ISSN 2409-2665
Journal of Logistics, Informatics and Service Science
Vol. 13 (2026) No. 9, pp. 17-38
DOI:10.33168/JLISS.2026.0902

Big Data Analytics and Dynamic CRM Capabilities in Telecommunications Service Systems: Evidence from Jordan

Raed Al Qirem, Ayman Bader, Amer Morshed*

Department of Accounting, Faculty of Business, Al-Zaytoonah University of Jordan, Amman, Jordan
a.morshed@zuj.edu.jo (Corresponding author)

Abstract. This study examines how big data analytics (BDA) and dynamic CRM capabilities support service-system performance in Jordan's telecommunications sector. Positioned within service informatics and service science, the paper treats CRM as a data-driven service information system through which customer data are captured, routed, interpreted, and converted into complaint handling, responsiveness, personalization, and digital service quality. Drawing on the Resource-Based View and Dynamic Capability View, the study explains BDA integration as a strategic digital resource and dynamic CRM capabilities as adaptive routines that transform analytics into service value. A structured questionnaire generated 296 valid responses from customers, telecom employees, CRM/managerial staff, and industry experts. The model tests two service-value channels: a decision-satisfaction channel linking BDA integration to CRM decision-making and customer satisfaction, and an adaptive-capability channel linking BDA integration to dynamic CRM capabilities and innovative marketing strategies. The measurement model shows acceptable standardized loadings (0.779-0.874), reliability (Cronbach's alpha = 0.760-0.870), composite reliability (0.862-0.912), convergent validity (AVE = 0.654-0.721), and discriminant validity (maximum HTMT = 0.645). Common method checks indicate that a single factor does not dominate the data (Harman first factor = 23.21%), and full collinearity VIFs remain below accepted thresholds (1.026-1.684). Bootstrapped results support all four hypotheses (beta = 0.429-0.560, $p < 0.001$). The study contributes by showing that analytics creates telecommunications service value when it is embedded in CRM decision routines and dynamic capability routines rather than treated as a stand-alone technology.

Keywords: Big Data Analytics; Dynamic CRM Capabilities; Service Systems; Service Informatics; Digital Service Quality; Telecommunications; Jordan

1. Introduction

Customer relationship management (CRM) is increasingly shaped by big data analytics (BDA), especially in telecommunications service systems. Telecom firms generate continuous information from mobile applications, billing systems, service usage, customer complaints, network-performance records, call-centre interactions, and digital support channels. Kastouni and Lahcen (2022) explain that telecommunications provides a data-intensive setting in which big data governance, architecture, and use cases are central to service improvement. These data can improve customer profiling, churn prediction, complaint routing, service personalization, and marketing responsiveness, but only when they are translated into usable CRM routines.

Jordan's telecommunications sector provides a relevant emerging-market context because service providers operate in a competitive and data-intensive environment. Khrisat et al. (2023) show that big data can support customer-behaviour prediction in Jordanian telecommunications companies when it is connected with business intelligence. In this setting, CRM is not only a marketing function; it is also a service information system through which customer data move across call centres, billing systems, marketing units, technical-support teams, and management dashboards.

The research gap is not limited to the lack of evidence from Jordan. Prior research has examined BDA and CRM in several sectors, but fewer studies explain the mechanism through which BDA is transformed into service value through CRM decision-making and dynamic CRM capabilities in emerging-market telecommunications service systems. Atmaja et al. (2024) highlight the importance of data needs and predictive models in broadband service development, which supports the need to examine how telecom data are organized for practical service decisions.

This study addresses that gap by investigating the relationships among BDA integration in CRM, CRM decision-making, customer satisfaction, dynamic CRM capabilities, and innovative marketing strategies. Brewis et al. (2023) present big data as part of a dynamic-capabilities logic for strategic marketing, which supports the study's focus on how analytics becomes valuable through adaptive CRM routines. The paper therefore combines the Resource-Based View with the Dynamic Capability View to explain both the resource and adaptation dimensions of CRM analytics.

The study makes a specific contribution by distinguishing two BDA-enabled service-value channels within an emerging-market telecommunications service system. First, BDA integration is associated with customer satisfaction through CRM decision-making. Second, BDA integration is associated with innovative marketing strategies through dynamic CRM capabilities. Zulkiflee et al. (2024) show that CRM dashboards and descriptive analytics can support recommendation quality, which is consistent with the paper's emphasis on converting analytics into decision support and service action.

2. Theoretical Framework and Hypotheses Development

2.1 Big data analytics and CRM in telecommunications service systems

Big data analytics has become a central component of customer relationship management because contemporary service firms increasingly depend on large, diverse, and continuously updated customer information. Del Vecchio et al. (2022) show that big data is particularly relevant to CRM because it allows firms to transform customer information into segmentation, targeting, personalization, and relationship-management knowledge. In telecommunications, this logic is especially important because customer data are generated continuously through service usage, billing behaviour, complaint records, call-centre interactions, mobile applications, network-quality indicators, and responses to promotional campaigns. Anshari et al. (2019) similarly connect big-data-enabled CRM with service personalization and customization, which supports the view that analytics must be tied to customer-facing routines.

CRM in this context is not only a marketing tool. It is also a service information system that connects customer data with managerial and operational action. Kamel (2023) argues that big data analytics can improve market performance when firms use customer information to support customization and personalization strategies. This is relevant to telecom providers because customers expect offers, service responses, and communication to match their actual usage patterns and service experiences. Tseng (2023) further emphasizes that customer-centered data power depends on sensing and responding capabilities, meaning that data must help firms detect customer needs and convert them into timely responses.

The telecommunications sector in Jordan provides a relevant emerging-market setting for this relationship. Al-Dmour et al. (2023) show that big data analytics applications can influence organizational performance in Jordanian banking, suggesting that data-driven decision logic is also important in regional service sectors. He et al. (2023) provide additional evidence from banking that analytics can reshape customer and operational decision processes. These insights support examining telecom CRM as a data-driven service system rather than as a traditional relationship-management activity.

Related Jordanian and regional digital-business studies further support this sectoral framing. Morshed (2024) provides direct UAE telecom evidence that advanced analytics can influence client management systems, making it closely related to the present CRM analytics model.

2.2 CRM as a service informatics and information-flow process

A service informatics perspective helps clarify how BDA creates value in CRM. Customer information must be captured, classified, cleaned, analysed, routed, and delivered to the relevant organizational unit. Saad et al. (2025) link customer relationship management objectives with broader service and supply-chain practices, which supports the idea that CRM requires coordination between organizational functions rather than isolated data storage. This view is directly related to telecom CRM because customer data are useful only when they are organized in ways that support decisions about service response, complaint handling, customer retention, and marketing communication.

CRM can therefore be viewed as an information-flow process. Customer complaints may need to move from call centres to technical-support units. Usage changes may need to move from billing systems to marketing teams. Repeated dissatisfaction signals may need to move from digital-service platforms to retention units. Shah et al. (2023) explain that big data analytics and artificial intelligence improve decision processes when they support intelligent information coordination in complex systems.

This view is important because telecom firms may own large databases without achieving strong CRM performance. Data must be timely, reliable, interpretable, and accessible to decision makers. Angelopoulos et al. (2023) describe digital transformation in operations management as a fundamental change in the way operational agency is organized, which supports treating CRM analytics as part of service-process coordination rather than as a stand-alone tool. The value of BDA is therefore not automatic; it depends on whether customer information is converted into practical decision support.

The information-flow view is also supported by operations and analytics research beyond telecommunications. Guida et al. (2023) show that artificial intelligence can change procurement processes by improving information use and decision support. Chatterjee and Chatterjee (2024) review how business analytics improves supply-chain performance, which helps justify the article's broader service-system framing. Ram and Zhang (2022) discuss the need to adopt BDA in business-to-business organizations, supporting the argument that analytics adoption must be linked to specific organizational needs.

2.3 Resource-Based View and BDA as a strategic CRM resource

The Resource-Based View explains why BDA integration may strengthen CRM decision-making. RBV argues that firms gain advantage from resources that are valuable, difficult to imitate, and embedded in organizational routines. Lukovszki et al. (2021) apply the resource-based view to innovation activity and show that organizational resources matter when they are connected to capability development. In CRM, BDA integration can represent a strategic resource because it combines data infrastructure, analytical tools, customer knowledge, managerial interpretation, and decision routines.

BDA is valuable in CRM because it reduces uncertainty in customer-related decisions. Nudurupati et al. (2024) argue that data-intensive organizations require resources and capabilities that support decision-making processes. This is directly applicable to telecom CRM because managers need evidence about customer needs, service failures, complaint history, profitability, retention risk, and campaign response. When CRM decisions rely on integrated data rather than intuition alone, firms can prioritize service actions more effectively and design more relevant responses.

However, the RBV argument also implies that technology by itself is not sufficient. A telecom provider may have large volumes of data, but fragmented or poorly interpreted data may not improve CRM decisions. Adam and Dempsey (2020) show that intuition remains relevant in decision settings involving risk and opportunity, which supports the need to combine analytics with managerial judgement. Therefore, BDA integration is expected to support CRM decision-making when it is embedded in routines through which managers analyse customer information, evaluate service alternatives, and choose appropriate responses.

The RBV argument is strengthened by studies that emphasize capability development and strategic information use. Garmaki et al. (2023) link big data analytics capability with firm performance through organizational learning, which suggests that analytics resources must be absorbed into firm routines. Mızrak (2023) discusses big data as a strategic-management perspective, supporting the treatment of BDA as a management resource rather than a purely technical asset. Alsmadi et al. (2024) show that big data analytics is linked with innovation in e-commerce, which directly supports treating analytics resources as decision-relevant digital capabilities in customer-facing business models. Aljawazneh and Abu Al-Ragheb (2026) further show that deep learning analytics and advanced data-balancing techniques can improve fraud prediction in e-commerce transactions, reinforcing the decision-support value of analytics in high-volume digital service settings.

2.4 CRM decision-making and customer satisfaction

Customer satisfaction in telecommunications depends on the customer's experience of service responsiveness, relevance, reliability, and communication quality. Ledro et al. (2022) explain that artificial intelligence and analytics in CRM can improve customer relationship activities when they support service personalization and customer knowledge. This means that customers do not benefit from data accumulation itself; they benefit when data improve the quality of decisions that shape their service experience.

CRM decision-making can improve satisfaction in several ways. It can help firms identify urgent complaints, detect repeated service problems, prioritize high-risk customers, and recommend suitable service packages. Pynadath et al. (2023) show that CRM has evolved toward data-mining-based customer relationship management, where customer data are used to support deeper understanding of customer needs and behaviour. In telecom services, this can improve satisfaction because customers are more likely to respond positively when service actions are relevant, timely, and based on their actual interaction history.

Customer satisfaction is also shaped by the integration of technology across sales and service processes. Bauer et al. (2024) describe an emergent sales-service techno-ecosystem in which technology changes how customer-facing functions interact. Giovannetti et al. (2022) show that salespeople may resist, accept, or lead customer-driven change, which supports the need for CRM decisions to be operationally accepted by employees. These arguments explain why analytics-supported CRM must be connected to human service routines if it is to improve satisfaction.

The customer-experience logic extends to digital service sectors beyond telecommunications. Bulchand-Gidumal et al. (2024) discuss the role of artificial intelligence in hospitality and tourism marketing, which reinforces the relevance of service personalization across data-rich settings. Zhang and Rodgers (2023) show that customers can react differently to AI-based targeting and data collection, highlighting the need for responsible customer-data practices.

2.5 Dynamic Capability View and adaptive CRM routines

The Dynamic Capability View extends RBV by explaining how firms renew and reconfigure resources in changing environments. Ghosh et al. (2022) argue that digital transformation requires dynamic capabilities because firms must adapt resources and routines in response to changing technological and market conditions. This perspective is particularly relevant to telecommunications because customer expectations, competitor offers, digital channels, and service-quality requirements change quickly.

Dynamic CRM capabilities refer to the firm's ability to sense customer needs, adjust service routines, reconfigure CRM processes, and respond to new market information. When telecom firms integrate customer data into CRM, they become better able to detect behavioural changes, dissatisfaction signals, usage shifts, and emerging service needs.

Dynamic CRM capabilities also require absorptive and adaptive processes that convert information into action. Makhloufi (2024) links big data analytics capability with absorptive capacity and eco-innovation, showing that data capabilities matter when firms can absorb and apply knowledge. Al-Omoush et al. (2025) further show that business analytics adoption is associated with innovative circular economy practices, reinforcing the view that analytics capabilities can support adaptive and innovation-oriented routines.

In AI-enabled CRM, adaptation is not limited to technology deployment; it also includes organizational learning and user guidance. Therefore, BDA integration is expected to improve dynamic CRM capabilities because integrated customer data make adaptation more evidence-based.

2.6 Dynamic CRM capabilities and innovative marketing strategies

Innovative marketing strategies require firms to move beyond standard campaigns and general promotions. Basu et al. (2023) describe marketing analytics as a bridge between customer psychology and marketing decision-making, showing that analytics helps firms understand customers and design more effective marketing actions. In telecommunications, innovative marketing may include personalized offers, lifecycle-based retention campaigns, targeted service bundles, proactive communication, and customer-segment-specific promotions.

Dynamic CRM capabilities support these strategies because they allow firms to reconfigure marketing actions when customer needs change. Treiblmaier (2023) argues that digital tokens and the internet of value create new issues for marketing researchers, which supports the wider point that digital innovation changes how firms design customer engagement. This is important because telecom customers differ in usage intensity, price sensitivity, service expectations, and loyalty risk.

Customer-focused marketing innovation also depends on technology-based relationship management. A static CRM system may only store customer data, but a dynamic CRM capability allows the firm to use that data to redesign campaigns and service offers.

At the same time, innovative marketing in telecom services should remain responsible and privacy-aware. Customers may value personalized offers, but they may also reject targeting that appears intrusive or unfair. Therefore, dynamic CRM capabilities are important not only because they enable innovation, but also because they help firms align marketing actions with customer expectations and service-system realities (Al-Afeef & Alsmadi, 2025).

Taken together, the literature indicates that BDA creates CRM value through two connected channels. The first channel links data integration to CRM decision-making and then to customer satisfaction. The second channel links data integration to dynamic CRM capabilities and then to innovative marketing strategies. This structure keeps the hypotheses aligned with the later empirical model and avoids treating BDA as a stand-alone technology.

2.7 Hypotheses development

Based on the RBV logic, BDA integration is expected to strengthen CRM decision-making because integrated customer data provide managers with more reliable evidence for segmentation, service prioritization, complaint handling, and retention decisions. Therefore:

H1: Big data integration in CRM is positively associated with CRM decision-making.

Because customer satisfaction depends on the quality, relevance, and timing of service responses, CRM decision-making is expected to improve satisfaction when customer information is converted into better service action. Therefore:

H2: CRM decision-making is positively associated with customer satisfaction.

Based on the Dynamic Capability View, BDA integration is expected to strengthen dynamic CRM capabilities because integrated customer data help firms sense customer changes and reconfigure CRM routines. Therefore:

H3: Big data integration in CRM is positively associated with dynamic CRM capabilities.

Because dynamic CRM capabilities allow firms to adapt customer knowledge into personalized offers, retention campaigns, and new targeting approaches, they are expected to support innovative marketing strategies. Therefore:

H4: Dynamic CRM capabilities are positively associated with innovative marketing strategies.

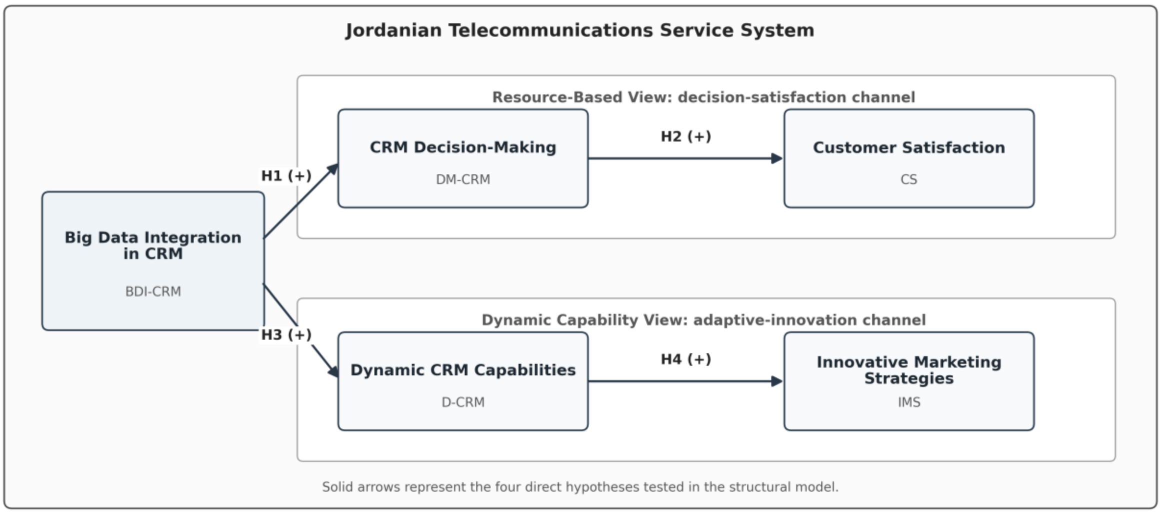

Fig.1: Conceptual framework linking BDA, CRM, and telecommunications service systems.

3. Methodology

3.1 Research design and data

The study applies a quantitative cross-sectional survey design and AMOS-based covariance-oriented structural equation modelling logic to test the proposed relationships. Aloulou et al. (2024) use sector-based empirical analysis to examine technology adoption and digital financial inclusion, which supports the use of structured quantitative designs for studying digital-service phenomena. The original item-level dataset contains 296 valid responses and 31 Likert-scale measurement items. All items were measured on a five-point scale, where higher values indicate stronger agreement with the relevant statement. The analysis covers nine constructs: BDA integration in CRM, CRM decision-making, customer satisfaction, dynamic CRM capabilities, innovative marketing strategies, leadership style, ethical use of data, financial constraints, and BDA complexity.

The structural model tests only the four direct hypotheses shown in Figure 1. Leadership style, ethical use of data, financial constraints, and BDA complexity are retained as contextual implementation constructs. In the present study, these constructs describe organizational and ethical conditions around BDA-based CRM, support descriptive and common-method checks, and inform interpretation, but they are not presented as structural mediators, moderators, or antecedents in the tested model.

3.2 Sampling strategy, respondent recruitment, and inclusion criteria

A purposive online survey approach was used because the study required respondents who had direct experience with telecommunications services or sector-related CRM practices in Jordan. The questionnaire link was distributed through online channels connected to telecom customers, employees, CRM/managerial staff, and sector observers. Respondents were included when they had sufficient familiarity with telecom service interactions, digital support channels, customer-service processes, or CRM practices to evaluate the statements in the questionnaire.

After screening for completeness, the final analyzable dataset included 296 valid responses. A conventional response rate could not be calculated because the survey was distributed through an online open-link approach rather than a closed sampling frame with a fixed number of invited respondents. Schmiedehaus et al. (2023) demonstrate how occupational groups can differ in their work-related perceptions, supporting the decision to retain respondent group as a control in robustness checks. The sampling strategy is therefore best described as purposive and cross-sectional, not probability-based.

Survey ethics were addressed through voluntary participation, anonymity, and aggregated reporting. Respondents were informed that the questionnaire was used for academic research on telecommunications CRM and service systems. No individual respondent or organization is identified in the analysis, and the results are reported only at aggregate level.

Table 1. Respondent profile and subgroup distribution

Respondent category	Frequency (%)	Analytical relevance
Customer	178 (60.1%)	Evaluates service experience, satisfaction, offers, and complaint response
Telecom employee	59 (19.9%)	Evaluates operational CRM processes and customer-service routines
Manager/CRM staff	35 (11.8%)	Evaluates CRM decision-making, analytics use, and resource allocation
Industry expert	24 (8.1%)	Evaluates sector-level CRM and digital service practices
Total	296 (100.0%)	Valid responses included in the analysis

3.3 Measurement instrument

Table 2 reports the measurement instrument used in the study. The items were adapted to the telecommunications-service context and aligned with prior research on BDA, CRM, dynamic capabilities, service informatics, customer satisfaction, and ethical data use. Bader et al. (2025) examine artificial intelligence and big data in Jordanian commercial banks, supporting the inclusion of analytics and data-use constructs in regional service research. The item codes match the original dataset used for analysis.

Table 2. Construct definitions and questionnaire items

Construct	**Item code**	**Item wording**	Measurement basis
BDI-CRM	BDI-CRM_1	Our telecom service interactions are supported by integrated customer data from multiple digital and operational touchpoints.	Adapted to the telecommunications CRM context.
BDI-CRM	BDI-CRM_2	Big data tools help combine customer usage, billing, service, and interaction data for CRM purposes.	Adapted to the telecommunications CRM context.
BDI-CRM	BDI-CRM_3	Customer data are available in a form that supports segmentation and service-response decisions.	Adapted to the telecommunications CRM context.
BDI-CRM	BDI-CRM_4	Analytics systems help convert customer data into useful CRM information.	Adapted to the telecommunications CRM context.
DM-CRM	DM-CRM_1	CRM decisions are based on reliable customer information rather than intuition alone.	Adapted to the telecommunications CRM context.
DM-CRM	DM-CRM_2	Data analysis helps prioritize customer-service actions and retention decisions.	Adapted to the telecommunications CRM context.
DM-CRM	DM-CRM_3	CRM information supports timely decisions about customer needs and service problems.	Adapted to the telecommunications CRM context.
DM-CRM	DM-CRM_4	Managers can use CRM data to improve targeting, complaint	Adapted to the telecommunications CRM context.

		handling, and service planning.	
CS	CS_1	Customers are generally satisfied with the responsiveness of telecom service interactions.	Adapted to the telecommunications CRM context.
CS	CS_2	CRM-supported services help improve the overall customer experience.	Adapted to the telecommunications CRM context.
CS	CS_3	Customers receive service responses that are relevant to their needs.	Adapted to the telecommunications CRM context.
CS	CS_4	Data-supported CRM contributes to customer satisfaction with telecom services.	Adapted to the telecommunications CRM context.
D-CRM	D-CRM_1	The organization can adapt CRM routines when customer needs change.	Adapted to the telecommunications CRM context.
D-CRM	D-CRM_2	CRM practices are adjusted in response to new service information and customer feedback.	Adapted to the telecommunications CRM context.
D-CRM	D-CRM_3	The organization can reconfigure customer-service processes using analytics evidence.	Adapted to the telecommunications CRM context.
D-CRM	D-CRM_4	CRM capabilities support flexible responses to changing market and service conditions.	Adapted to the telecommunications CRM context.
IMS	IMS_1	Analytics-supported CRM helps design innovative marketing campaigns.	Adapted to the telecommunications CRM context.
IMS	IMS_2	Customer data are used to develop personalized service offers and retention programs.	Adapted to the telecommunications CRM context.

IMS	IMS_3	CRM analytics supports new approaches to customer targeting and service promotion.	Adapted to the telecommunications CRM context.
LS	LS_1	Leadership supports the use of analytics in CRM and service decisions.	Adapted to the telecommunications CRM context.
LS	LS_2	Managers encourage employees to use customer data responsibly in decision-making.	Adapted to the telecommunications CRM context.
LS	LS_3	Leadership provides direction for analytics-enabled customer-service improvement.	Adapted to the telecommunications CRM context.
EUD	EUD_1	Customer data are used in ways that respect privacy and consent.	Adapted to the telecommunications CRM context.
EUD	EUD_2	Data-driven CRM practices are guided by transparency and responsible use.	Adapted to the telecommunications CRM context.
EUD	EUD_3	The organization avoids intrusive or unfair uses of customer data.	Adapted to the telecommunications CRM context.
FC	FC_1	Financial limitations restrict investment in advanced CRM analytics.	Adapted to the telecommunications CRM context.
FC	FC_2	The cost of analytics systems creates challenges for CRM improvement.	Adapted to the telecommunications CRM context.
FC	FC_3	Budget constraints affect the ability to implement data-driven service solutions.	Adapted to the telecommunications CRM context.
BDAC	BDAC_1	BDA tools and processes are technically complex for CRM users.	Adapted to the telecommunications CRM context.

BDAC	BDAC_2	Integrating multiple customer-data sources into CRM is difficult.	Adapted to the telecommunications CRM context.
BDAC	BDAC_3	Analytics complexity creates challenges for using BDA in customer-service decisions.	Adapted to the telecommunications CRM context.

3.4 Analysis procedure

The analysis followed a staged validation procedure. First, descriptive statistics were calculated for each construct using item averages. Second, internal consistency was evaluated using Cronbach's alpha. Third, standardized measurement loadings, composite reliability, and average variance extracted were used to evaluate convergent validity. Fourth, discriminant validity was assessed through the Fornell-Larcker logic and the heterotrait-monotrait ratio. Greenland (2023) distinguishes evidence-oriented p-values from decision p-values, which supports reporting significance levels as evidence rather than as automatic proof of causal effects. Finally, the structural paths were tested using standardized coefficients, standard errors, t-values, exact p-value levels, and 2,000 bootstrap confidence intervals.

The reporting sequence follows the logic of SEM: the measurement model is presented first, including item loadings, reliability, convergent validity, discriminant validity, and common method bias diagnostics. The structural model is then presented with model-fit indices, bootstrapped path coefficients, and respondent-group robustness checks. Elgendy et al. (2022) propose a modern data-driven decision theory for big data and analytics, which supports the article's staged movement from data validation to decision-oriented interpretation.

The analysis also followed a transparency logic across procedural documentation and model-specific interpretation. Rajput (2023) emphasizes that digital-solution delivery requires clear documentation of system architecture and workflow.

4. Results

The results section presents the empirical assessment of the proposed BDA–CRM model. It begins with descriptive statistics to summarize the main constructs, followed by measurement-model tests for reliability, convergent validity, discriminant validity, multicollinearity, and common method bias. After confirming that the measurement properties are acceptable, the section reports the structural model fit and bootstrapped path results used to test the four hypotheses. The final part presents a robustness check using respondent-group controls to verify whether the main relationships remain stable across the mixed sample of customers, telecom employees, CRM/managerial staff, and industry experts.

4.1 Descriptive statistics

Table 3. Descriptive statistics for the study constructs

Construct	Description	Mean	SD	Min	Max
BDI-CRM	Big data integration in CRM	3.60	0.63	2.00	5.00
DM-CRM	CRM decision-making	3.92	0.65	2.00	5.00

CS	Customer satisfaction	3.70	0.68	1.50	5.00
D-CRM	Dynamic CRM capabilities	3.62	0.65	2.00	5.00
IMS	Innovative marketing strategies	3.37	0.70	1.33	5.00
LS	Leadership style	3.77	0.65	1.00	5.00
EUD	Ethical use of data	3.38	0.65	1.67	5.00
FC	Financial constraints	4.22	0.62	2.33	5.00
BDAC	BDA complexity	4.34	0.58	2.00	5.00

The highest mean values are observed for BDA complexity, financial constraints, and CRM decision-making. This pattern suggests that respondents perceive decision-making benefits from CRM analytics while also recognizing analytics complexity and resource constraints as important implementation conditions. Innovative marketing strategies record the lowest mean, indicating that analytics-enabled marketing innovation remains less mature than basic CRM decision support.

4.2 Measurement model: reliability and convergent validity

Table 4. Standardized measurement loadings

Construct	Item	Standardized loading	Decision
BDI-CRM	BDI-CRM_1	0.817	Retained
BDI-CRM	BDI-CRM_2	0.844	Retained
BDI-CRM	BDI-CRM_3	0.796	Retained
BDI-CRM	BDI-CRM_4	0.810	Retained
DM-CRM	DM-CRM_1	0.839	Retained
DM-CRM	DM-CRM_2	0.856	Retained
DM-CRM	DM-CRM_3	0.842	Retained
DM-CRM	DM-CRM_4	0.822	Retained
CS	CS_1	0.871	Retained
CS	CS_2	0.874	Retained
CS	CS_3	0.836	Retained
CS	CS_4	0.815	Retained
D-CRM	D-CRM_1	0.851	Retained
D-CRM	D-CRM_2	0.812	Retained
D-CRM	D-CRM_3	0.792	Retained
D-CRM	D-CRM_4	0.779	Retained
IMS	IMS_1	0.871	Retained

IMS	IMS_2	0.848	Retained
IMS	IMS_3	0.820	Retained
LS	LS_1	0.846	Retained
LS	LS_2	0.841	Retained
LS	LS_3	0.826	Retained
EUD	EUD_1	0.840	Retained
EUD	EUD_2	0.817	Retained
EUD	EUD_3	0.808	Retained
FC	FC_1	0.848	Retained
FC	FC_2	0.827	Retained
FC	FC_3	0.854	Retained
BDAC	BDAC_1	0.803	Retained
BDAC	BDAC_2	0.848	Retained
BDAC	BDAC_3	0.845	Retained

All standardized loadings exceed the commonly accepted 0.60 threshold, ranging from 0.779 to 0.874. These results support item retention and indicate that the indicators adequately represent their intended latent constructs.

Table 5. Reliability and convergent validity

Construct	**No. of items**	**Cronbach alpha**	**CR**	**AVE**	**Assessment**
BDI-CRM	4	0.834	0.889	0.667	Acceptable
DM-CRM	4	0.861	0.906	0.706	Acceptable
CS	4	0.870	0.912	0.721	Acceptable
D-CRM	4	0.824	0.883	0.654	Acceptable
IMS	3	0.802	0.884	0.717	Acceptable
LS	3	0.787	0.876	0.702	Acceptable
EUD	3	0.760	0.862	0.675	Acceptable
FC	3	0.796	0.881	0.711	Acceptable
BDAC	3	0.778	0.871	0.693	Acceptable

Cronbach's alpha ranges from 0.760 to 0.870 and composite reliability ranges from 0.862 to 0.912, exceeding the minimum reliability benchmark of 0.70. AVE values range from 0.654 to 0.721, supporting convergent validity for all constructs.

4.3 Discriminant validity and multicollinearity

Table 6. Fornell-Larcker matrix: square root of AVE on the diagonal

Construct	BDI-CRM	DM-CRM	CS	D-CRM	IMS	LS	EUD	FC	BDAC
BDI-CRM	0.817	0.457	0.419	0.429	0.248	0.279	0.301	0.097	0.124
DM-CRM	0.457	0.840	0.560	0.186	0.200	0.239	0.234	0.105	0.086
CS	0.419	0.560	0.849	0.273	0.244	0.243	0.333	0.102	0.154
D-CRM	0.429	0.186	0.273	0.809	0.475	0.168	0.067	0.012	0.239
IMS	0.248	0.200	0.244	0.475	0.847	0.191	0.083	-0.006	0.208
LS	0.279	0.239	0.243	0.168	0.191	0.838	0.077	0.112	0.039
EUD	0.301	0.234	0.333	0.067	0.083	0.077	0.822	0.047	-0.022
FC	0.097	0.105	0.102	0.012	-0.006	0.112	0.047	0.843	0.002
BDAC	0.124	0.086	0.154	0.239	0.208	0.039	-0.022	0.002	0.832

Table 7. HTMT discriminant validity matrix

Construct	BDI-CRM	DM-CRM	CS	D-CRM	IMS	LS	EUD	FC	BDAC
BDI-CRM	-	0.538	0.490	0.517	0.306	0.345	0.378	0.122	0.152
DM-CRM	0.538	-	0.645	0.220	0.242	0.293	0.289	0.127	0.108
CS	0.490	0.645	-	0.323	0.291	0.295	0.410	0.124	0.187
D-CRM	0.517	0.220	0.323	-	0.584	0.208	0.103	0.062	0.298
IMS	0.306	0.242	0.291	0.584	-	0.238	0.108	0.074	0.262
LS	0.345	0.293	0.295	0.208	0.238	-	0.105	0.143	0.051
EUD	0.378	0.289	0.410	0.103	0.108	0.105	-	0.067	0.040
FC	0.122	0.127	0.124	0.062	0.074	0.143	0.067	-	0.054
BDAC	0.152	0.108	0.187	0.298	0.262	0.051	0.040	0.054	-

The Fornell-Larcker matrix shows that the square root of AVE for each construct exceeds its correlations with other constructs. The HTMT values remain below the conservative 0.85 threshold. This directly addresses the potential concern that earlier high correlations indicated conceptual overlap. In the final validated construct matrix, the highest core-model HTMT value is 0.645, supporting discriminant validity.

Table 8. Full collinearity VIF by construct

Construct	Full collinearity VIF
BDI-CRM	1.639
DM-CRM	1.622
CS	1.684
D-CRM	1.550
IMS	1.352
LS	1.138
EUD	1.188

FC	1.026
BDAC	1.089

Full collinearity VIFs range from 1.026 to 1.684, below the 3.3 threshold commonly used for common method and collinearity diagnostics. The results indicate that multicollinearity is not a substantive threat to interpretation.

4.4 Common method bias

Table 9. Common method bias assessment

Test/remedy	Result	Assessment
Procedural remedies	Anonymity, voluntary participation, aggregated reporting, and separation of construct sections	Applied
Harman's single-factor test	First unrotated factor explained 23.21% of total variance	Below 50%
Full collinearity VIF	Construct-level VIFs ranged from 1.026 to 1.684	Below 3.3

Because all responses were collected through a single questionnaire, common method bias was evaluated explicitly. Harman's single-factor result is below 50%, and all full collinearity VIF values are below 3.3. These results indicate that common method bias is unlikely to dominate the reported relationships.

4.5 Structural model and hypothesis testing

Table 10. Model fit indices

Fit index	Value
Chi-square	100.23
Degrees of freedom	80
CMIN/df	1.253
GFI	0.95
CFI	0.97
RMSEA	0.05

The model fit indices indicate acceptable fit. CMIN/df is below 3.0, GFI and CFI exceed 0.90, and RMSEA equals 0.05. These values support the adequacy of the proposed structural model.

Table 11. Bootstrapped structural path results

Hyp.	Path	Beta	SE	t-value	p-value	95% bootstrap CI	Decision
H1	BDI-CRM -> DM-CRM	0.457	0.052	8.798	<0.001	[0.369, 0.543]	Supported

H2	DM-CRM -> CS	0.560	0.048	11.596	<0.001	[0.472, 0.643]	Supported
H3	BDI-CRM -> D-CRM	0.429	0.053	8.143	<0.001	[0.332, 0.521]	Supported
H4	D-CRM -> IMS	0.475	0.051	9.257	<0.001	[0.383, 0.557]	Supported

All confidence intervals are positive and exclude zero. The strongest structural association is between CRM decision-making and customer satisfaction (beta = 0.560), followed by dynamic CRM capabilities and innovative marketing strategies (beta = 0.475), BDA integration and CRM decision-making (beta = 0.457), and BDA integration and dynamic CRM capabilities (beta = 0.429). This pattern supports the interpretation that BDA contributes to service-system outcomes through decision quality and adaptive CRM routines rather than through data accumulation alone.

Table 12. Robustness check with respondent-group controls

Hyp.	**Path with respondent-group controls**	**Beta**	**SE**	**t-value**	**p-value**
H1	BDI-CRM -> DM-CRM	0.458	0.052	8.760	<0.001
H2	DM-CRM -> CS	0.560	0.048	11.553	<0.001
H3	BDI-CRM -> D-CRM	0.433	0.053	8.176	<0.001
H4	D-CRM -> IMS	0.474	0.052	9.195	<0.001

The respondent-group control check confirms that the main paths remain positive and statistically significant after accounting for the mixed sample composition. Respondent group is the most relevant available control because the dataset combines customers, employees, CRM/managerial staff, and experts, who may evaluate service-system CRM from different positions. The control check therefore strengthens confidence that the four supported paths are not only an artefact of respondent-category composition.

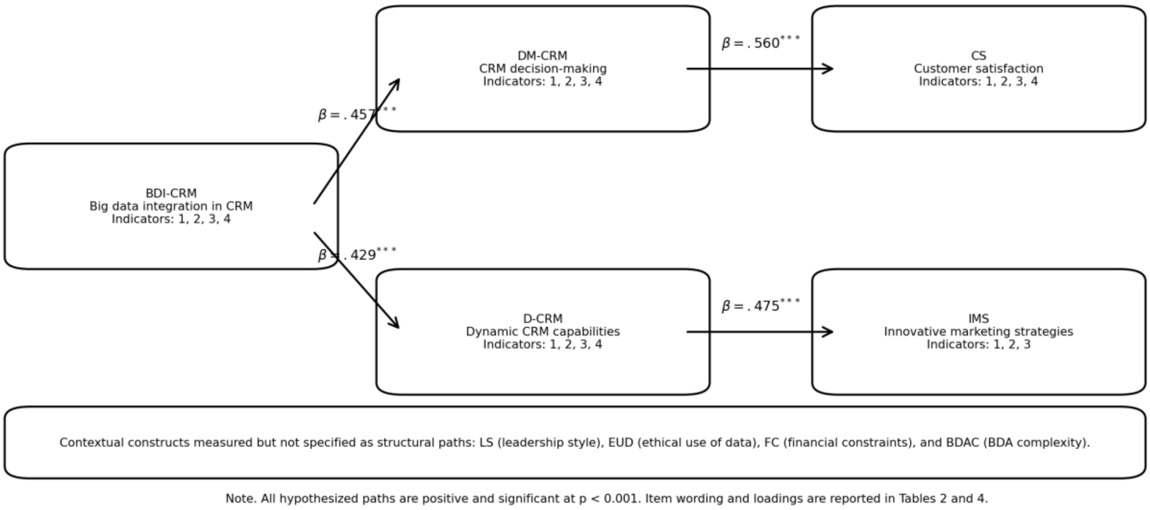

Fig.2: AMOS-style structural model with latent constructs, indicators, and standardized paths.

5. Discussion and Implications

5.1 Interpretation of findings

The results support the argument that BDA is associated with stronger CRM performance when it is converted into decision-making quality and dynamic CRM capability. The positive BDI-CRM to DM-CRM relationship is consistent with RBV because analytics integration represents a valuable digital resource linked to a stronger information base for CRM decisions. In Jordanian telecommunications, this includes customer segmentation, churn-risk identification, service-demand anticipation, and more evidence-based customer-support priorities.

The strongest path is DM-CRM to customer satisfaction. This result is theoretically and practically meaningful. It suggests that customers do not benefit directly from data accumulation; they benefit when data improve the quality, timing, and relevance of CRM decisions. Telecom satisfaction depends on complaint handling, personalized offers, service continuity, and communication quality. This explains why CRM decision-making has a stronger association with satisfaction than the paths related to marketing innovation.

The positive BDI-CRM to D-CRM and D-CRM to IMS paths support the DCV logic. BDA integration is associated with stronger sensing of customer needs and reconfiguration of CRM routines, while dynamic CRM capabilities are associated with more innovative marketing strategies. However, innovative marketing strategies have the lowest descriptive mean. This suggests that telecom firms may be more advanced in using analytics for decision support than for fully developed lifecycle-based marketing innovation.

The findings are consistent with the literature review but are discussed here without repeating citations already used in the theoretical section. They show that customer data, dashboards, predictive models, and adaptive routines matter most when they are converted into service decisions and customer-facing action. This interpretation preserves the distinction between data possession, decision quality, and service-system value.

The discussion also indicates that BDA should not be interpreted as a direct replacement for managerial judgement. Instead, analytics should improve the evidence base available to managers, while CRM routines should ensure that information reaches the correct service or marketing unit. This is important because the empirical results support both a decision-satisfaction channel and an adaptive capability-marketing innovation channel.

5.2 Ethical data use as a contextual implementation condition

Ethical data use is not tested as a mediator, moderator, or antecedent in the structural model. It is treated as a contextual implementation condition because privacy, consent, transparency, and responsible targeting affect whether customers accept analytics-enabled CRM. This distinction avoids overclaiming and keeps the empirical model aligned with the four tested hypotheses.

The contextual results suggest that data-driven CRM should be implemented with privacy-aware targeting, customer communication standards, and governance rules for data access and use. In telecom service systems, ethical data use is especially important because customers may perceive personalized offers as useful when transparent but intrusive when consent and fairness are unclear.

The ethical interpretation is therefore practical rather than causal. Ethical data use helps describe the implementation environment around BDA-based CRM, but the tested model remains limited to the four direct hypotheses. This framing prevents the paper from claiming untested mediation or moderation effects.

5.3 Theoretical contribution

The study contributes to CRM, big data, and service informatics research by specifying the mechanism through which BDA integration becomes service value. Rather than treating BDA as a purely technical asset, the study shows that analytics resources are associated with customer satisfaction through CRM decision-making and with marketing innovation through dynamic CRM capabilities. This combined RBV-DCV explanation clarifies how customer information is transformed into service-system outcomes in an emerging-market telecommunications context.

5.4 Managerial and service-system implications

For telecom managers, the findings suggest that BDA investments should be tied directly to CRM decisions and service delivery processes. Practical applications include churn prediction, complaint prioritization, personalized service packages, call-centre analytics, customer journey tracking, proactive service recovery, and privacy-aware targeting. These practices convert analytics from a back-office reporting tool into a service information capability.

Managers should also improve coordination between marketing teams, call centres, technical-support units, billing departments, and digital-service teams. The value of CRM analytics depends on whether information reaches the right operational unit quickly enough to support action. For example, churn-risk alerts should feed retention teams, repeated complaint patterns should inform service-quality units, and usage-pattern changes should inform personalized package design.

Managerially, the findings suggest that telecom firms should connect analytics investment with service decisions, marketing routines, and organizational learning. The supported paths imply that CRM analytics should be evaluated not only by data availability but also by whether it improves decisions, service responsiveness, adaptive routines, and innovation in customer communication.

6. Conclusion

This study examined how big data analytics (BDA) integration is associated with CRM decision-making, customer satisfaction, dynamic CRM capabilities, and innovative marketing strategies in Jordan’s telecommunications sector. The paper repositioned CRM as part of a telecommunications service system in which customer information is captured, routed, interpreted, and converted into service action. This framing is important because telecom firms operate in data-intensive environments where billing records, usage patterns, complaints, mobile-app activity, and digital support interactions continuously generate customer information. The study shows that the value of these data depends on how effectively they are embedded in CRM routines and service-response processes.

The findings support all four proposed hypotheses. BDA integration is positively associated with CRM decision-making, indicating that integrated customer data strengthen the informational basis for segmentation, complaint handling, service planning, and retention decisions. CRM decision-making is positively associated with customer satisfaction, showing that analytics become valuable when they improve the timing, relevance, and quality of customer-facing actions. BDA integration is also positively associated with dynamic CRM capabilities, suggesting that analytics help telecom firms sense changing customer needs and adjust CRM routines. Finally, dynamic CRM capabilities are positively associated with innovative marketing strategies, indicating that adaptive CRM routines support personalized offers, targeted campaigns, and lifecycle-based retention programs.

The central conclusion is that BDA does not create service value merely through data collection. Its value emerges when customer data are transformed into better decisions, faster information flows, and adaptive customer-response capabilities. Analytics should therefore be treated not as a stand-alone technology, but as an organizational capability that connects data infrastructure, managerial interpretation, CRM routines, and service delivery. This insight is especially relevant for telecommunications firms because customer value depends on coordination among call centres, billing departments, technical-support units, marketing teams, and digital-service platforms.

The study contributes theoretically by integrating the Resource-Based View and the Dynamic Capability View in one analytics-enabled CRM model. From the RBV perspective, BDA integration functions as a strategic digital resource when it improves CRM decision-making. From the DCV perspective, dynamic CRM capabilities explain how firms adapt customer-facing processes in response to changing service expectations and market conditions. The study also contributes to service informatics by explaining CRM as an information-flow and service-response system rather than only a marketing database.

Managerially, the findings suggest that telecom firms should connect BDA investments directly to practical CRM applications such as churn prediction, complaint prioritization, call-centre analytics, customer journey tracking, proactive service recovery, personalized offers, and privacy-aware targeting. Managers should also ensure that customer insights reach the right operational units quickly enough to support action.

The study has limitations. The data are cross-sectional and perception-based, so the results should be interpreted as associations rather than causal effects. The sample combines customers, employees, managers, CRM staff, and experts, although robustness checks support the stability of the main relationships. Future research should use longitudinal data, firm-level CRM records, multi-country telecom samples, and more detailed tests of leadership, ethical data use, financial constraints, BDA complexity, and customer trust.

References

Adam, F., & Dempsey, E. (2020). Intuition in decision making—Risk and opportunity. Journal of Decision Systems, 29(sup1), 98–116. https://doi.org/10.1080/12460125.2020.1848375

Al-Afeef, M. A., & Alsmadi, A. A. (2025). Digital empowerment: Unraveling the impact of digital literacy on financial mastery. *Discover Sustainability*, *6*(1), Article 311. https://doi.org/10.1007/s43621-025-01137-5

Al-Dmour, H., Saad, N., Basheer Amin, E., Al-Dmour, R., & Al-Dmour, A. (2023). The influence of the practices of big data analytics applications on bank performance: Filed study. VINE Journal of

Information and Knowledge Management Systems, 53(1), 119–141. https://doi.org/10.1108/VJIKMS-08-2020-0151

Aljawazneh, H., & Abu Al-Ragheb, F. (2026). Fraud prediction in e-commerce transactions using TabNet with advanced data balancing techniques. *Al-Zaytoonah University Journal of Business, 1*(3). https://doi.org/10.15849/zjjb.v1i03.51

Al-Omoush, K. S., Alsmadi, A. A., & Alqirem, R. (2025). Exploring the drivers and relationship between business analytics adoption and innovative circular economy practices. Circular Economy and Sustainability, 5(7), 6003–6035. https://doi.org/10.1007/s43615-025-00683-4

Aloulou, M., Grati, R., Al-Qudah, A. A., & Al-Okaily, M. (2024). Does FinTech adoption increase the diffusion rate of digital financial inclusion? A study of the banking industry sector. Journal of Financial Reporting and Accounting, 22(2), 289–307. https://doi.org/10.1108/JFRA-05-2023-0224

Alsmadi, A. A., Shuhaiber, A., Al-Okaily, M., Al-Gasaymeh, A., & Alrawashdeh, N. (2024). Big data analytics and innovation in e-commerce: Current insights and future directions. Journal of Financial Services Marketing, 29(4), 1635–1652. https://doi.org/10.1057/s41264-023-00235-7

Angelopoulos, S., Bendoly, E., Fransoo, J. C., Hoberg, K., Ou, C. X., & Tenhiälä, A. (2023). Digital transformation in operations management: Fundamental change through agency reversal. Journal of Operations Management, 69(6), 876–889. https://doi.org/10.1002/joom.1271

Anshari, M., Almunawar, M. N., Lim, S. A., & Al-Mudimigh, A. (2019). Customer relationship management and big data enabled: Personalization & customization of services. Applied Computing and Informatics, 15(2), 94–101. https://doi.org/10.1016/j.aci.2018.05.004

Atmaja, W. H. K., Haryono, H., Ramadhan, A., & Zarlis, M. (2024). Examining data needs and predictive models for broadband take-up ratio estimation through CRISP-DM and literature review. Journal of Logistics, Informatics and Service Science, 11(6), 77–91. https://doi.org/10.33168/JLISS.2024.0605

Bader, A., Qtaish, A., Odeh, K., & Sa’d, H. (2025). Artificial intelligence and big data in accounting: The case of commercial banks in Jordan. Al-Zaytoonah Journal of Business, 1(3), 1–18. https://journals.zuj.edu.jo/zjjb/Published-Papers/2025.3.1.pdf

Basu, R., Lim, W. M., Kumar, A., & Kumar, S. (2023). Marketing analytics: The bridge between customer psychology and marketing decision-making. Psychology & Marketing, 40(12), 2588–2611. https://doi.org/10.1002/mar.21908

Bauer, C., Galvan, J. M., Hancock, T., Hunter, G. K., Nelson, C. A., Riley, J., & Tanner, E. C. (2024). Integrating technology within the sales-service ecosystem: The emergent sales techno-ecosystem. European Journal of Marketing, 58(3), 782–811. https://doi.org/10.1108/EJM-04-2023-0221

Brewis, C., Dibb, S., & Meadows, M. (2023). Leveraging big data for strategic marketing: A dynamic capabilities model for incumbent firms. Technological Forecasting and Social Change, 190, 122402. https://doi.org/10.1016/j.techfore.2023.122402

Bulchand-Gidumal, J., William Secin, E., O’Connor, P., & Buhalis, D. (2024). Artificial intelligence’s impact on hospitality and tourism marketing: Exploring key themes and addressing challenges. Current Issues in Tourism, 27(14), 2345–2362. https://doi.org/10.1080/13683500.2023.2229480

Chatterjee, A., & Chatterjee, D. (2024). A journey of business analytics in improving supply chain performance: A systematic review of literature. Management and Labour Studies, 49(2), 337–361. https://doi.org/10.1177/0258042X231208586

Del Vecchio, P., Mele, G., Siachou, E., & Schito, G. (2022). A structured literature review on big data for customer relationship management: Toward a future agenda in international marketing. International Marketing Review, 39(5), 1069–1092. https://doi.org/10.1108/IMR-01-2021-0036

Elgendy, N., Elragal, A., & Päivärinta, T. (2022). DECAS: A modern data-driven decision theory for big data and analytics. Journal of Decision Systems, 31(4), 337–373. https://doi.org/10.1080/12460125.2021.1894674

Garmaki, M., Gharib, R. K., & Boughzala, I. (2023). Big data analytics capability and contribution to firm performance: The mediating effect of organizational learning on firm performance. Journal of Enterprise Information Management, 36(5), 1161–1184. https://doi.org/10.1108/JEIM-06-2021-0247

Ghosh, S., Hughes, M., Hodgkinson, I., & Hughes, P. (2022). Digital transformation of industrial businesses: A dynamic capability approach. Technovation, 113, 102414. https://doi.org/10.1016/j.technovation.2021.102414

Giovannetti, M., Sharma, A., Cardinali, S., Cedrola, E., & Rangarajan, D. (2022). Understanding salespeople’s resistance to, and acceptance and leadership of customer-driven change. Industrial Marketing Management, 107, 433–449. https://doi.org/10.1016/j.indmarman.2022.10.021

Greenland, S. (2023). Divergence versus decision p-values: A distinction worth making in theory and keeping in practice. Scandinavian Journal of Statistics, 50(1), 54–88. https://doi.org/10.1111/sjos.12625

Guida, M., Caniato, F., Moretto, A., & Ronchi, S. (2023). The role of artificial intelligence in the procurement process: State of the art and research agenda. Journal of Purchasing and Supply Management, 29(2), 100823. https://doi.org/10.1016/j.pursup.2023.100823

He, W., Hung, J.-L., & Liu, L. (2023). Impact of big data analytics on banking: A case study. Journal of Enterprise Information Management, 36(2), 459–479. https://doi.org/10.1108/JEIM-05-2020-0176

Kamel, M. A. (2023). Big data analytics and market performance: The roles of customization and personalization strategies and competitive intensity. Journal of Enterprise Information Management, 36(6), 1727–1749. https://doi.org/10.1108/JEIM-04-2022-0114

Kastouni, M. Z., & Lahcen, A. A. (2022). Big data analytics in telecommunications: Governance, architecture and use cases. Journal of King Saud University - Computer and Information Sciences, 34(6), 2758–2770. https://doi.org/10.1016/j.jksuci.2020.11.024

Khrisat, R. M., Khaddam, A. A., & Abusweilem, M. A. (2023). The role of using big data in predicting customer behaviour: The intermediary role of business intelligence in Jordanian telecommunications companies. International Journal of Business Information Systems, 42(1), 23–42. https://doi.org/10.1504/IJBIS.2023.128298

Ledro, C., Nosella, A., & Vinelli, A. (2022). Artificial intelligence in customer relationship management: Literature review and future research directions. Journal of Business & Industrial Marketing, 37(13), 48–63. https://doi.org/10.1108/JBIM-07-2021-0332

Lukovszki, L., Rideg, A., & Sipos, N. (2021). Resource-based view of innovation activity in SMEs: An empirical analysis based on the global competitiveness project. Competitiveness Review: An International Business Journal, 31(3), 513–541. https://doi.org/10.1108/CR-01-2020-0018

Makhloufi, L. (2024). Predicting the impact of big data analytics capability and green absorptive capacity on green entrepreneurship orientation and eco-innovation. Journal of Enterprising Communities: People and Places in the Global Economy, 18(4), 746–770. https://doi.org/10.1108/JEC-05-2023-0069

Mızrak, F. (2023). Use of big data in strategic management as a new perspective. In New perspectives and possibilities in strategic management in the 21st century: Between tradition and modernity (pp. 409–425). IGI Global. https://doi.org/10.4018/978-1-6684-9261-1.ch020

Morshed, A. (2024). Evaluating the influence of advanced analytics on client management systems in UAE telecom firms. Innovative Marketing, 20(4), 41–51. https://doi.org/10.21511/im.20(4).2024.04

Nudurupati, S. S., Tebboune, S., Garengo, P., Daley, R., & Hardman, J. (2024). Performance measurement in data-intensive organisations: Resources and capabilities for decision-making process. Production Planning & Control, 35(4), 373–393. https://doi.org/10.1080/09537287.2022.2084468

Pynadath, M. F., Rofin, T. M., & Thomas, S. (2023). Evolution of customer relationship management to data mining-based customer relationship management: A scientometric analysis. Quality & Quantity, 57(4), 3241–3272. https://doi.org/10.1007/s11135-022-01500-y

Rajput, W. (2023). Understanding digital solutions. In Solutions architecture: A modern approach to cloud and digital systems delivery (pp. 1–30). Springer. https://doi.org/10.1007/978-1-4842-9657-8_1

Ram, J., & Zhang, Z. (2022). Examining the needs to adopt big data analytics in B2B organizations: Development of propositions and model of needs. Journal of Business & Industrial Marketing, 37(4), 790–809. https://doi.org/10.1108/JBIM-10-2020-0464

Saad, N. A., Kac, S. M., & Elgazzar, S. (2025). Linking supply chain management practices of micro, small, and medium-sized enterprises to customer relationship management objectives: A proposed framework. Business Perspectives and Research, 13(1), 89–110. https://doi.org/10.1177/22785337221148891

Schmiedehaus, E., Cordaro, M., Perrotte, J., Stern, M., Dailey, S., & Howard, K. (2023). The great resignation in higher education: An occupational health approach to understanding intentions-to-quit for faculty in higher education. Teaching and Teacher Education, 123, 103992. https://doi.org/10.1016/j.tate.2022.103992

Shah, H. M., Gardas, B. B., Narwane, V. S., & Mehta, H. S. (2023). The contemporary state of big data analytics and artificial intelligence towards intelligent supply chain risk management: A comprehensive review. Kybernetes, 52(5), 1643–1697. https://doi.org/10.1108/K-05-2021-0423

Treiblmaier, H. (2023). Beyond blockchain: How tokens trigger the internet of value and what marketing researchers need to know about them. Journal of Marketing Communications, 29(3), 238–250. https://doi.org/10.1080/13527266.2021.2011375

Tseng, H.-T. (2023). Customer-centered data power: Sensing and responding capability in big data analytics. Journal of Business Research, 158, 113689. https://doi.org/10.1016/j.jbusres.2023.113689

Zhang, W., & Rodgers, S. (2023). Linking ethnicity targeting with artificial intelligence and data collection: Perceptions and behavioral responses of Black consumers. Journal of Current Issues & Research in Advertising, 44(3), 373–391. https://doi.org/10.1080/10641734.2023.2212022

Zulkiflee, I. B., Haw, S.-C., Palanichamy, N., Yeoh, E.-T., & Tong, Y.-C. (2024). Customer relationship management dashboard with descriptive analytics for effective recommendation. Journal of Logistics, Informatics and Service Science, 11(4), 180–202. https://doi.org/10.33168/JLISS.2024.0411