

Online–Offline Channel Integration and Sales Performance in BYD 4S Dealerships

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Abstract

As China's new energy vehicle (NEV) market evolves from policy-induced expansion to intense rivalry and competition, dealership profitability increasingly depends on after-sales services rather than vehicle transactions. This research examines the transformation from traditional sales to life-cycle services of BYD authorized 4S dealerships in an integrated online–offline network. The research extends service-dominant logic and services marketing theory to examine the interaction effects of six operational determinants of dealership performance. A stratified random sample of 120 dealerships yielded 36 months of operational data, resulting in 4,320 store-month observations. Hierarchical regression analysis indicated that the six factors increased explained performance variance from 31.0% to 68.0%. App inquiry response time ($\beta = -0.43$), online lead conversion ($\beta = 0.47$), and follow-up call completion ($\beta = 0.42$) are significant predictors. Online conversion positively interacts with offline reception ($\beta = 0.17$), indicating complementary channel effects. All seven hypotheses are supported, suggesting that controllable operational practices matter for dealership performance beyond location and scale. This study suggests a manufacturer-driven dual-channel enablement platform, along with a three-phase implementation approach, to improve operational efficiency, service integration, and the profitable sustainability of dealerships

Keywords: Dual-Network Operation, Automobile 4S Stores, Service Marketing, Channel Coordination, Regression Analysis

Abstrak

Dengan perkembangan pasar kendaraan energi baru (NEV) Tiongkok dari ekspansi yang didorong oleh kebijakan menuju persaingan dan kompetisi yang intens, profitabilitas diler semakin bergantung pada layanan purna jual, bukan pada transaksi kendaraan itu sendiri. Penelitian ini mengkaji transformasi dari penjualan tradisional menjadi layanan siklus hidup di diler 4S resmi BYD dalam jaringan terpadu online-offline. Penelitian ini memperluas logika dominan layanan dan teori pemasaran berbasis layanan untuk mengevaluasi dampak interaksi enam faktor operasional terhadap kinerja diler. Sampel acak terstratifikasi sebanyak 120 diler menghasilkan data operasional selama 36 bulan, dengan total 4.320 observasi bulan-toko. Analisis regresi hierarkis menunjukkan bahwa enam faktor tersebut meningkatkan varians kinerja yang dijelaskan dari 31,0% menjadi 68,0%. Waktu respons aplikasi ($\beta = -0,43$), konversi lead daring ($\beta = 0,47$), dan penyelesaian panggilan lanjutan ($\beta = 0,42$) merupakan prediktor yang signifikan. Konversi daring berinteraksi secara positif dengan penerimaan offline ($\beta = 0,17$), menunjukkan efek saluran yang saling melengkapi. Ketujuh hipotesis tersebut semuanya didukung, menunjukkan bahwa praktik operasional yang dapat dikendalikan penting bagi kinerja dealer, baik di luar lokasi maupun dalam skala. Studi ini menyarankan platform pemberdayaan saluran ganda yang digerakkan oleh produsen, bersama dengan pendekatan implementasi tiga tahap untuk meningkatkan efisiensi operasional, integrasi layanan, serta keberlanjutan yang menguntungkan bagi diler.

Kata Kunci: Operasi Jaringan Ganda, Diler Otomotif 4S, Pemasaran Layanan, Koordinasi Saluran, Analisis Regresi

INTRODUCTION

New energy vehicle retail is increasingly integrating digital exploration with physical service. In the Chinese market, BYD's authorized 4S dealers are the environment where lead acquisition, the test-driving experience, the transaction process, and after-sales support must be coordinated. Recent NEV marketing materials suggest that relationship management and integration across multiple customer touchpoints are important (Chen, 2024; Pan, 2024; Wu, 2022). This research links dealer data to customer-journey coordination. It focuses only on sales revenue and operational correlation, not lifecycle profitability or the causal effect of the business strategy. The customer touchpoints are online and offline channels. This analysis focuses on channel integration, not a comparison between the two dealer networks.

Verhoef et al. (2015) note that in omnichannel retailing, synchronizing different customer contact points is of first importance. Similarly, Payne and Frow (2005) emphasize the importance of keeping information flows and interactions consistent in CRM. Responsiveness and fulfillment relate to service-quality theory, as Parasuraman et al. (1988) discussed. Operational data records do not reflect how customers perceive service quality. This paper deals with three main issues: the relationship of the six particular operational metrics with sales revenue, an eventual interaction between the online conversion rate and an offline reception service, and the search for the operational things that should be improved and will have to be assessed in the future. The main idea is to link the observable things that can be done in the dealership with the monthly revenue made from new vehicle sales. It is important to distinguish between the estimated statistical relationship and the proposed strategic intervention.

RESEARCH METHOD

This research is based on services marketing theory. The paradigm states that services differ from tangible goods because of four attributes: intangibility; production and consumption at the same time; the organization should take a systematic approach to the management of its service quality through the services marketing mix, which is commonly called the 7Ps, e.g., product, price, place, promotion, people, process, and physical evidence. In the automobile industry, many scholars have used the 7Ps model to study the service marketing strategy of 4S dealerships. Recently, some academic queries have combined relationship marketing and network theory in the marketing of new energy vehicles (NEVs). For example, the case study uses the 4R theory, which suggests that NEVs should not focus on a single transaction but

should build long-term relationship management. The aim is to build customer loyalty through relevance and response.

(Wu, 2022) connection, and incentives (Wu, 2022). Academic research on the "Internet Plus" period also emphasizes the need to converge digital and physical interaction points.

The theoretical framework of the omnichannel customer journey helps clarify stages with no direct customer involvement. As stated in an integrative analysis performed by Gereia et al. (2021), the omnichannel customer experience is defined as the whole perception that people build when they move effortlessly through the different channels and interaction points in their purchasing activities. Other studies focused on conceptualizing and measuring customer experience. They also note that customers' perceptions of the company are shaped by experiences such as the physical store, the digital website, and the mobile app, as well as indirect influences such as advertising campaigns and word-of-mouth communications (Gahler et al., 2023). In the foundational literature of this subject, it is also underlined that the customer experience is, in principle, a subjective and global evaluation done by the consumer, not by the corporation. Therefore, although the firm can control touchpoint quality, it cannot prescribe or determine customers' feelings (Becker & Jaakkola, 2020).

The analytical structure proposed here distinguishes the following elements across four dimensions: Technology, Organization, Process, and Data. In the technological dimension, we have only partial representation, with measures such as the percentage of electronic work orders and the time needed to answer inquiries logged digitally. In the process dimension, we track several operational measures, such as the rate of online lead conversion, the number of offline receptions, and the completion of after-sales and follow-up. All of these measure actions across different phases of the customer journey. On the organizational side, we focus on role responsibilities, how staff is coordinated, and the incentive structure. For the data domain, we consider shared terminology, information accessibility, and record coherence. Neither the organizational nor the data dimensions are directly measured by specific constructs in the present regression analysis. So, although they provide useful context and inform manager recommendations, we do not present empirical results for them.

Thus, the proposed model links some of the technological and procedural metrics we consider to the sales revenue obtained by the dealerships and acknowledges that broader organizational competencies and data-governance structures are not covered by the present procurement specifications. It yields six hypotheses about the direction of the relations and

one hypothesis on the interaction effects. The expected relations are reported in Table 1; note that the above propositions concern correlative relations, not causal impact.

Table 1. Research hypotheses and theoretical basis

No.	Hypothesis	Theoretical basis	Expected direction
H1	The online lead conversion rate has a significant positive effect on average monthly store sales	Omnichannel customer journey theory: the efficiency with which online touchpoints convert into offline fulfillment is the first gateway to journey integration; NEV consumers rely heavily on online information in purchase decisions, and the path by which policy and product information shapes purchase intention through online channels has been validated	+
H2	Offline test-drive and reception volume has a significant positive effect on average monthly store sales	Services marketing theory: people and process are core elements of the service mix, and reception volume reflects both the customer-flow base and the utilization of reception capacity; refined management of in-store reception is the key to channel quality and efficiency gains	+
H3	After-sales service fulfillment coverage has a significant positive effect on average monthly store sales	Digital servitization theory: after-sales fulfillment is a source of servitized revenue	+
H4	App inquiry response time has a significant negative effect on average monthly store sales	Customer experience research: response speed is one of the dimensions of service to which customers are most sensitive; fast, transparent online responses are a prerequisite for winning younger consumers	-
H5	Electronic work-order coverage has a significant positive effect on average monthly store sales	The micro-mechanisms of digital servitization: process digitalization is the carrier through which service capability is accumulated	+
H6	Customer follow-up call completion rate has a significant positive effect on average monthly store sales	Relationship marketing theory: proactive post-sale contact is the core action for maintaining customer relationships and generating referrals and repeat visits	+
H7	The interaction term between online lead conversion and offline reception volume has a significant positive effect on average monthly store sales; that is, a multiplicative synergy exists between the two networks	Service ecosystem theory: coordination among multiple actors generates systemic value beyond the sum of individual contributions; if the two networks merely stack up, the total effect should equal the sum of the two coefficients, whereas genuine synergy requires a significantly positive interaction term	+

Sampling and data collection

This study used stratified random sampling, which is based on probability theory. In the sampling frame, the target population is BYD-authorized 4S dealer stores that have been continuously operating for at least one year, as listed in the official dealer registry. We chose probability sampling over convenience sampling to ensure the sample reflects the national distribution of these stores. This methodological choice avoids the selection bias that would occur if the research were conducted on high-performing outlets or on those accessible because of geographic proximity.

The stratification methodology is based on three different dimensions. In the first dimension, cities are classified as first-tier, new first-tier, second-tier, or third-tier or lower. This is because market tiers differ not only in customer-traffic dynamics, but also in the intensity of competitive pressure. The second dimension is annual revenue, which is divided into those less than RMB 50 million, those between RMB 50 million and RMB 150 million, and those higher than RMB 150 million. This matters because larger operational scale makes organizational structures and processes more complex. The third factor is the ownership structure, which is divided among the outlet that is controlled by manufacturers, the dealer group, and independent investors. This is because the policy is executed according to the ownership type. After multi-dimensional stratification, stores were selected from each stratum with equal probability to form a random sample.

The sample size was determined using the formula $n = Z^2\sigma/e^2$, with $Z = 1.96$, $\sigma = .78$, and $e = 0.15$, yielding an estimated need of about 104 retail outlets. The study shows that both the planned and actual samples comprise 120 stores. They are distributed across city tiers as follows: 18 from first-tier cities, 32 from new first-tier cities, 41 from second-tier cities, and 29 from third-tier or lower-level cities. It should be checked whether the stated adjustment for a 15% rate of invalid responses is correct, since 104 divided by 0.85 would suggest that about 123 invitations would be needed. Finally, achieving worldwide representativeness is not possible without details of the sampling frame distribution and the probabilities of inclusion.

The research is based on three different but complementary sources of information. First, the primary data are operational logs extracted from the BYD Dealer Management System (DMS), where the main variables are monthly sales, the number of customer visits, the number of service work orders, the number of follow-up calls made, and the number of digital interactions. As for the second dataset, we collected it via structured surveys on customer satisfaction that the dealerships ran at a random spot after a maintenance service; this way, we were able to have at least fifty valid answers per outlet at least one time a month, and the measurements were taken with a five-point Likert scale. To build the regional control variables, we used the most recent publicly available data from the China Passenger Car Association (CPCA) plus local statistical publications.

The construction of the survey tool was done in a structured, three-phase way: item construction, expert assessment, and a first test with a small cohort. We adapted some measurement scales that were already validated, and so we changed the original questions

in order to be closer to the operative reality of 4S dealerships, which created the first set of 32 items. A panel of two marketing academics and three automotive dealership general managers tested this draft for content validity. During the review of the draft, the items that were seen as too vague or not in the context of the survey were removed. We then conducted a preliminary pilot study with 60 respondents across three dealership sites. After a statistical evaluation of discriminant validity, some items were removed. The final instrument consists of 24 items divided into six specific dimensions: perceived online service quality, in-store reception experience, consistency between price and entitlements, and perceived after-sales service fulfillment.

These aspects align with the six operative variables above, i.e., the digital instruments and the feeling of relationship maintenance. The unit of observation is the dealership-month. The target data set is made up of 120 dealerships being tracked on the basis of a monthly basis from January 2022 through December 2024, so that in principle we have at most 4.320 observations before any data exclusions. The main dependent variable is monthly income from new vehicle sales; i.e., we exclude income from financing, insurance, and after-sales.

The metrics for online lead conversion, after-sales service fulfillment, electronic work-order coverage, and follow-up completion rate are all encoded as proportions from 0 to 1. Offline reception volume is measured as the mean number of customer groups per day during the reporting month. First response time on the apps is measured as the monthly median of the time, in minutes, between the customer and the first meaningful response. Table 2 summarizes these operational variables. Note that the constructs coming from the customer survey are supplementary measures and are not the same as the operational indicators in the DMS.

Table 2. Variable definitions and measurement

Variable type	Symbol	Variable name	Measurement	Expected direction
Dependent variable	Y	Average monthly store sales (log)	Total monthly new-car sales revenue (RMB 10,000), natural logarithm	—
Independent variable	X1	Online lead conversion rate	Share of online leads in the month who completed an in-store test drive or placed an order	+
Independent variable	X2	Average daily offline reception volume	Average daily number of customer groups received on site in the month	+
Independent variable	X3	After-sales service fulfillment coverage	Share of maintenance orders fully executed to the manufacturer's standard process	+
Independent variable	X4	App first-response time	Median minutes to first reply to online inquiries in the month	—
Independent variable	X5	After-sales electronic work-order coverage	Share of work orders circulated and archived through the electronic system	+
Independent variable	X6	Full follow-up call completion rate	Share of work orders receiving a standardized follow-up call within 72 hours after service	+
Interaction term	X1×X2	Dual-network synergy interaction	Product of mean-centered X1 and X2	+
Control variables	Z	City tier, store floor area, headcount, same-city competitors, charging infrastructure	Dummy and continuous variables	—

Measurement assessment and analytical specification

Cronbach's alpha for the full scale was 0.873; subscale coefficients ranged from 0.81 to 0.88; corrected item-total correlations ranged from 0.52 to 0.74; and the Kaiser-Meyer-Olkin measure was 0.812. Exploratory analysis identified six factors accounting for 71.4% of total variance. Factor loadings ranged from .61 to .86, average variance extracted (AVE) values ranged from .53 to .68, and composite reliability scores ranged from .82 to .90. These statistics do not support the DMS instruments. The problem to clarify is the Bartlett test statistic ($\chi^2 = 4,863.52$, $df = 153$) in the case of the 24-item survey tool. The exact items used must be specified for each validity test.

The models to be estimated contain fixed effects for the dealerships and calendar months. Dealership fixed effects control for time-invariant heterogeneity across outlets, and calendar month fixed effects control for common shocks affecting all dealerships in a given month. To address possible heteroscedasticity and serial correlation across dealerships, errors are clustered at the dealership level.

The complete model specification is defined as follows:

The econometric specification is given by the following equation: $\ln(\text{Revenue}_{it}) = \alpha_i + \lambda_t + \beta_k X_{kit} + \gamma_1 (X_{1it} - c_1) + \gamma_2 (X_{2it} - c_2) + \gamma' Z_{it} + \varepsilon_{it}$, where the subscript i stands for individual dealerships and t for the specific calendar month. In this equation, the fixed effects in i , that is, α_i , are the fixed effects for each dealership, and the fixed effects in t , that is, λ_t , are the time-specific ones across calendar months. The vector Z_{it} is a set of verified control variables that vary over time. The terms c_1 and c_2 are centering constants, equal to the sample averages of online conversion and offline reception, respectively.

The estimation goes in three steps. Model 1 includes only the fixed effects and the available time-varying controls. Model 2 adds the six different operational indicators. Model 3 adds the interaction term. Characteristics that do not vary over time, such as whether the dealership is in a fixed network or which city tier it is located in, are fully absorbed by the dealership fixed effects; they are not estimated as separate coefficients.

The coefficients obtained are associations within individual dealerships over time periods conditioned on the included covariates and the fixed effects. We note that the modeling does not preclude, a priori, omitted-variable bias, nor does it establish, a priori, causality.

Observational studies still have large problems with reverse causality and confounding that varies over time. For example, higher sales numbers may give dealerships the money to buy better digital infrastructure or hire more workers. Also, the number of customers who ask questions generally reflects local market demand, while conversion rates may reflect the same transactional mechanisms that generate revenue. Also, things that can change over time, like the promotional campaigns, the amount of stock of product that is on the market, or changes in management, could change at the same time as both the operational measures and the sales. Therefore, models that use lagged predictors serve only as a sensitivity check, not as evidence that reverse causality has been ruled out. In the absence of another source of exogenous variation that has been validated on the outside or a prospective experimental setup, the results should be viewed as representing the conditional association and not as causal.

The manuscript above includes both the first hierarchical ordinary least squares (OLS) framework and the new fixed-effects models. In fact, the numerical data in the regression tables are kept exactly as reported in the original manuscript. However, it is necessary to check a number of methodological points with respect to the final statistical results: which estimation techniques have been used, how the standard errors have been treated, what is the composition of the sample with the exclusion criteria, what is the definition of the model fit,

and how it is done for the standardization. This phase of manuscript formatting and editing does not include any new computational estimates.

RESULT AND DISCUSSION

Sample characteristics

Descriptive statistics show that mean log sales revenue is 6.21, with a standard deviation of .83. Average online conversion is 18.6%, with a standard deviation of 6.4 percentage points. For reception services, the average is 42.7 daily customer groups, with a standard deviation of 15.2. The average service fulfillment rate is 78.5% (standard deviation 11.3 percentage points). The average app response time is 3.6 minutes (SD = 2.1 minutes). The average electronic work order rate is 64.2% (SD = 18.7 percentage points). The average follow-up completion rate is 71.3% (SD = 14.6 percentage points). Online conversion and revenue are positively correlated ($r = .61$), and revenue is negatively correlated with response time ($r = -.52$). The first descriptive summary does not report the number of observations, the range of values, or the variation within the dealership.

Model fit and regression estimates

The model-fit statistics as they were presented in the source manuscript before are summarized in Table 3. With six operational indicators, the reported R^2 is raised to 0.310 to 0.680, and with the subsequent addition of an interaction term it is only marginally raised to 0.681. These variations in the fit metrics characterize only the specified models and do not indicate that operational actions causally dominate the context. Therefore, both the goodness-of-fit measures and the F-test computations have to be checked for the final fixed-effects model specification.

Table 3. Reported model summary and F-test results

Model	R	R ²	Adjusted R ²	F	Significance
Model 1 (controls only)	.557	.310	.309	387.63	$p < .001$
Model 2 (main effects)	.825	.680	.679	760.24	$p < .001$
Model 3 (with interaction)	.825	.681	.680	762.70	$p < .001$

Table 4 retains the main-effect coefficient estimates as in the paper. All six associations found are in the hypothesized direction. The standardized magnitudes describe only the comparisons and should not be taken as an order of investment returns; in addition, the standardization procedure we used has not yet been fully described.

Table 4. Reported main-effect regression coefficients

Independent variable	Unstandardized coefficient (B)	Standardized coefficient (β)	t	Significance
(Constant)	12.47	—	3.21	p < .01
Online conversion rate (X1)	.58	.47	5.63	p < .01
Offline reception volume (X2)	.31	.39	4.87	p < .01
After-sales service coverage (X3)	.18	.24	2.45	p < .05
App first-response time (X4)	-.52	-.43	-5.21	p < .01
Electronic work-order coverage (X5)	.29	.39	2.38	p < .05
Full follow-up call completion rate (X6)	.38	.42	4.96	p < .01

As shown in Table 5, the empirical analysis provides evidence in favor of hypotheses H1 through H7. It should be noted that these are, of course, results that will hold only if we are able to check that the estimates that we have presented and the statistical inference procedures used are as what holds in the final model specification.

Table 5. Reported hypothesis test results

Hypothesis	Tested path	Standardized coefficient (β)	t	Conclusion
H1	X1→Y	.47	5.63 (p < .01)	Supported
H2	X2→Y	.39	4.87 (p < .01)	Supported
H3	X3→Y	.24	2.45 (p < .05)	Supported
H4	X4→Y	-.43	-5.21 (p < .01)	Supported
H5	X5→Y	.39	2.38 (p < .05)	Supported
H6	X6→Y	.42	4.96 (p < .01)	Supported
H7	X1×X2→Y	.17	3.68 (p < .01)	Supported

The estimated percentage change in revenue for a change of Δx in a predictor variable, with all other covariates held fixed, is given by the formula $100 [\exp(B \Delta x) - 1]$. For predictors which are set as ones for proportions from 0 to 1, one rise in percentage points is equivalent to $\Delta x = 0.01$. Note that the coefficients are not the values in RMB.

A positive coefficient for the interaction term means that there is some complementarity between the two operational metrics. However, this does not mean that every online and offline activity is complementary, that there is necessarily a multiplicative effect everywhere, or that improving one channel will necessarily yield greater returns when the other channel is also improved. Therefore, these results apply only to the range observed in the sample.

For example, using the stated unstandardized coefficient for online conversion ($B = .58$) and a rate increase from 18.6% to 25%, x changes by .064. Holding other variables in the model fixed, this is associated with about a 3.8% change in revenue. Note that this is a correlational finding, not a causal financial prediction.

Operational recommendations

These suggestions shift the research focus to operational pilot testing. They are not to be read as treatment impacts that have been demonstrated or as a ranking in terms of return on investment. Rather, the order of implementing these should depend on the factors of the individual dealership, for instance, the starting performance level, the amount of available personnel, the structure of the expenses, and the needs of the client. Proposals that go beyond the measured scope, e.g., ESG programs, facility visits, virtual-reality display areas, or extending the number of products on the checklist, are outside the current specification and require their own rationale to be independent. Table 6 converts the assessed activities into suggested measures, assigned duties, limitations, and assessment metrics.

Table 6. Proposed operational actions and evaluation indicators

Operational problem	Proposed action	Responsible party	Main constraint	Evaluation indicator
Delayed inquiry responses	Assign inquiry ownership, backup coverage and escalation rules	Dealership sales manager; manufacturer platform team	Staffing and platform notifications	Median and 90th-percentile substantive response time; unanswered-inquiry rate
Lost leads during handover	Record appointment status and require receiving-team confirmation	CRM coordinator; reception team	Duplicate records and unclear ownership	Appointment attendance; handover completion; consistently defined conversion
Incomplete service fulfillment	Introduce audited completion checklists and exception handling	After-sales manager; service advisors	Workshop capacity and documentation quality	Verified fulfillment; unresolved exceptions; repeat complaints
Fragmented work-order records	Standardize electronic records and access permissions	Manufacturer IT team; dealership data steward	Interface compatibility and privacy	Electronic coverage; missing fields; reconciliation errors
Incomplete follow-up	Assign eligible cases, monitor deadlines and audit contact quality	Customer-care supervisor	Staff time and contact preferences	Verified follow-up completion; overdue cases; complaint resolution

Alternative solutions and platform proposal

Three approaches are proposed: a store improvement toolkit, a manufacturer-run platform, and third-party coaching. Table 7 compares these approaches based on managers' perceptions and estimated resources, not empirically measured results.

Table 7. Proposed alternatives and implementation trade-offs

Comparison dimension	Solution A: Store self-help package	Solution B: Manufacturer enablement platform	Solution C: Third-party in-store coaching
Up-front investment	Low (about RMB 20,000–30,000 per store)	High (system development plus training and incentives, tens of millions of yuan nationwide)	Medium (paid per store per period)
Speed of results	Slow; depends on the general manager's initiative	Medium; visible 3–6 months after system launch	Fast; improvement visible in the first month on site
Replicability	Medium; tools can be distributed but execution varies	High; standardized processes can roll out nationwide	Low; limited consultant resources cannot cover thousands of stores
Fit with empirical findings	Covers all six factors but lacks system backstop	Maps directly onto the six factors and the interaction term; highest fit	Focuses on three links: reception, follow-up, work orders
Principal risks	Becomes a formality; execution decays	Large investment, long cycle; the appraisal switch may trigger resistance	Rebound likely once the consultants leave

The store toolkit includes self-assessment tools, question scripts, reception duties checklists, follow-up protocols, and digital templates for work orders. Sources say direct financial spend is RMB 20k-30k per store. Labor and implementation are not included. A platform that would be orchestrated by the manufacturer would bring in: operational dashboards, tools to route the inquiries, standard procedures for handover of a customer, electronic work orders, training, and certification. Store toolkits and focused coaching could also be added as additional resources on this platform. The main motivation for this proposal is to interface with the platform and align metric definitions; we have not empirically checked whether this is better.

The external coaching services would provide support for a while on topics such as reception management, follow-up activities, and work order management. If any fee is linked to the result, it will be based on verified results and a common evaluation timeline. It should be noted that the timings indicated for the expected results are proposed times for evaluation, and not proven results.

Implementation risks and safeguards

Another important hazard is inconsistent data across platforms. The proposed methodology is strongly based on the information coming from the DMS, the official application, and the electronic work-order system. If the same concepts are understood in a different way in the three different systems (for instance, different standards of what is a quality lead, of what is a reception done, of what is a service request fulfilled, of what is a follow-up concluded), the resulting dashboard may show figures that look as if they were correct but that are obviously deceiving to the managers who have to take decisions. Then, correction strategies

should start with the setting up of a common data dictionary. Every metric must have one and only one definition, one and only one way to calculate it, one and only one data steward, and one and only one audit trail. Before linking the performance assessment to this platform, review the history for irregularities, missing data, duplications, and discrepancies in reporting procedures across store locations.

A third possible risk is performance manipulation. If financial rewards and performance are linked to some quantitative measures, namely the response latency, the number of work orders, and the number of follow-ups completed, the people could work to inflate these numbers instead of improving the customer experience. For example, a worker could send just a superficial initial response to stop the response-time clock, mark a follow-up as completed even if it is not, and avoid the real subsequent communication. To avoid these practices, quantitative evaluation must be paired with qualitative evaluation. The answer should be considered valid only if it truly answered the client's question at the time. The follow-up can be verified through random call audits or with the customer. Electronic work orders should be judged not only by quantity but also by the quality of their resolution and the overall work.

The fourth possible risk relates to gaps in front-line capabilities. Deploying digital infrastructure alone is not enough to build the corresponding digital skills. For instance, in some of the retail outlets, the more experienced sales and service staff may not be familiar with data visualization interfaces, with the standardized lead management procedures, or with the unified customer profiles that are used in all the phases of the consumer journey. Therefore, training must be designed around the job role and the context of use. Sales associates must know the standards for categorizing online queries and how to ensure on-time responses. Service advisors must be monitored more closely on electronic work orders and on the proper delivery of the designated services. Store managers need the dashboard to evaluate performance metrics and identify operational constraints. Regional supervision should focus on coaching branches and using the system as a didactic tool, not only a punitive one. The process of certification should.

The focus should be on evaluating actual, hands-on performance rather than merely tracking attendance at training sessions. The fifth possible risk is over-standardization. On the one hand, it is important to set nationwide goals to ensure consistent data and a consistent customer experience. But we have to accept that local markets have very different client density, traffic, competition, and service intensity. "Targets that are too hard and inflexible

can lead to unfair comparison or disincentives which undermine overall performance. So platforms have to distinguish between common procedures and local operational goals. For example, definitions, how we handle data, policies about customer entitlements, etc., should be the same nationwide. In contrast, the things we measure- the number of people we have, the volume of leads, the availability of appointments, marketing intensity, etc should be the ones that can change depending on the city classification, the size of the store, for example. This way, we can compare performance without hiding the legitimate differences between regions.

The sixth potential danger relates to execution strain. If enterprises try to introduce new frameworks, measurement indicators, educational programs, assessment procedures, and reporting obligations in parallel, it might lead to staff exhaustion and lower acceptance. Thus, the three-phase approach proposed in this study can help reduce these risks. The first effort should be focused on a few actions with big results. The second phase should focus on linking data infrastructure to operational flow. The last stage must be focused on the expansion of the incentive schemes and the improvement of the process. Each phase needs different benchmarks to define where it starts and ends. In particular, an organization has to check that the basic data and procedures from the previous stage have stability before going to more complex evaluation needs.

Phased implementation and resources

Rather than presenting it as a completed undertaking, the implementation strategy is set up as a pilot in several phases. The first step is to match the data sets, set the baseline, and clarify operational duties between the different players. Then the participating dealerships will launch specific protocols for how they handle response, handover, work orders, and follow-up. To test efficacy, dealership-level assignment should be as random as possible. In the case where it is not possible to randomize, we should use a comparison group, and in that case we have to look very carefully at the selection biases, at the different trajectories before the intervention, and at the simultaneous changes that may be made outside. Before we start, we must clearly define the primary outcome measures, the evaluation duration, implementation costs, and when and how we will scale up.

We set provisional operational goals and then check them against current baseline conditions. A decision to increase operations is based on: 1) checking data integrity, 2) maintaining continuous process improvements, 3) having satisfactory results from

customers, and 4) having a good financial justification. The current observational analysis provides no evidence that the proposed implementation approach is effective.

The schedule that is proposed here puts the first six months for pilot testing, the next phase of the deployment from month seven to month eighteen, and the last period, from month nineteen to thirty-six, for the refinement. In the original proposal, the tentatively proposed pilot-phase targets were response times under two minutes and follow-up completion above 85 percent; however, these must be questioned against today's baseline. For each project stage, criteria must define continuation, correction, and termination.

Regarding human resources, the manufacturer's project team should include at least thirty people, including, for instance, product managers, data engineers, process managers, and other trainers. For regional supervision, one supervisor for fifteen coupons of the retail is recommended, and we need one or two operations experts in each store to be hired or assigned. For some technical infrastructure and data assets, we must pay attention to the interfaces linking DMS, the official mobile application, and the electronic work order system. For the standard documentation, the performance indicators should be specified, and mechanisms for auditing the data quality should be set. For institutional resources, we must revise the dealer evaluation and rebate policy, add a data-usage clause to the dealer contract, and publish the standard operating manual for dual-network operations.

CONCLUSIONS AND RECOMMENDATIONS

The empirical results show that all six operating measures relate to monthly revenue from new-vehicle sales as expected. In particular, the standardized coefficients are very large for online lead conversion rates, response latency, and completion of follow-up actions. The positive interaction we observe between conversion and reception also aligns with the idea of complementarity in the studied sample. These interpretations are observational and depend on matching the data tables we presented with the final fixed-effects model specification.

This study contributes by using operational records to examine different activities in the customer journey and, in doing so, not treating digital transformation as an undifferentiated capability. Moreover, the analysis distinguishes between quantified operational indicators and the broader organizational and data-governance contexts in which the proposed managerial recommendations are set.

The practical suggestions focus on handling inquiries, transferring leads, providing services, processing the e-work order, and follow-up. It is suggested to have a platform that is coordinated by the manufacturer for the assessment, but the relative effectiveness, the costs of implementation, and the return on investment have not yet been checked empirically. This work is limited by the fact that we work with only one brand, so sample-selection bias, measurement error, and reverse causality may be present. Moreover, sales revenue is a very poor proxy for profitability, customer loyalty, or lifetime value. The following studies should be done in a prospective design to test the interventions, to go beyond one brand and one dealer network, and to use metrics independently of each other to analyze the customer-related and financial results.

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