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Data-driven retail service operations: big data analytics capability, market orientation, innovation and marketing capabilities in Thailand's retail sector

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Abstract: The research examines relationships among big data analytics capability, market orientation, innovation and marketing capabilities in Thailand's retail sector and compares SME-sized retailers with large retailers. Drawing on the resource-based view and dynamic capabilities perspective, a nationwide stratified-quota survey was conducted from January to March 2026. Of 1,552 invited firms, 500 provided usable responses, equally divided by firm size. Descriptive statistics, Welch's t-tests, confirmatory factor analysis and structural equation modelling were applied. The final model showed strong fit (CMIN-p = 0.306, CMIN/DF = 1.046, GFI = 0.961, RMSEA = 0.010). Big data analytics capability was strongly associated with market orientation and positively associated with innovation and marketing capabilities; market orientation was positively associated with both downstream capabilities. Large retailers reported higher capability levels. The findings position data-driven retail strategy as an interconnected capability pattern within retail service operations.

Keywords: big data analytics; retail service operations; market orientation; innovation; marketing capabilities; Thailand retail sector.

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1 Introduction

Retail competition increasingly depends on converting customer, transaction and channel data into operationally useful insights. As service encounters extend across stores, websites, mobile applications, social platforms and delivery systems, retailers must coordinate channels, redesign processes and deliver consistent customer-facing operations (Bin-Obaidellah et al., 2024; Kumar and Ayodeji, 2022; Nayeri et al., 2022).

From a services and operations management perspective, data create value when embedded in organisational routines supporting service delivery, process improvement, innovation and operational execution. This capability-based interpretation aligns with the resource-based view and dynamic capabilities perspective, which emphasise strategic resources and firms' ability to sense, seize and transform under changing conditions (Barney, 1991; Teece et al., 1997; Teece, 2007).

Retailing is particularly relevant because the boundaries among marketing, service delivery and operations are increasingly blurred. Omnichannel retailing requires coordinated decisions concerning customer information, fulfilment, communication, merchandising, service recovery and digital interaction (Bin-Obaidellah et al., 2024; Kumar and Ayodeji, 2022; Saadat et al., 2022). In a sustainability-oriented Thai business context, green omnichannel capability has similarly been conceptualised as a market-facing innovation capability that integrates channel coordination, fulfilment, communication and customer relationship practices (Sukhawattanakun, 2026). Prior studies have examined web analytics, e-commerce success, retail service quality, new-service development, analytics capability, innovation and market orientation (Bin-Obaidellah et al., 2024; Dang et al., 2025; Haque et al., 2023; Haverila and Haverila, 2024; Kumar and Ayodeji, 2022; Morimura and Sakagawa, 2023; Nayeri et al., 2022; Saadat et al., 2022). However, their integration within an operations-oriented capability system remains underexplored. The central challenge is therefore to translate data into repeatable routines for sensing customers, coordinating channels, redesigning services and maintaining operational consistency (Haque et al., 2023; Morimura and Sakagawa, 2023; Saadat et al., 2022).

Thailand provides a relevant setting because retailers differ substantially in resources and digital maturity. National establishment data indicate that medium and large enterprises report near-universal computer and internet use, while large enterprises adopt cloud services and advanced business applications more extensively than MSMEs. Larger firms therefore appear better positioned to integrate digital technologies into operations, whereas MSMEs continue to face financial, technological and managerial constraints

(World Bank, 2023, 2025). These disparities have important managerial and policy implications.

Accordingly, this study tests a structural equation model of data-driven retail service operations in Thailand. Big data analytics capability represents information-processing routines; market orientation captures market-sensing and interpretive routines; innovation reflects service and process renewal; and marketing capabilities represent market execution. By integrating these constructs, the framework explains how retailers detect changes in demand, coordinate channels, and translate customer information into repeatable operational actions.

The study focuses on capabilities underpinning retail service operations rather than direct performance outcomes. Service quality, fulfilment reliability, productivity, waiting time, inventory availability and process performance remain important directions for future research. This capability-based framework therefore positions data-driven retail strategy within the broader services and operations management literature.

2 Literature review and hypotheses

2.1 *Data-driven retail service operations*

Data-driven retail service operations use data, analytics and evidence-informed routines to support service delivery, channel coordination, customer experience and execution. As journeys span physical, digital and social channels, retailers must connect data with timely responses and process adjustment (Bin-Obaidellah et al., 2024; Kumar and Ayodeji, 2022; Nayeri et al., 2022).

Retail service operations are information-intensive because variable, participatory encounters are shaped by demand, stock availability, delivery accuracy, queueing, recovery and channel switching. Data-driven routines can identify such issues and coordinate responses, making analytics an operational as well as promotional resource (Haque et al., 2023; Saadat et al., 2022).

Capability integration is essential: transaction data strengthen operations only when connected with market interpretation, priorities and execution. Even firms with limited digital resources can capture feedback, monitor sales, share intelligence and address service problems. Analytics value therefore depends on complementary capabilities and routines (Barney, 1991; Morimura and Sakagawa, 2023; Teece et al., 1997; Teece, 2007).

2.2 *Theoretical foundation: resource-based view and dynamic capabilities*

The resource-based view attributes competitive advantage to valuable, rare, inimitable and organisationally embedded resources (Barney, 1991). Data generate value when interpreted, integrated and deployed through routines supporting service delivery, customer experience and market action. Accordingly, big data analytics capability creates value when aligned with strategy and dynamic capabilities rather than treated as isolated technology (Akter et al., 2016; Wamba et al., 2017).

The dynamic capabilities perspective extends this reasoning by emphasising firms' ability to sense opportunities and threats, seize opportunities and transform resources under changing market conditions (Teece et al., 1997; Teece, 2007). Evidence from Thailand's industrial value chain supports this reasoning by showing that

resource adaptability is associated with operational value when coordinated with employee-centred governance and integrated knowledge routines (Sukhawattanakun and Pongsuwan, 2026). Within the proposed framework, big data analytics capability supports sensing and information processing, market orientation facilitates interpretation, and innovation and marketing capabilities enable renewal and service execution.

Together, the perspectives distinguish analytics resources from the routines that mobilise them: the resource-based view explains their potential value, while dynamic capabilities explain value creation through sensing, interpretation and transformation. The integration suits service operations, where continuous adaptation matters more than a single technology investment. Analytics therefore becomes strategically meaningful when connected with market-oriented interpretation and service execution.

2.3 *Big data analytics capability and market orientation*

Big data analytics capability combines analytics-related skills, data governance, cross-channel integration, experimentation, insight communication and data-quality routines. It represents organisational analytics capability rather than technical sophistication and supports monitoring of customers, demand, channels, service failures, competitors and bottlenecks. Market orientation involves generating and disseminating market intelligence and responding to customers, competitors and market conditions (Kohli and Jaworski, 1990; Narver and Slater, 1990).

Analytics capability may strengthen the sensing function of market orientation by improving the availability, timeliness, scope and accuracy of market intelligence. Evidence from online retail indicates that web analytics supports consumer-behaviour tracking, operational planning and decision optimisation (Kumar and Ayodeji, 2022). Market orientation is also positively associated with the performance of micro and small enterprises (Bin-Obaidellah et al., 2024), while retail research links analytics capability with market orientation and firm performance (Morimura and Sakagawa, 2023).

Operationally, analytics enables retailers to detect changes in traffic, purchasing frequency, fulfilment expectations, complaints and competitor activity, while market orientation translates those signals into service and channel decisions. Big data analytics capability is therefore expected to be positively related to market orientation.

H1 Big data analytics capability has a positive direct relationship with market orientation.

2.4 *Big data analytics capability, innovation and marketing capabilities*

Big data analytics capability is expected to relate positively to innovation and marketing capabilities. In retail service operations, analytics can identify unmet needs, reduce uncertainty and reveal opportunities from customer, transaction, channel and market signals. Prior evidence links innovation, strategic orientation and market orientation with new-service development and retail innovation (Dang et al., 2025; Morimura and Sakagawa, 2023; Nayeri et al., 2022).

Marketing capabilities deploy knowledge and routines to understand markets, design value propositions, communicate, manage relationships and execute programmes (Vorhies and Morgan, 2005). Here they represent retail service-execution capabilities spanning segmentation, communication, relationships, channels, stores and

merchandising. Evidence connects these capabilities with retail outcomes, analytics quality, agility and strategic alignment (Akter et al., 2016; Haque et al., 2023; Haverila and Haverila, 2024; Saadat et al., 2022; Vesterinen et al., 2025; Wamba et al., 2017).

Operationally, marketing capabilities align customer promises with fulfilment through coordinated inventory, staff responsiveness, channel access and service recovery.

H2 Big data analytics capability has a positive direct relationship with marketing capabilities.

H3 Big data analytics capability has a positive direct relationship with innovation.

2.5 Market orientation, innovation and marketing capabilities

Market orientation connects customer and competitor information with organisational response. Customer focus identifies unmet needs, competitor awareness reveals gaps, and interfunctional coordination converts intelligence into services, processes and experiences. Prior evidence links market orientation with learning, analytics, technology adoption, innovation and adaptive response (Gangwani and Bhatia, 2024; Itani et al., 2026; Song and Liao, 2024).

Market orientation is also expected to be positively related to marketing capabilities because market-oriented firms are more likely to translate customer and competitor intelligence into segmentation, positioning, communication, customer relationship management, pricing, channel coordination and operational execution. Prior research similarly links market orientation to marketing capability development and performance-related outcomes (Morgan et al., 2009; Ngo and O'Cass, 2012; Shanka et al., 2025).

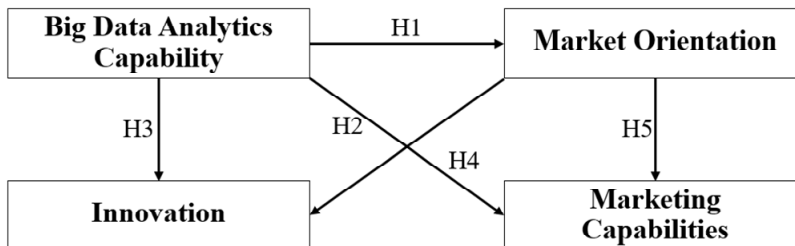
H4 Market orientation has a positive direct relationship with innovation.

H5 Market orientation has a positive direct relationship with marketing capabilities.

2.6 Research framework

Although analytics, digital transformation, innovation and market-facing capabilities attract growing interest, they are often examined separately. The deductive model addresses this gap by assigning distinct functions to big data analytics capability, market orientation, innovation and marketing capabilities without treating their ordering as a verified causal sequence.

Figure 1 Conceptual framework of data-driven retail service operations



The four constructs form a connected system of market interpretation, service renewal and retail execution.

Figure 1 presents the associations among the four capabilities and compares SME-sized and large retailers in Thailand.

3 Methodology

3.1 Research design

A quantitative, cross-sectional and deductive design examined relationships among the four capabilities and compared firm-size groups. The retail firm was the unit of analysis, represented by one entrepreneur, owner or branch manager involved in relevant operational, marketing, digital or strategic decisions. Survey instructions and screening enforced the one-response-per-firm protocol.

3.2 Population and sample

The target population estimate was based on data from the Office of Trade Policy and Strategy (2025). The recruitment frame was compiled from publicly available business directories and contact sources.

Eligible informants were entrepreneurs, owners or branch managers aged 20–60 years who participated in relevant decisions and understood the firm's marketing, data-use and innovation activities. The minimum age ensured legal capacity to provide independent consent, while the upper age limit followed the eligibility criteria specified in the ethics-approved research protocol.

Non-probability stratified-quota sampling classified firms as SME-sized retailers (≤ 100 employees) or large retailers (> 100 employees). The cut-off follows Thailand's upper employment threshold for MSMEs in trade and services (Ministry of Industry, 2019). The SME group combined micro, small and medium enterprises for analysis; this operational classification did not reproduce the full statutory scheme, which also considers revenue.

The final sample comprised 250 firms per group. Equal allocation supported balanced comparisons rather than population proportionality. Firms with available contact information were approached until both quotas were filled; stratification organised recruitment but did not provide probability selection within strata. Revenue was collected only for descriptive profiling and was not used to determine firm-size group membership. Other organisational characteristics included legal form, type of retail business, business model, years of operation and geographical region.

3.3 Data collection

Data were collected from 3 January to 31 March 2026 following ethical approval. The survey was administered mainly through e-mail invitations and direct electronic communication, while printed questionnaires or postal invitations were used where online access was limited. Invitations explained the research purpose, eligibility criteria, voluntary participation and confidentiality protections.

Electronic consent preceded screening for age, organisational role and decision-making involvement. Ineligible respondents could not access the questionnaire, whose closed-ended items required responses to minimise missing data. No respondent or firm identifiers were collected, and invitations specified that only one knowledgeable informant should respond for each firm.

Of 1,552 invitations, 500 complete eligible questionnaires were retained, yielding 32.22% of invitations sent. All firm-size quotas were met, and the final dataset contained no missing values. This percentage represents a usable-response yield rather than a disposition-adjusted response rate.

The sample size was considered adequate for covariance-based structural equation modelling, given the number of observed indicators and model complexity (Hair et al., 2019). Respondent and firm-size profiles are presented in Table 1, while organisational characteristics are reported in Table 3.

Table 1 Firm-size distribution and respondent profile

<i>Characteristic</i>	<i>Category</i>	<i>n</i>	<i>Percent (%)</i>
Firm size	SME-sized retailers (≤ 100 employees)	250	50.00
	Large retailers (> 100 employees)	250	50.00
Current position	Entrepreneur/owner	108	21.60
	Branch manager	392	78.40
Age	20–30 years	68	13.60
	31–40 years	298	59.60
	41–50 years	85	17.00
	51–60 years	49	9.80

Note: The equal allocation was predetermined to provide balanced group sizes for firm-size comparison and does not represent the actual population proportions of Thai retail businesses. Percentages are based on the final valid sample of 500 participants, with one respondent representing each participating firm.

3.4 Research instrument and measurement development

The questionnaire drew on the framework and prior literature. Its 48 measurement items – 12 per construct – used a five-point scale from 1 = lowest to 5 = highest (Batterton and Hale, 2017), alongside respondent, organisational, practice, obstacle and comment sections.

As all respondents were Thai, data were collected using the Thai-language questionnaire. Five experts reviewed the instrument for clarity, contextual appropriateness and consistency with the intended constructs. The English version presented in Appendix A is provided for publication transparency.

The item-objective congruence (IOC) index for each item was calculated by summing the ratings of the five experts and dividing the total by five. Each expert assigned +1 for congruent, 0 for uncertain and –1 for incongruent. The resulting IOC values ranged from 0.80 to 1.00, exceeding the acceptance criterion of 0.67.

A pilot test with 30 comparable respondents yielded corrected item-total correlations of 0.330–0.890. Cronbach's alpha coefficients were 0.940 for big data analytics capability, 0.900 for market orientation, 0.920 for innovation and 0.910 for marketing

capabilities. The overall 48-item instrument achieved an alpha of 0.929, exceeding the recommended reliability criterion (Churchill, 1979; Stockemer and Bordeleau, 2023).

Table 2 Instrument structure and final measurement properties

<i>Construct</i>	<i>Number of initial items</i>	<i>Main measurement domains</i>	<i>Indicators retained in the final measurement model</i>	<i>Standardised loading range</i>	<i>Cronbach's alpha</i>	<i>CR</i>	<i>AVE</i>
Big data analytics capability	12	Data acquisition, integration, interpretation, application, governance and data quality	BA2, BA4, BA5, BA7, BA10, BA12	0.681–0.736	0.851	0.851	0.488
Market orientation	12	Customer attention, market intelligence, information sharing and responsiveness	MO4, MO5, MO8, MO9, MO10	0.706–0.730	0.842	0.841	0.514
Innovation	12	Service, process, customer-experience and market-response renewal	IN3, IN5, IN7, IN8, IN11, IN12	0.708–0.742	0.868	0.868	0.523
Marketing capabilities	12	Value communication, customer relationship management, channel execution, store operations, merchandising and marketing implementation	MC1, MC4, MC7, MC9, MC10, MC12	0.690–0.744	0.862	0.862	0.510

Note: CR – composite reliability; AVE – average variance extracted. Despite a marginal AVE of 0.488, big data analytics capability demonstrated adequate convergent validity, as evidenced by its CR of 0.851 and standardised loadings (Fornell and Larcker, 1981). Appendix A presents the full questionnaire; Appendix B, Tables B1–B2 report item development and indicator retention, respectively.

Items captured organisational routines: big data analytics capability covered data acquisition, integration, interpretation, application, governance and quality; market orientation covered intelligence and responsiveness; innovation covered service, process and experience renewal; and marketing capabilities covered communication, relationships, channels, stores, merchandising and implementation.

Iterative, conservative respecification reduced the initial 48-item model to 23 items. Decisions jointly considered loadings, residuals, redundancy, reliability, validity, fit and theoretical relevance rather than modification indices alone.

Table 2 summarises the instrument and final measurement properties. Appendix A provides the complete questionnaire; Table B1 in Appendix B reports the item-development mapping, while Table B2 documents the transition from the initial 48 items to the final 23 retained indicators, including the omitted items.

3.5 Data analysis

SPSS 29 and AMOS 30 were used. Descriptive statistics summarised profiles, constructs and highest-rated items. The overall composite was the unweighted mean of the four construct composites; Welch's independent-samples t-test compared firm-size groups.

Data screening assessed errors, outliers, distributional assumptions and potential ceiling effects using skewness, kurtosis and Mahalanobis distance. The results supported maximum likelihood estimation. Construct-level ceiling effects were limited, although substantial maximum-score response concentrations occurred for several individual items. The findings were therefore interpreted cautiously (Appendix B, Table B3).

Confirmatory factor analysis (CFA) preceded structural testing. The retained structure was assessed through standardised loadings, Cronbach's alpha, composite reliability (CR), average variance extracted (AVE) and discriminant validity (Fornell and Larcker, 1981; Hair et al., 2019; Henseler et al., 2015). Discriminant validity was further assessed using the heterotrait-monotrait ratio (HTMT) and bootstrapped confidence intervals (Henseler et al., 2015). HTMT values ranged from 0.894 to 0.923; all remained below 0.95, although some exceeded the more conservative 0.90 benchmark. None of the 95% bootstrapped confidence intervals included 1.00. Initial and final model-fit statistics documented the measurement respecification.

Indicator retention was guided by factor loadings, redundancy, residual patterns, reliability, validity, model fit and theoretical coverage. Items with acceptable loadings were removed only when conceptual overlap or residual dependence warranted exclusion without compromising construct coverage. Modification indices were used diagnostically rather than as stand-alone criteria. The hypothesised structural paths remained unchanged, and no error covariances were introduced solely to improve fit. Appendix B, Table B2 documents all indicator-level decisions. The resulting structure represents a theory-guided and empirically supported measurement model that warrants further validation in independent samples.

Structural equation modelling (SEM) with maximum likelihood estimation tested the five hypothesised relationships in the pooled sample. Model fit was assessed using CMIN-*p*, CMIN/DF, GFI, RMSEA, CFI, TLI and SRMR (Arbuckle, 2022). Although the measurement model was refined, all five hypothesised structural paths were retained without modification.

Robustness checks addressed construct distinctiveness, multicollinearity, common method variance, firm-size comparability and indirect associations. Alternative measurement models, descriptive correlations, VIF diagnostics (maximum = 2.515) and bootstrapped HTMT intervals were examined.

Potential common method variance was addressed through procedural controls and evaluated using Harman's single-factor test and comparisons between one- and four-factor CFA models (Podsakoff et al., 2003). A proportionally stratified post hoc split-sample analysis further supported the internal stability of the model, providing a basis for subsequent validation with independent samples.

Multi-group CFA assessed configural and metric invariance using changes in CFI, RMSEA and SRMR. Scalar invariance was not assessed and therefore was not established. Accordingly, firm-size differences were examined using observed composite scores rather than latent means. Indirect effects were estimated using 5,000 bias-corrected bootstrap resamples with 95% confidence intervals.

Consistent with the cross-sectional, single-informant design, the structural coefficients were interpreted as theoretically specified associations. The pooled SEM provided an integrated assessment of the overall pattern of relationships among the four capability domains.

3.6 Ethical considerations

The study obtained informed consent from all participants. Respondents were informed about the purpose, procedures, voluntary participation, confidentiality and right to withdraw without penalty. No personal identifiers were reported.

4 Results

4.1 Respondent profile

After data screening, 500 valid responses were retained. Table 3 summarises the sample profile of surveyed organisations. The sample was evenly divided between SME-sized retailers and large retailers, with 250 respondents in each group. Limited companies formed the largest legal-form group. The sample covered retail firms across six regions of Thailand, with the largest proportion located in the central region. Speciality stores were the largest retail type, and omnichannel selling was the most common sales model. Businesses operating for 15 years or more formed the largest group, and those reporting average annual organisational revenue of more than 50 million Thai baht formed the largest revenue group.

4.2 Descriptive statistics and firm-size differences

All four constructs received high ratings, led by market orientation, followed by marketing capabilities, innovation and big data analytics capability (Table 4). Large retailers scored higher than SME-sized retailers across all four constructs (Welch's $t = 6.703\text{--}7.871$, $p < 0.001$; Cohen's $d = 0.600\text{--}0.704$). These moderate observed-score differences indicate association, not a causal effect of firm size.

Item-level results from the original 48-item questionnaire showed that the highest-rated practices concerned adaptation, responsiveness, execution and data governance. The leading items involved customer listening and the use of customer information in marketing decisions for market orientation ($M = 4.58$, $S.D. = 0.87$), adjustment of the shopping experience for innovation ($M = 4.55$, $S.D. = 0.80$), systematic store operations and merchandising for marketing capabilities ($M = 4.52$, $S.D. = 0.84$), and customer-data privacy and security for big data analytics capability ($M = 4.50$, $S.D. = 0.78$). These figures describe items from the original questionnaire rather than only the retained SEM indicators. For concise reporting, Appendix B, Table B4 presents the highest-rated items from the original questionnaire, selected based on their mean scores.

Table 3 Sample profile of surveyed organisations

<i>General information</i>	<i>Frequency</i>	<i>Percentage</i>
Legal form		
Sole proprietorship	89	17.80
Limited partnership	63	12.60
Limited company	298	59.60
Public limited company	50	10.00
Region of business location		
Central region	145	29.00
Northern region	65	13.00
Western region	40	8.00
Northeastern region	105	21.00
Eastern region	70	14.00
Southern region	75	15.00
Type of retail business		
Convenience store	95	19.00
Grocery store	105	21.00
Speciality store	130	26.00
Supermarket	65	13.00
Hypermarket	35	7.00
Department store/shopping centre	70	14.00
Sales model of the retail business		
Offline selling	180	36.00
Online selling	40	8.00
Omnichannel selling	280	56.00
Years of operation		
5 years or less	90	18.00
6–10 years	120	24.00
11–15 years	120	24.00
More than 15 years	170	34.00
Average annual organisational revenue		
Less than 1 million baht	25	5.00
1–10 million Thai baht	105	21.00
11–50 million Thai baht	145	29.00
More than 50 million Thai baht	225	45.00

Note: n = 500. Percentages are based on the final valid sample of 500 participating retail firms. Each response represented one participating retail firm. The revenue categories were used for descriptive profiling only; firm-size grouping in the main analysis was based on the employee threshold.

Table 4 Descriptive statistics and firm-size mean comparisons

<i>Construct</i>	<i>Overall mean (S.D.)</i>	<i>SME mean (S.D.)</i>	<i>L mean (S.D.)</i>	<i>Welch's t</i>	<i>df</i>	<i>Cohen's d</i>	<i>p-value</i>
Overall	4.38 (0.66)	4.22 (0.68)	4.55 (0.64)	7.090	495.290	0.634	<0.001
Market orientation	4.42 (0.68)	4.23 (0.69)	4.60 (0.62)	7.871	493.310	0.704	<0.001
Marketing capabilities	4.40 (0.60)	4.24 (0.58)	4.57 (0.60)	7.161	492.280	0.641	<0.001
Innovation	4.37 (0.68)	4.22 (0.66)	4.52 (0.68)	6.703	497.664	0.600	<0.001
Big data analytics capability	4.35 (0.65)	4.20 (0.60)	4.51 (0.64)	6.926	496.470	0.620	<0.001

Note: SME – SME-sized retailers; L – large retailers. Welch's independent-samples t-test was used for all firm-size comparisons. Positive Cohen's d values indicate higher scores among large retailers. All comparisons were significant at $p < 0.001$.

4.3 *Measurement model, reliability, validity and common method bias*

In the initial 48-indicator model, all standardised factor loadings were statistically significant and ranged from 0.585 to 0.754. At the construct level, the loadings ranged from 0.585 to 0.722 for big data analytics capability, 0.684 to 0.754 for market orientation, 0.696 to 0.735 for innovation and 0.652 to 0.738 for marketing capabilities. Although all initial standardised loadings exceeded 0.50, the initial model did not meet all recommended fit criteria, particularly CMIN-p and GFI. Accordingly, measurement respecification was based on the joint consideration of loading magnitude, item redundancy, localised residual patterns, measurement quality, overall model fit and theoretical coverage rather than on a loading cut-off alone.

The final measurement model retained 23 of the original 48 indicators: six for big data analytics capability, five for market orientation, six for innovation and six for marketing capabilities. Retention was based jointly on empirical contribution and theoretical coverage, not modification indices alone (Appendix B, Table B2).

Both post hoc subsamples produced acceptable fit and comparable loading ranges, providing limited internal stability evidence. Because the full dataset had already determined the 23-indicator structure, independent replication remains necessary (Appendix B, Table B6).

The four-factor model fitted better than the one-factor and combined-construct alternatives (Appendix B, Table B5), supporting empirically distinguishable but closely related capability dimensions.

Standardised loadings ranged from 0.681 to 0.744; Cronbach's alpha from 0.842 to 0.868; CR from 0.841 to 0.868; and AVE from 0.488 to 0.523 (Table 5). Big data analytics capability was retained despite $AVE = 0.488$ because its CR was high, loadings were significant and the indicators remained theoretically relevant.

All HTMT values were below 0.95, although several modestly exceeded the more conservative threshold of 0.90. Importantly, the 95% bootstrap confidence intervals for

all construct pairs excluded 1.00, supporting empirical distinctiveness among the four closely related constructs (Appendix B, Table B7).

Harman's first factor accounted for 45.38% of the variance, and the one-factor CFA fitted substantially worse than the four-factor model. Together, these diagnostics suggest that no single factor dominated the covariance structure, although common method variance cannot be ruled out (Appendix B, Tables B5 and B8).

Preliminary multi-group CFA supported configural and metric invariance across firm-size groups. The configural model demonstrated a good fit to the data ($\chi^2 = 571.584$, $df = 448$, $CMIN/DF = 1.276$, $CFI = 0.977$, $TLI = 0.974$, $RMSEA = 0.024$ and $SRMR = 0.037$), indicating that the same four-factor measurement structure was applicable to both groups. The metric model also showed a good fit ($\chi^2 = 593.521$, $df = 467$, $CMIN/DF = 1.271$, $CFI = 0.977$, $TLI = 0.975$, $RMSEA = 0.023$ and $SRMR = 0.045$). The changes in fit indices were small ($\Delta CFI = -0.001$, $\Delta RMSEA < 0.001$ and $\Delta SRMR = 0.008$), supporting the comparability of factor loadings across firm-size groups. Overall, the results indicate that the measurement structure operated consistently across the two groups at the configural and metric levels (Appendix B, Table B9).

Table 5 Confirmatory factor analysis results

<i>Construct</i>	<i>Retained indicators</i>	<i>Standardised loading range</i>	<i>Cronbach's alpha</i>	<i>CR</i>	<i>AVE</i>
Big data analytics capability	BA2, BA4, BA5, BA7, BA10, BA12	0.681–0.736	0.851	0.851	0.488
Market orientation	MO4, MO5, MO8, MO9, MO10	0.706–0.730	0.842	0.841	0.514
Innovation	IN3, IN5, IN7, IN8, IN11, IN12	0.708–0.742	0.868	0.868	0.523
Marketing capabilities	MC1, MC4, MC7, MC9, MC10, MC12	0.690–0.744	0.862	0.862	0.510

Note: CR – composite reliability; AVE – average variance extracted.

Table 6 Model fit before and after measurement respecification

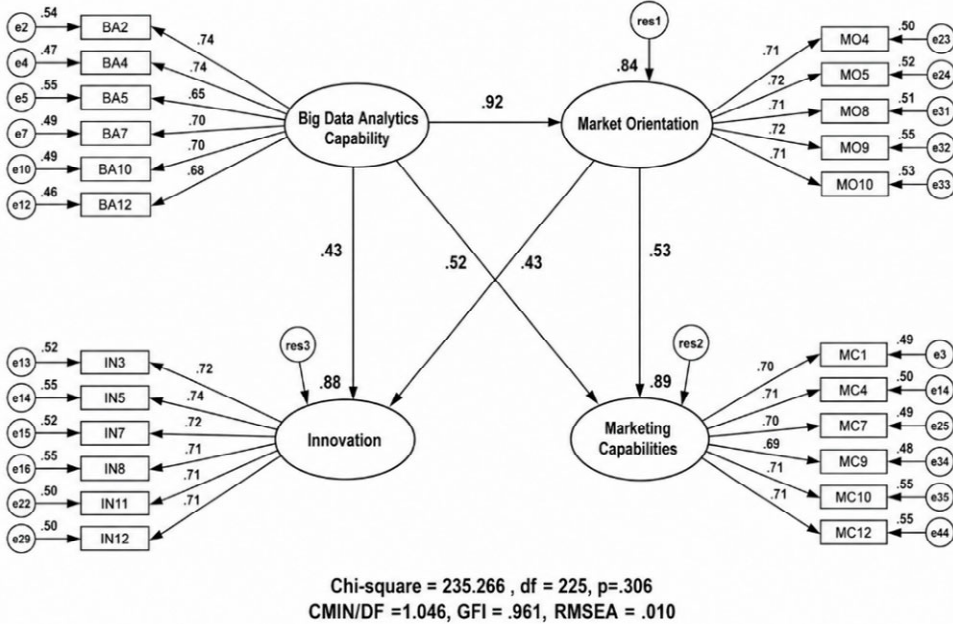
<i>Fit index</i>	<i>Recommended value</i>	<i>Initial 48-indicator model</i>	<i>Final 23-indicator model</i>
CMIN-p	≥ 0.050	0.000	0.306
CMIN/DF	≤ 2.000	1.422	1.046
GFI	≥ 0.900	0.884	0.961
RMSEA	≤ 0.080	0.029	0.010
CFI	≥ 0.900	0.967	0.998
TLI	≥ 0.900	0.966	0.998
SRMR	≤ 0.080	0.010	0.008

Note: Both models retained the same five hypothesised structural paths; improvement in model fit resulted solely from theory-constrained indicator-level measurement respecification.

4.4 Structural model fit

Following theory-constrained respecification of the measurement model, the final structural model, comprising 23 indicators and all five hypothesised paths, demonstrated substantially improved fit: CMIN-p = 0.306, CMIN/DF = 1.046, GFI = 0.961, RMSEA = 0.010, CFI = 0.998, TLI = 0.998 and SRMR = 0.008 (Figure 2 and Table 6).

Figure 2 Final structural equation model with standardised estimates



4.5 Hypothesis testing and structural path results

The pooled model supported all five direct relationships. Big data analytics capability was strongly and positively associated with market orientation (H1) and positively associated with innovation and marketing capabilities (H2–H3). Market orientation was positively associated with both downstream capabilities (H4–H5). Table 7 reports the standardised coefficients.

The model accounted for 84.3% of the variance in market orientation, 88.0% in innovation and 89.1% in marketing capabilities.

Bias-corrected bootstrapping (5,000 resamples; 95% confidence intervals) identified significant indirect associations between big data analytics capability and innovation through market orientation ($\beta = 0.481$, 95% bias-corrected confidence interval [BC CI] = 0.189–0.910, $p = 0.010$) and between big data analytics capability and marketing capabilities through market orientation ($\beta = 0.490$, 95% BC CI = 0.181–0.938, $p = 0.011$). Consistent with the cross-sectional design, these findings represent theoretically specified indirect associations (Table 8).

Table 7 Hypothesis testing results

<i>Hypothesis</i>	<i>Structural path</i>	<i>Standardised estimate</i>	<i>C.R.</i>	<i>p-value</i>	<i>Result</i>
H1	Big data analytics capability → Market orientation	0.918	14.468	<0.001	Supported
H2	Big data analytics capability → Marketing capabilities	0.429	3.482	<0.001	Supported
H3	Big data analytics capability → Innovation	0.434	3.525	<0.001	Supported
H4	Market orientation → Innovation	0.524	4.194	<0.001	Supported
H5	Market orientation → Marketing capabilities	0.534	4.263	<0.001	Supported

Note: Estimates are standardised coefficients from the pooled SEM; C.R. = critical ratio. Structural paths are interpreted as associations due to the cross-sectional, self-reported design.

Table 8 Bootstrapped indirect effects

<i>Indirect relationship</i>	<i>Mediating construct</i>	<i>Standardised indirect effect</i>	<i>95% BC bootstrap CI</i>	<i>p-value</i>	<i>Interpretation</i>
BA → Innovation	Market orientation	0.481	0.189–0.910	0.010	Significant indirect association
BA → Marketing capabilities	Market orientation	0.490	0.181–0.938	0.011	Significant indirect association

Note: BA – big data analytics capability; BC = bias-corrected. Confidence intervals were based on 5,000 usable bootstrap samples. Effects are standardised estimates. Indirect effects are interpreted as associations rather than causal mediation under the cross-sectional, self-reported design.

4.6 Direct, indirect and total effects

Direct, indirect and total effects are summarised in Table 9. Through market orientation, big data analytics capability had total associations of 0.915 with innovation and 0.920 with marketing capabilities.

Table 9 Direct, indirect and total effects of the structural model

<i>Predictor</i>	<i>Outcome</i>	<i>Direct effect</i>	<i>Indirect effect</i>	<i>Total effect</i>
Big data analytics capability	Market orientation	0.918	0.000	0.918
Big data analytics capability	Innovation	0.434	0.481	0.915
Big data analytics capability	Marketing capabilities	0.429	0.490	0.920
Market orientation	Innovation	0.524	0.000	0.524
Market orientation	Marketing capabilities	0.534	0.000	0.534

Note: Values are standardised estimates. Indirect effects are model-implied associations and should not be interpreted as causal mediation.

Table 8 reports bootstrapped indirect-effect inference, whereas Table 9 decomposes standardised effects. Market orientation is a model-implied interpretive link, and innovation was specified as an outcome rather than another mediator.

4.7 Correlation analysis

All retained construct composites showed positive correlations ($r = 0.774\text{--}0.787$, $p < 0.001$). Interpreted with HTMT intervals and VIF diagnostics, the pattern supports theoretically distinct but closely connected capabilities rather than standalone evidence of discriminant validity (Appendix B, Tables B10–B11).

5 Discussion

5.1 Overview of the findings

The findings support a capability-based model of data-driven retail service operations in Thailand. All five hypothesised relationships were supported. Big data analytics capability was strongly associated with market orientation and positively associated with innovation and marketing capabilities, while market orientation was positively associated with both downstream capabilities. The four capability domains were therefore closely connected while remaining theoretically distinct.

Collectively, the results suggest that analytics is most relevant to retail service operations when data-processing routines are accompanied by market interpretation, operational renewal and market-facing execution. This interpretation does not imply a verified causal sequence; rather, it reflects the theoretically specified pattern of associations observed in the cross-sectional model. Evidence from Thailand's industrial value chain similarly indicates that organisational adaptability is associated with the alignment of dynamic resources, employee-centred systems and integrated knowledge processes (Sukhawattanakun and Pongsuwan, 2026).

Related studies document the roles of web analytics in retail planning (Kumar and Ayodeji, 2022), service quality and infrastructure in e-commerce success (Saadat et al., 2022), and operational capabilities in service and retail outcomes (Bin-Obaidallah et al., 2024; Haque et al., 2023). The present study integrates these previously dispersed domains within a unified retail service-operations framework.

5.2 Analytics capability as an upstream retail service-operations capability

Support for H1 indicates a positive association between big data analytics capability and market orientation. Routines for collecting, processing and interpreting data are closely connected with firms' ability to sense and respond to changes in customers, competitors and markets (Kohli and Jaworski, 1990; Narver and Slater, 1990; Teece, 2007). From an operations perspective, this relationship links data-related sensing with managerial interpretation, internal coordination and response. Analytics thus appears most useful when information becomes accessible and meaningful to those responsible for operational decisions.

Support for H2 indicates a positive association between big data analytics capability and marketing capabilities. Analytics can help translate market knowledge into

customer-facing implementation through segmentation, communication, customer relationship management and channel coordination (Day, 1994; Kumar and Ayodeji, 2022; Vorhies and Morgan, 2005). These routines connect market information with the organisation and delivery of retail activities across physical and digital channels. The relationship therefore indicates that analytics is associated not only with information processing but also with the retailer's capacity to execute market-facing activities consistently.

Support for H3 indicates a positive association between big data analytics capability and innovation. Analytics may help retailers identify emerging needs, recognise service problems, reduce information uncertainty and adapt services, processes and customer experiences. This interpretation aligns with research connecting market orientation and strategic orientation with new-service development (Nayeri et al., 2022) and linking analytics and digital capabilities with retail innovation (Dang et al., 2025; Morimura and Sakagawa, 2023). The finding suggests that data routines can provide an informational basis for operational renewal, although the cross-sectional design does not establish the direction or timing of capability development.

Collectively, these findings emphasise organisational capability rather than advanced technology alone. The retained big data analytics capability measure primarily captures routines for accessing, integrating, testing, interpreting, communicating and maintaining data. H1–H3 therefore position big data analytics capability as an upstream capability because it is directly associated with the other three domains in the proposed model. This designation reflects its theoretically specified position rather than an empirically established temporal sequence, which requires longitudinal examination.

5.3 Market orientation as an interpretive mechanism

Support for H4 indicates a positive association between market orientation and innovation. Innovation is therefore related not only to data availability but also to organisational routines for interpreting customer needs, competitor actions and market opportunities. Market intelligence becomes operationally valuable when it informs the adaptation of services, processes and customer experiences. This interpretation accords with evidence linking market orientation to new-service development (Nayeri et al., 2022), technology adoption, innovation capability and adaptive responses (Gangwani and Bhatia, 2024; Itani et al., 2026).

Market orientation consequently has both cultural and operational relevance. It encompasses the generation and dissemination of market intelligence and organisational responsiveness (Kohli and Jaworski, 1990), together with customer orientation, competitor orientation and interfunctional coordination (Narver and Slater, 1990). These routines help convert dispersed market signals into shared organisational understanding, providing a theoretically plausible basis for the observed relationship with innovation.

Support for H5 indicates a positive association between market orientation and marketing capabilities. Market-oriented retailers may be better positioned to translate customer and competitor intelligence into customer management, communication, channel coordination and related market-facing activities. This interpretation is consistent with evidence connecting market orientation with small-firm performance (Bin-Obaidellah et al., 2024) and with marketing capability development and performance-related outcomes (Morgan et al., 2009; Ngo and O'Cass, 2012; Shanka

et al., 2025). The finding highlights the operational importance of disseminating market knowledge across functions rather than retaining it within isolated units.

The indirect effects position market orientation as a model-implied interpretive link between big data analytics capability and the two downstream domains. Data may become more operationally useful when integrated with customer sensing, competitor awareness and interfunctional coordination; however, these cross-sectional associations do not establish causal mediation or temporal sequencing.

5.4 Innovation and marketing capabilities as service-execution outcomes

Innovation and marketing capabilities represent complementary outcomes within the proposed service-operations capability system. Innovation enables retailers to renew services, processes and customer experiences in response to changing market information and expectations. This interpretation is consistent with research on new-service development (Nayeri et al., 2022), retail service quality (Haque et al., 2023), and the roles of customer insight, contextual readiness and service redesign in retail innovation (Alam et al., 2021; Dang et al., 2025).

From a service-operations perspective, innovation supports operational adaptation, whereas marketing capabilities translate market knowledge into repeatable customer-facing execution (Day, 1994; Vorhies and Morgan, 2005). Evidence from Thai businesses supports this execution-oriented view by conceptualising green omnichannel capability as an integrated market-facing capability encompassing communication, fulfilment and customer relationship practices (Sukhawattanakun, 2026). The observed structural relationships indicate that data processing and market interpretation are associated with operational renewal and consistent implementation across communication, customer management and channel activities.

5.5 Firm-size differences and the retail capability development gap

Large retailers reported higher observed composite scores than SME-sized retailers across all four constructs and the overall composite, with substantively meaningful effect sizes. This difference may reflect larger retailers' greater access to financial resources, digital infrastructure, specialised personnel and formal data-governance systems, which may facilitate more systematic data integration, cross-functional coordination, service innovation and market execution. Although these mechanisms were not directly measured, this interpretation is consistent with evidence that market-oriented and digital practices in smaller enterprises depend on organisational and technological capabilities (Bin-Obaidallah et al., 2024; Kumar and Ayodeji, 2022).

In Thailand, technology adoption has also been associated with perceived usefulness, technological knowledge, cost, customer pressure and competitive pressure (Alam et al., 2021), while digital innovation has been linked to contextual readiness, stakeholder input and coordinated support (Thawesaengskulthai et al., 2025; Wathahong et al., 2025).

5.6 Theoretical and practical implications

The principal theoretical contribution lies in positioning market orientation as a model-implied interpretive capability that conceptually connects analytics-related information processing with service renewal and market-facing execution. The resource-

based view explains the potential strategic value of analytics-related resources, whereas the dynamic capabilities perspective explains why such value depends on organisational routines for sensing, interpretation, renewal and execution (Barney, 1991; Teece et al., 1997; Teece, 2007). By assigning distinct functions to big data analytics capability, market orientation, innovation and marketing capabilities, the proposed framework extends service-operations research beyond technology adoption and explains how these capability domains operate as a connected organisational system. Given the cross-sectional design, this contribution concerns theoretically specified capability relationships rather than verified causal or temporal sequencing.

Managerially, retailers should connect analytics systems with specific operational decisions, cross-functional coordination, innovation and service delivery. Dashboards should therefore be designed to support clearly defined planning, service and operational outcomes rather than provide information without an explicit decision purpose (Kumar and Ayodeji, 2022; Saadat et al., 2022).

SME-sized retailers can begin with customer-feedback tracking, sales monitoring, basic segmentation and channel reviews before investing in advanced infrastructure. At the ecosystem level, resilience depends on structural adaptation, relational-contractual integration, institutional alignment and cross-layer coordination rather than on firm-level capabilities alone (Supapon et al., 2026). The four capability domains provide a diagnostic framework for identifying gaps, prioritising development and allocating resources. Support agencies can complement digital access with training in data interpretation, responsible governance and service-process improvement.

6 Conclusions, limitations and future research

The analysis supported all five proposed relationships among big data analytics capability, market orientation, innovation and marketing capabilities in Thailand's retail sector. Large retailers reported higher observed composite scores across all four constructs, indicating observed firm-size differences in reported capability levels. The findings extend data-driven retailing beyond technology adoption by positioning analytics, market interpretation, innovation and customer-facing execution as complementary organisational capabilities, while providing a practical basis for capability assessment and development.

The cross-sectional, single-informant design supports theoretically specified associations but not causal or temporal ordering. Although the common-method diagnostics indicated no dominant single-factor pattern, common method variance remains possible. Longitudinal, multi-informant and archival research could test directionality and examine whether innovation strengthens subsequent market execution or established marketing capabilities facilitate innovation.

Stratified-quota recruitment enabled balanced firm-size comparisons, although firms were not selected probabilistically within strata. Probability sampling and non-response analysis could strengthen the transferability of future findings. Multi-group CFA supported configural and metric invariance; because scalar invariance was not assessed, firm-size comparisons were appropriately limited to observed composite scores rather than latent means. Future studies could assess scalar invariance and examine whether

technological investment, analytics literacy, personnel expertise, data governance and managerial formalisation explain firm-size capability differences.

Bootstrapped HTMT results and theory-guided measurement respecification provided qualified support for the empirical distinctiveness of the four closely related capability domains. Because respecification was conducted using the same dataset, independent cross-validation is needed to assess the generalisability of the retained structure. Overall, the study provides a theory-grounded and empirically supported framework for understanding data-driven retail service operations and offers a foundation for research linking these capabilities to service quality, productivity, customer experience and firm performance.

Appendices/Supplementary materials are available on request by emailing the corresponding author.

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Declarations

This study was conducted with informed consent from all participants. Participants were informed of the study's purpose, procedures, confidentiality protections, and their right to withdraw at any time without penalty. The study protocol was approved by the Kasetsart University Research Ethics Committee (Certificate of Approval No. COE68/042, issued on 25 December 2025).

During the preparation of this work, the authors used ChatGPT (OpenAI) and Grammarly to support English-language editing, readability improvement and grammar checking. After using these tools, the authors reviewed, verified and edited the content as needed and take full responsibility for the content of the published article.

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