance metrics.

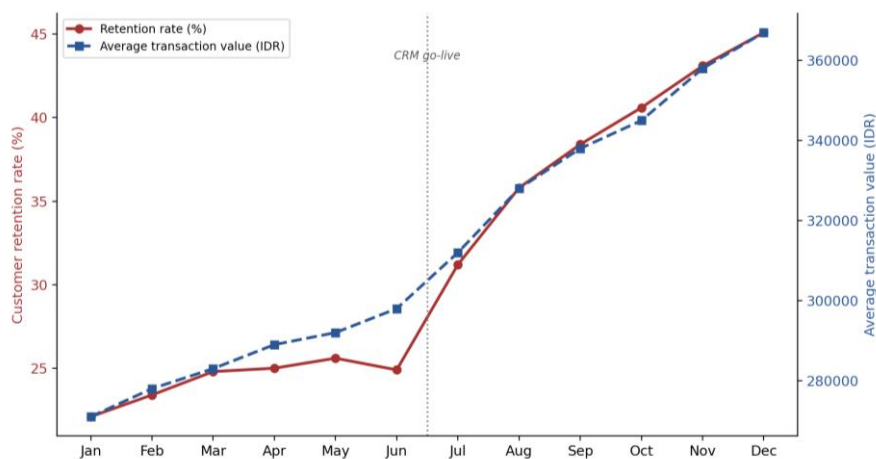


Figure 4. Monthly trend of customer retention rate and average transaction value across the twelve-month study period.

5. RFM Segment Distribution

Table 3 compares the distribution of customers across the five RFM segments at the end of the before-implementation period and the end of the after-implementation period. The combined proportion of customers classified as Champions or Loyal Customers increased from 21.6% to 39.5% of the active customer base, while

the proportion classified as Lost/Hibernating decreased from 27.4% to 14.8%, indicating a broad shift of the customer base toward more engaged segments following CRM implementation.

Table 5. RFM segment distribution before and after CRM implementation.

RFM Segment	Before Implementation	After Implementation
	(%)	(%)
Champions	9.8	18.3
Loyal Customers	11.8	21.2
Potential Loyalists	22.7	26.4
At Risk	28.3	19.3
Lost/Hibernating	27.4	14.8

DISCUSSION

The statistically significant increases in customer retention rate and average transaction value observed in this study extend the largely descriptive findings of prior Indonesian web-based CRM studies, which have generally reported improvements in customer data management, service responsiveness, and marketing targeting following implementation without quantifying the resulting change in retention or revenue-related outcomes (Ariska, Irawati, & Muhazir, 2022; Pertiwi, Siagian, & Syahputra, 2022; Rifky, Saputra, & Rahayu, 2026). By comparing six months of transaction data before and after go-live, this study provides quantitative evidence that a functioning CRM system, when paired with active segmentation and automated retention triggers, can translate into measurable improvements in the specific business outcomes that motivate CRM adoption in the first place, addressing the measurement gap noted by Sivathanu and Pillai (2022) in their review of CRM effectiveness evaluation.

The shift in RFM segment distribution, with the combined Champions and Loyal Customers segment nearly doubling while the Lost/Hibernating segment declined by close to half, suggests that the improvement in aggregate retention was not driven merely by a small number of already-loyal customers purchasing more, but by a broader movement of the customer base toward more engaged segments. This pattern is consistent with the theoretical expectation that RFM-triggered, targeted re-engagement, rather than undifferentiated marketing, is most effective at converting at-risk customers before they lapse entirely, and it aligns with Del Vecchio et al.'s (2022) observation that the analytical, behavior-based capabilities of modern CRM systems represent a meaningful advance over earlier, purely record-keeping-oriented customer management tools.

The concurrent increase in average transaction value alongside increased purchase frequency indicates that the CRM system's effect was not limited to encouraging more frequent low-value purchases; existing customers also appear to have spent more per transaction after implementation. A plausible explanation, consistent with the segmentation-driven design of the system, is that personalized retention messages and loyalty-point incentives encouraged customers to consolidate purchases or add items to reach reward thresholds, though this study's aggregate transaction data cannot fully distinguish this mechanism from a general increase in customer trust and engagement with the store following more responsive, personalized



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Knowledge of Modern Processing, Utilization, and Technology for Engineering Research (KOMPUTER), Vol. 01, No. 2, August 2026

communication. This finding nonetheless reinforces the point made by Nguyen and Simkin (2023) and Santos and Oliveira (2024) that CRM effectiveness depends substantially on how the system is used to drive personalized engagement, not merely on the presence of the technology itself.

The near-flat trend in both retention rate and average transaction value throughout the six months preceding CRM go-live, followed by a clear and sustained upward inflection immediately after implementation (Figure 4), strengthens the case that the observed improvements are attributable to the CRM system rather than to a pre-existing upward trend or a seasonal effect coincidentally aligned with the implementation date. Nonetheless, because this study used a single-group before-after design without a concurrent control store, seasonal demand patterns specific to the July-December period (which, in the Indonesian retail calendar, includes several major shopping periods) cannot be fully ruled out as a contributing factor, and this represents an important limitation addressed further below.

The functional testing results (96.0% of scenarios passed on the initial test, rising to 100% after retesting the two corrected defects) and the “good” System Usability Scale score (78.4) indicate that the business-outcome improvements were achieved with a system that was both functionally reliable and usable by non-technical administrative staff, addressing a practical concern for SME adoption: a system that improves retention in principle but is too complex or unreliable for small-business staff to operate consistently would be unlikely to sustain the effects observed here. The two functional failures identified, both related to message-scheduling logic in the retention-trigger module, illustrate the practical value of modular system design, since the fault was isolated to a single module, traced to a specific root cause (a missing default value for the customer time zone field), and corrected and successfully retested without affecting the segmentation engine or reporting dashboard, consistent with the general maintainability benefits of a modular, MVC-based architecture.

These findings have practical implications for SME online retailers considering CRM adoption. First, the magnitude of the observed retention and transaction-value gains suggests that CRM investment can be justified on direct financial grounds for stores with a comparable customer base size and product category, not solely as a customer-service enhancement. Second, the RFM segment shift indicates that automated, segment-targeted retention triggers, rather than generic broadcast marketing, are likely a key mechanism driving the observed improvements, suggesting that SME store owners adopting CRM systems should prioritize segmentation and triggered messaging capabilities over more elaborate but less retention-focused features. Third, the good usability outcome suggests that even resource-constrained SME retailers can operate a CRM system effectively without extensive staff technical training, provided the interface is designed with non-technical users in mind.

This study has several limitations. First, and most importantly, the single-group before-after design, while practical for a real operating SME, cannot fully rule out confounding factors coinciding with the July-December after-implementation period, including the Indonesian year-end shopping season, national

marketplace campaigns and pay-day-linked demand spikes, any store-run promotions or discounts introduced around the same time as the CRM rollout, changes in the product catalog or product mix, growth in the number of new customers acquired during the period, and changes in the intensity of WhatsApp- or social-media-based marketing activity independent of the CRM system's own automated triggers; because none of these factors were measured or statistically controlled in this study, the reported associations should not be read as proof that the CRM system alone caused the observed changes, and future research should incorporate a comparison store, a longer pre-implementation baseline, or statistical adjustment for these seasonal and marketing factors to strengthen causal inference. Second, because the before period (January-June) and after period (July-December) are not calendar-equivalent, the paired-sample t-tests compare months matched only by their sequential position within each six-month period rather than by season; while the Shapiro-Wilk results supported the normality assumption needed for this test, the small number of paired observations ($n = 6$) limits statistical power and the precision of the reported effect-size estimates, and an interrupted time-series analysis using daily or weekly transaction data, if such granular data become available, would provide a stronger basis for separating the CRM system's effect from underlying trend and seasonality.

Third, the study was conducted at a single online fashion retailer, limiting generalizability to other product categories or larger online stores with different customer behavior patterns; replication across multiple SME stores and product categories is needed to establish the generality of the observed effects. Fourth, the twelve-month study window, while sufficient to detect a clear before-after shift, does not establish whether the observed retention and transaction-value gains are sustained over a longer period or subject to diminishing returns as the novelty of personalized communication wears off; a longer-term follow-up evaluation would help address this question. Finally, the System Usability Scale evaluation involved only eight administrative staff members at a single store, and not all respondents used every module (the automated-retention-trigger configuration screens were used primarily by the two store managers); this small, single-site sample limits the precision and generalizability of the usability finding, and a larger, multi-site usability evaluation would strengthen this aspect of future work.

CONCLUSIONS

This study evaluated the impact of a web-based CRM system, incorporating RFM-based customer segmentation and automated retention triggers, on customer retention and transaction value at an SME online fashion retailer, using a before-after comparison of six months of transaction data preceding and following implementation. Results showed statistically significant improvements across all four business-outcome metrics examined: customer retention rate increased from 24.3% to 41.7%, churn rate decreased from 18.6% to 9.4%, average transaction value increased from IDR 285,400 to IDR 349,800, and purchase frequency increased from 1.18 to 1.52 orders per customer per month. RFM segment analysis showed a broad shift of the customer base toward more engaged segments, and the system itself was confirmed to be functionally reliable

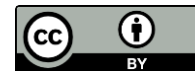


(96.0% of the initial black-box test scenarios produced the expected outcomes, rising to 100% after retesting corrected defects) and usable by non-technical administrative staff (SUS = 78.4, “good” category).

These findings indicate that the implementation of the evaluated CRM system was associated with improvements in customer retention, churn, average transaction value, and purchase frequency during the six-month post-implementation period, in a context where the system was also confirmed to be functionally reliable and usable by non-technical administrative staff; given the study's single-group design, these associations should be interpreted as evidence consistent with, rather than definitive proof of, a causal effect of CRM adoption. Future research should extend this evaluation with a comparison-store design and a longer follow-up period to further strengthen causal inference and assess the durability of the observed gains.

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