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Utilization of CRM-Based Customer Data for Sales Decision-Making in MSME-Scale E-Commerce

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ABSTRACT
Data-driven decision-making is increasingly vital for Micro, Small, and Medium Enterprises (MSMEs) in e-commerce, yet empirical evidence on how Customer Relationship Management (CRM) data improves sales decisions remains limited. This study examines the role of CRM-derived customer data such as purchase history, segmentation, returns, browsing behavior, feedback, loyalty metrics, and social media interactions in enhancing sales decision-making. Using a mixed-methods approach, quantitative data were collected from 240 MSME operators across five Indonesian sectors over a nine-month intervention, complemented by in-depth interviews with 20 participants.Results show a significant 50.2% improvement in decision accuracy (from 2.70 to 4.06, $p < .001$). MSMEs fully adopting CRM achieved 84.3% sales forecast accuracy compared to 51.2% among intuition-based operators, alongside higher monthly revenue growth (33.8% vs. 5.1%). Regression analysis indicates that CRM data utilization breadth ($\beta = .512$), update frequency ($\beta = .341$), and owner digital literacy ($\beta = .274$) strongly influence decision quality ($R^2 = 0.681$, $p < .001$).Qualitative findings reveal key barriers, including data fragmentation, limited analytical skills, tool incompatibility, and inconsistent data updates. Overall, the study provides strong empirical support for CRM-based data utilization as a scalable strategy to improve sales decision-making and competitiveness among MSMEs in Indonesia's e-commerce sector.

INTRODUCTION

The capacity to make informed, timely, and evidence-based sales decisions constitutes one of the most consequential determinants of competitive performance for businesses operating in digital commerce environments. In rapidly evolving e-commerce markets, characterized by volatile consumer preferences, dynamic pricing pressures, and increasingly sophisticated platform algorithms, the ability to anticipate demand shifts, optimize inventory allocation, and personalize promotional interventions in real time is no longer a strategic luxury reserved for large enterprises it is an operational necessity (Davenport & Harris, 2017). For Micro, Small, and Medium Enterprises (MSMEs), which constitute over 99% of all businesses in Indonesia and contribute approximately 61% of national gross domestic product (Ministry of Cooperatives and SMEs, 2023), the integration of customer data analytics into sales decision-making processes represents a transformative yet largely unrealized opportunity.

Customer Relationship Management (CRM) systems generate extensive repositories of customer behavioral data through their native tracking and recording functions, encompassing transaction histories, browsing patterns, product preferences, feedback submissions, loyalty program interactions, and service complaint records (Buttle & Maklan, 2019). When systematically organized, analyzed, and applied to sales planning processes, this data provides MSME operators with actionable intelligence that can inform decisions regarding product assortment optimization, promotional timing and targeting, pricing strategy, stock replenishment, and customer reactivation campaigns (Kumar & Reinartz, 2018; Ngai et al., 2021). The analytical utilization of CRM data for sales decision support a practice well-established in enterprise retail contexts—has been shown to reduce forecast error rates, minimize inventory inefficiencies, and improve promotion return on investment across multiple industry sectors (Davenport & Harris, 2017; Chen et al., 2022).

Despite the demonstrated potential of CRM-based data utilization, the majority of Indonesian MSMEs engaged in e-commerce continue to rely predominantly on intuitive, experience-based sales decision-making approaches that are unstructured, inconsistently applied, and highly susceptible to cognitive biases (Rahayu & Day, 2017; Purwanto et al., 2022). A 2023 survey by the Indonesian E-Commerce Association (idEA) found that only 28% of MSME e-commerce operators in Indonesia had implemented any form of formal customer data analytics for sales planning, with the majority citing technological complexity, cost barriers, and analytical skill gaps as primary obstacles. This reality stands in stark contrast to the evidence suggesting that data-driven SMEs grow two to three times faster than their intuition-reliant counterparts (McKinsey Global Institute, 2022).

The academic literature on CRM utilization in MSME contexts reveals several important gaps. First, most empirical studies examining CRM data and decision-making have been conducted in large enterprise or B2B contexts that are structurally and operationally distinct from the MSME e-commerce environment (Soltani & Navimipour, 2016; Rababah et al., 2022). Second, research specifically examining the differential impact of distinct CRM data types such as segmentation analytics versus behavioral browsing data versus complaint logs on the quality of sales decisions is notably absent from the MSME literature. Third, while qualitative accounts of barriers to CRM adoption in small businesses are available (Mazzarol, 2015; Rahayu & Day, 2017), rigorous quantitative evaluation of how varying levels of CRM data utilization affect measurable sales outcomes in MSME e-commerce remains underdeveloped.

This study addresses these gaps by empirically evaluating the utilization of seven distinct categories of CRM-based customer data as inputs to sales decision-making across 240 MSME e-commerce operators in Indonesia over a nine-month intervention period. The study's objectives are to: (1) measure pre- and post-intervention changes in decision accuracy associated with each CRM data type; (2) compare key sales performance outcomes across MSMEs at different CRM maturity levels; (3) identify the strongest predictors of sales decision quality through multiple regression analysis; and (4) qualitatively characterize the barriers that impede effective CRM data utilization. The findings contribute to both the academic literature on small business digital transformation and the practical literature on MSME data-driven management.

The resource-based view of the firm (Barney, 2001) provides a foundational theoretical lens through which CRM-based customer data can be understood as a strategic asset rare, valuable, and organizationally embedded in ways that are difficult for competitors to replicate. Within this framework, the depth, accuracy, and analytical utilization of a firm's customer data repository constitutes a dynamic capability that systematically enhances the quality and speed of sales decisions over time (Teece, 2018). Davenport and Harris (2017) characterize data-driven decision-making as an organizational competency encompassing the capacity to collect relevant data, build analytical models, and translate model outputs into operational sales actions with speed and consistency.

In the CRM literature, customer data is typically categorized into three levels of analytical maturity: descriptive analytics (summarizing what has occurred in historical transactions), predictive analytics (forecasting future purchasing behavior), and prescriptive analytics (recommending optimal interventions based on predictive models) (Ngai et al., 2021). Each successive analytical maturity level increases the informational value of CRM data for sales decision-making but also demands correspondingly greater technological infrastructure and analytical skill from the operating enterprise. For MSMEs, descriptive analytics accessible through basic CRM dashboards and platform analytics tools represents the most immediately actionable form of CRM data utilization and serves as the entry point for data-driven sales management practices (Chen et al., 2022).

Purchase history and transaction records constitute the most foundational and widely utilized form of CRM data in MSME e-commerce, providing the basis for demand forecasting, bestseller identification, and seasonal replenishment planning (Kumar & Reinartz, 2018). Customer segmentation data derived from clustering algorithms applied to demographic, behavioral, and transactional variables enables MSMEs to differentiate their promotional and pricing strategies across distinct customer value segments, thereby improving the efficiency of marketing resource allocation (Payne & Frow, 2017). Product return and complaint logs provide critical diagnostic signals about product quality, size or fit inconsistencies, and logistical failures that directly inform procurement and supplier management decisions (Grewal et al., 2021).

Browsing and wishlist behavior data increasingly available through e-commerce platform APIs and integrated CRM tools reveals latent demand that has not yet converted into purchases, enabling proactive promotional interventions such as abandoned-cart recovery campaigns and personalized discount offers (Lambrecht & Tucker, 2019). Customer feedback and review analysis, whether quantitative (star ratings) or qualitative (text reviews analyzed through sentiment analysis), provide actionable signals for product development, packaging improvement, and customer communication strategies (Liu et al., 2020). Loyalty program engagement metrics tracking point accumulation patterns, redemption frequency, and tier advancement rates inform decisions about reward program design, promotional timing, and customer reactivation priority (Yi & Jeon, 2018). Finally, social media interaction data, including comment sentiment, share rates, and influencer campaign attribution data, increasingly informs MSME content strategy and product launch timing decisions (Appel et al., 2020).

Despite the theoretical and empirical evidence supporting CRM data-driven decision-making, small businesses face distinctive structural barriers to realizing this potential. Mazzarol (2015) identifies technological complexity, cost constraints, and time limitations as the three primary inhibitors of CRM adoption and utilization in small enterprises. Rahayu and Day (2017), in an Indonesian MSME context, document that low owner digital literacy and insufficient trust in automated analytics outputs frequently lead to selective CRM usage, in which operators record data but do not systematically consult it in decision-making. Data fragmentation arising from the use of multiple disconnected platforms for sales, communication, and inventory management produces siloed data repositories that are difficult to consolidate and interpret holistically (Soltani & Navimipour, 2016).

Low data update discipline represents a particularly pervasive barrier in MSME contexts, where data entry is performed manually by owner-managers whose primary focus is operational execution rather than data stewardship (Rababah et al., 2022). Incomplete or outdated CRM records undermine the reliability of any analytical outputs derived from them, creating a negative feedback loop in which poor data quality produces unreliable insights that erode operator trust in CRM analytics and discourage further investment in data quality improvement. Addressing these barriers through a combination of tool simplification, digital literacy investment, and organizational process redesign represents a central challenge for CRM adoption support initiatives targeting the MSME sector.

METHODS

This study employed a convergent mixed-methods research design in which quantitative and qualitative data were collected simultaneously, analyzed separately, and integrated at the interpretation stage, following Creswell and Creswell (2018). The quantitative component applied a pre–post intervention design to measure the impact of Customer Relationship Management (CRM)-based customer data utilization on sales decision quality and business performance, while the qualitative component explored underlying mechanisms, enabling conditions, and barriers through in-depth interviews. The study population consisted of MSME e-commerce operators registered with the Indonesian Trade Ministry across five sectors: fashion and apparel, food and beverage, craft and accessories, electronics and gadgets, and miscellaneous consumer goods. A purposive-stratified sampling technique was used to recruit 240 participants, stratified by sector, business scale, and province (East Java, West Java, and South Sulawesi). Inclusion criteria required participants to actively operate on at least one major platform (Tokopedia, Shopee, Bukalapak, or Lazada), have a minimum of six months of operational history, and maintain at least 150 registered customers. Additionally, 20 informants were selected using maximum variation sampling for the qualitative strand to ensure diverse representation of CRM adoption levels and business contexts.

The intervention was conducted over nine months (February–October 2024) and consisted of structured CRM data literacy training delivered through online modules, fortnightly coaching sessions, and individualized platform support. The program focused on seven CRM data domains: purchase history analysis, customer segmentation, return and complaint analysis, browsing behavior analysis, feedback and review mining, loyalty metrics analysis, and social media analytics. Participants were guided to integrate CRM insights into routine sales decision-making using structured templates and data review checklists. Quantitative data were collected at two time points: pre-intervention (January 2024) and post-intervention (November 2024), using a structured questionnaire that measured decision accuracy on a five-point Likert scale. Additional performance metrics, including sales forecast accuracy, stock-out and overstock rates, promotion return on investment, decision lead time, monthly revenue growth, and customer satisfaction, were extracted from platform dashboards and verified with transaction records. A composite Sales Decision Quality Index (SDQI) was constructed from the seven domain scores ($\alpha = 0.88$). Data analysis involved paired t-tests with Cohen's d to assess pre–post changes, multiple regression analysis to identify predictors of decision quality, and one-way ANOVA with Tukey post hoc tests to compare performance across CRM maturity levels. Qualitative data were analyzed using reflexive thematic analysis following Braun and Clarke (2021), employing iterative coding to identify key themes related to barriers and enabling factors, which were then integrated with quantitative findings to provide a comprehensive interpretation of the results.

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RESULTS

1. Respondent Profile

Table 1 presents the demographic and operational profile of the 240 MSME participants. Fashion and apparel constituted the largest sector representation (30.0%), followed by food and beverage (24.2%) and craft and accessories (22.5%). Small-scale businesses with 10 to 49 employees were the most prevalent (45.0%), and the majority of respondents reported annual revenues between USD 10,000 and USD 50,000 (42.5%). At baseline, nearly half (47.5%) reported partial CRM data utilization, while 30.0% were full CRM users and 22.5% relied exclusively on intuition-based decision-making.

Table 1. Demographic and Operational Profile of MSME Participants (N = 240)

Characteristic	Category	Frequency (n)	Percentage (%)
Business Sector	Fashion & Apparel	72	30.0%
Business Sector	Food & Beverage	58	24.2%
Business Sector	Craft & Accessories	54	22.5%
Business Sector	Electronics & Gadgets	36	15.0%
Business Sector	Others	20	8.3%
Business Scale	Micro (< 10 employees)	96	40.0%
Business Scale	Small (10–49 employees)	108	45.0%
Business Scale	Medium (50–99 employees)	36	15.0%
Annual Revenue (USD)	< $10,000	84	35.0%
Annual Revenue (USD)	$10,000 – $50,000	102	42.5%
Annual Revenue (USD)	> $50,000	54	22.5%
Data Decision Practice	Data-driven (formal CRM)	72	30.0%
Data Decision Practice	Partially data-driven	114	47.5%
Data Decision Practice	Intuition-based only	54	22.5%

Source: Primary survey data, 2024

2. CRM Data Utilization and Decision Accuracy Improvement

Table 2 presents the utilization rate, pre-intervention, and post-intervention decision accuracy scores for each of the seven CRM data types, along with the percentage improvement. All seven CRM data types demonstrated statistically significant improvements in decision accuracy following the nine-month intervention (all $p < .001$, Cohen's d ranging from 1.31 to 1.48, indicating large effect sizes). The mean decision accuracy score across all seven data types improved from 2.70 to 4.06, representing a 50.2% relative improvement. Product return and complaint log utilization and social media interaction data utilization demonstrated the largest relative improvements (51.0% each), likely reflecting the comparatively low baseline utilization rates of these data types (52.1% and 43.8%, respectively) and the high informational value they provided to operators unfamiliar with their systematic application. Purchase history and transaction records remained the most widely utilized data type (78.3%) and also produced substantial decision accuracy improvement (+50.5%).

Table 2. CRM Customer Data Types: Utilization Rates and Decision Accuracy Scores (Pre/Post-Intervention)

CRM Customer Data Type	Utilization Rate (%)	Decision Accuracy Score (Pre)	Decision Accuracy Score (Post)	Improvement (%)
Purchase History & Transaction Records	78.3%	2.91	4.38	+50.5%
Customer Segmentation Data	64.2%	2.74	4.12	+50.4%
Product Return & Complaint Logs	52.1%	2.63	3.97	+51.0%

Browsing & Wishlist Behavior	47.5%	2.58	3.88	+50.4%
Customer Feedback & Review Analysis	71.3%	2.85	4.24	+48.8%
Loyalty Program Engagement Metrics	55.8%	2.69	4.01	+49.1%
Social Media Interaction Data	43.8%	2.51	3.79	+51.0%
Overall Mean	59.0%	2.70	4.06	+50.2%

Source: Primary data, 2024. Decision Accuracy scored on 5-point Likert scale (1=Highly Inaccurate, 5=Highly Accurate). All improvements significant at p < .001.

3. Sales Decision Outcomes by CRM Maturity Level

Table 3 presents seven key sales decision performance outcomes disaggregated by CRM maturity level. One-way ANOVA confirmed statistically significant between-group differences for all seven indicators ($p < .001$). Full CRM adopters achieved a sales forecast accuracy of 84.3%, compared to 68.7% for partial adopters and 51.2% for intuition-based operators, representing a 33.1 percentage point accuracy advantage over the intuition-based group. Stock-out incidents declined dramatically with CRM maturity, from a mean of 6.8 per month for intuition-based operators to 1.1 per month for full CRM adopters. Overstock rates similarly declined from 22.4% to 6.3%. Promotion ROI exhibited a particularly striking pattern, rising from 118% for non-CRM operators to 264% for full CRM adopters more than doubling the return on promotional investment. Average decision lead time decreased from 5.2 days to 1.4 days, and monthly revenue growth improved from 5.1% to 33.8%. Customer satisfaction scores followed a consistent positive gradient with CRM maturity (3.08, 3.71, 4.46). Tukey post hoc tests confirmed that all pairwise group differences were statistically significant for all indicators.

Table 3. Sales Decision Performance Outcomes by CRM Maturity Level

Performance Indicator	Intuition-Based (n=54)	Partial CRM (n=114)	Full CRM (n=72)	ANOVA F / p
Sales Forecast Accuracy (%)	51.2%	68.7%	84.3%	F=62.4, p<.001
Stock-Out Incident Rate (per month)	6.8	3.4	1.1	F=57.8, p<.001
Overstock Rate (% of inventory)	22.4%	14.1%	6.3%	F=49.2, p<.001
Promotion ROI (%)	118%	187%	264%	F=71.3, p<.001
Avg. Decision Lead Time (days)	5.2	3.1	1.4	F=83.6, p<.001
Monthly Revenue Growth (%)	5.1%	17.4%	33.8%	F=66.9, p<.001
Customer Satisfaction Score (1–5)	3.08	3.71	4.46	F=88.2, p<.001

Source: Platform analytics and primary data, 2024. Post hoc Tukey tests confirmed significant pairwise differences between all three groups on all indicators (p < .05).

4. Multiple Regression: Predictors of Sales Decision Quality

Table 4 presents the multiple regression model predicting the Sales Decision Quality Index (SDQI) from six organizational and CRM utilization predictors. The overall model was statistically significant ($F(6, 233) = 83.24$, $p < .001$) and explained 68.1% of the variance in SDQI ($R^2 = 0.681$, Adjusted $R^2 = 0.673$), indicating a highly robust predictive model. CRM data utilization breadth emerged as the strongest predictor ($\beta = .512$, $t = 8.234$, $p < .001$), confirming that operators who systematically utilize a wider range of CRM data types consistently make higher-quality sales decisions. Data update frequency was the second-strongest predictor ($\beta = .341$, $p < .001$), underscoring the critical importance of maintaining current and accurate customer data records. Owner digital literacy ($\beta = .274$, $p < .001$) and CRM-platform integration level ($\beta = .228$, $p < .001$) also contributed significantly, while business scale ($\beta = .148$, $p = .006$) and years in operation ($\beta = .108$, $p = .023$) produced smaller but statistically significant positive contributions.

Table 4. Multiple Regression Analysis: Predictors of Sales Decision Quality Index (SDQI)

Predictor Variable	B (Unstd.)	SE	β (Std.)	t-value	p
(Constant)	0.412	0.183	—	2.251	.025
CRM Data Utilization Breadth	0.387	0.047	.512	8.234	<.001
Data Update Frequency	0.261	0.038	.341	6.868	<.001
Owner Digital Literacy Score	0.198	0.033	.274	6.000	<.001
CRM–Platform Integration Level	0.172	0.041	.228	4.195	<.001
Business Scale (SME=1)	0.143	0.052	.148	2.750	.006
Years in Operation	0.089	0.039	.108	2.282	.023
$R^2 = 0.681$ Adjusted $R^2 = 0.673$ $F(6, 233) = 83.24$ $p < .001$ Dependent variable: Sales Decision Quality Index					

Source: Primary data, 2024. Dependent variable: Sales Decision Quality Index (composite of 7 CRM data domain accuracy scores, $\alpha = 0.88$).

5. Qualitative Findings: Barriers to CRM Data Utilization

Thematic analysis of 20 in-depth interviews produced four primary barrier themes impeding effective CRM data utilization for sales decision-making. The first and most pervasive theme, 'Data Fragmentation Across Platforms,' was articulated by 17 of 20 informants, who described operating simultaneously across two to five distinct platforms each maintaining separate customer databases without any integration mechanism to consolidate data into a unified analytical view. Participants reported that this fragmentation made it practically impossible to obtain an accurate aggregate picture of customer behavior, forcing them to rely on platform-specific data that captured only a partial slice of each customer's actual engagement with their business. The second theme, 'Analytical Skill Deficit,' was expressed by 15 informants as a combination of unfamiliarity with CRM dashboard interpretation, discomfort with numerical data, and uncertainty about how to translate analytical outputs into specific operational decisions. Several informants described a pattern of accessing CRM reports but then reverting to intuition-based decisions because they lacked confidence in their ability to correctly interpret the analytical signals. The third theme, 'Tool Incompatibility and Cost Barriers,' encompassed informant accounts of misalignment between the CRM tools they could afford and those that offered the analytical capabilities required for meaningful sales decision support; several described investing in low-cost CRM solutions that lacked API connectivity with their primary sales platforms, rendering data export manual and time-prohibitive. The fourth theme, 'Low Data Update Discipline,' captured a widely shared pattern of irregular and incomplete data entry driven by time pressure, particularly among micro-enterprise operators performing all business functions personally; informants in this cluster acknowledged that their CRM data was frequently weeks or months out of date, severely limiting its reliability as a decision input.

DISCUSSION

The findings of this study provide compelling and comprehensive empirical evidence that the systematic utilization of CRM-based customer data significantly and substantially improves the quality of sales decision-making in MSME-scale e-commerce contexts. The 50.2% mean improvement in decision accuracy scores and the large effect sizes observed across all seven CRM data types (Cohen's d range: 1.31–1.48) establish that the benefits of CRM data utilization are not marginal but transformative, even within the resource-constrained operational environment characteristic of small businesses in Indonesia's developing digital economy. These results meaningfully extend the existing literature, which has primarily demonstrated CRM decision support benefits in enterprise contexts, by confirming that analogous benefits are achievable at MSME scale when appropriate training and implementation support is provided.

The regression model's identification of CRM data utilization breadth as the strongest predictor of sales decision quality ($\beta = .512$) carries important practical implications. It suggests that MSME operators derive the greatest decision quality gains not from deep proficiency in any single CRM data type, but from achieving competent utilization across the full spectrum of available customer data signals. This finding challenges a prevalent pattern in MSME CRM adoption, in which operators gravitate toward familiar and easily accessible data types primarily purchase histories and star ratings while neglecting behaviorally rich data streams such as browsing behavior, wishlist analytics, and complaint pattern analysis. A portfolio approach to CRM data utilization, in which operators are systematically trained to integrate all major data types into their decision workflows, appears to generate multiplicative rather than merely additive improvements in decision quality.

The primacy of data update frequency as the second-strongest predictor ($\beta = .341$) directly validates the theoretical concern, articulated by Rababah et al. (2022) and Mazzarol (2015), that data quality is the foundational precondition for any analytical capability. CRM data that is outdated by weeks or months does not merely reduce analytical precision it actively misleads decision-makers by presenting a customer behavior landscape that may no longer reflect current market reality. For MSME operators whose business environments can shift significantly within weeks due to platform promotional seasons, viral social media trends, or supply chain disruptions, the real-time currency of CRM data is particularly critical. Practical interventions to improve data update frequency including automated data synchronization between sales platforms and CRM tools, mobile-first data entry interfaces optimized for rapid use, and gamified data quality scorecards—warrant prioritization in MSME CRM support programs.

The performance divergence between CRM maturity groups documented in Table 3 reveals the cumulative strategic disadvantage faced by intuition-based MSME operators. A sales forecast accuracy gap of 33.1 percentage points (84.3% vs. 51.2%) between full CRM and intuition-based operators translates directly into systematic inventory mismanagement: the 6.8 monthly stock-out incidents versus 1.1 for full CRM operators represent not only lost sales but customer dissatisfaction events that elevate churn risk. The overstock rate differential (22.4% vs. 6.3%) reflects the capital efficiency costs of poor demand forecasting, as excess inventory ties up working capital that could otherwise fund growth investments. The 264% promotion ROI achieved by full CRM operators more than double the 118% achieved by intuition-based operators—demonstrates that CRM data enables MSMEs to identify and target their highest-value customer segments with relevant offers at optimal timing, dramatically increasing the economic productivity of promotional expenditure (Lambrecht & Tucker, 2019; Kumar & Reinartz, 2018).

The qualitative finding that data fragmentation across multiple platforms is the most pervasive barrier to CRM data utilization highlights a structural challenge that individual operator behavior change cannot fully resolve. The multi-platform architecture of Indonesian e-commerce where customers may interact with the same MSME through Shopee, Tokopedia, WhatsApp, and Instagram simultaneously creates inherently fragmented data trails that no single platform's native analytics can consolidate. This finding suggests a systemic market gap for affordable data integration middleware solutions designed specifically for MSME multi-platform environments. Technology developers and government digitalization support programs should prioritize the development and subsidization of such tools, which would unlock the consolidated customer data visibility that is currently available only to large enterprises with the resources to deploy sophisticated data warehouse solutions.

The identification of analytical skill deficit as the second most prevalent utilization barrier resonates strongly with the digital literacy literature on MSME technology adoption in developing economies (Rahayu & Day, 2017; Purwanto et al., 2022). The pattern of operators accessing CRM reports but reverting to intuition-based decisions due to interpretive uncertainty suggests that data access without analytical confidence produces only the appearance of data-driven practice, not the reality. This finding argues for a reconceptualization of CRM training programs for MSMEs, shifting emphasis from tool operation instruction toward decision translation practice that is, training that explicitly develops operators' ability to read a CRM output and identify the specific sales decision it should inform. Contextually anchored, sector-specific case studies and peer coaching from more analytically advanced MSME operators appear particularly promising as pedagogical modalities for developing this capability.

Several limitations of the study should be acknowledged. The geographic restriction of the sample to three Indonesian provinces may not capture the full heterogeneity of MSME digital infrastructure and market conditions across Indonesia's 38 provinces. The nine-month intervention period, while longer than most comparable studies, does not allow observation of how CRM data utilization competencies develop and consolidate over multiple annual business cycles. The self-report component of decision accuracy measurement introduces potential social desirability bias, though this was partially mitigated by cross-validation against platform-derived performance data. Future research should employ randomized experimental designs with matched control groups, extend observation periods to two or more years, and examine cross-national comparisons to assess the contextual transferability of the Indonesian findings.

CONCLUSIONS

This study provides rigorous empirical evidence that the systematic utilization of CRM-based customer data represents a transformative capability for MSME e-commerce operators, delivering statistically significant and practically substantial improvements in sales decision quality and business performance outcomes. A nine-month CRM data utilization intervention across 240 Indonesian MSME operators produced a 50.2% mean improvement in decision accuracy, reduced stock-out incidents by 83.8% among full CRM adopters, increased promotion ROI by 123.7%, and drove monthly revenue growth to 33.8% for full CRM users versus 5.1% for intuition-based operators. The regression model confirmed that CRM data utilization breadth, data update frequency, and owner digital literacy are the three strongest predictors of sales decision quality, collectively explaining 68.1% of outcome variance.

For MSME practitioners, the study's most actionable implication is that decision quality improvement requires not selective reliance on familiar CRM data types, but deliberate development of a broad CRM data portfolio practice that systematically incorporates purchase analytics, segmentation data, complaint intelligence, behavioral browsing signals, feedback mining, loyalty metrics, and social media insights into regular sales planning cycles. Maintaining high data currency through automated synchronization or disciplined manual updating is equally critical, as analytical outputs derived from stale data can actively mislead rather than inform. For policymakers and business development organizations, the study establishes a clear evidence-based rationale for prioritizing CRM data literacy development particularly decision translation skills as a core component of MSME digitalization support programs, and for investing in the development of affordable data integration tools that resolve the multi-platform fragmentation barrier identified by the majority of qualitative informants.

Future research should investigate the differential impact of AI-powered predictive CRM analytics including machine learning-based demand forecasting and natural language processing of customer reviews on MSME sales decision quality, as these capabilities are rapidly becoming accessible through cloud-based platforms at SME-compatible price points. Longitudinal panel studies tracking CRM data maturity trajectories over three to five years would substantially advance understanding of how CRM data capabilities compound over time and their long-term contributions to MSME survival and growth.

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