Artykuły
Articles

PRZESTRZEŃ Społeczna

Social SPACE

Volume 23 Issue 04
2023

The Effect of Data Mining and Knowledge Management on Customer Relationship Management: Moderating Influence of Innovation Capability

Fahad Aldhaban

MIS Department, College of Business Administration, University of Business and Technology, Jeddah 21448, Saudi Arabia

Email: aldhaban@ubt.edu.sa

Abstract

The aim of this investigation was to scrutinize the influence of data mining and knowledge management on customer relationship management (CRM) within industrial entities operating in Saudi Arabia, while also exploring the moderating role of innovation capability (IC). A questionnaire was disseminated, yielding a sample of 196 information technology managers and supervisors. The study employed sophisticated statistical techniques including path coefficients, means, standard deviations, T statistics, and p-values, analysed via the Smart PLS program to ensure methodological rigor. Significant findings were revealed, contributing to the existing body of knowledge. Notably, the utilization of data mining techniques within CRM demonstrated a statistically significant positive impact. Furthermore, a significant association between knowledge management and CRM was identified. The moderating effect of IC was found to be significant in the relationship between data mining and CRM, amplifying their positive correlation and underscoring the importance of cultivating an innovative culture. Additionally, IC emerged as a positive moderator in the relationship between knowledge management and CRM, augmenting its influence within organizations that prioritize innovation initiatives.

Keywords: Data Mining, Innovation Capability, Knowledge Management, Customer Relationship Management.

1. Introduction

An organization's objective is to build and maintain relationships with customers, also known as customer retention. This is a crucial marketing strategy because it is less expensive than acquiring new clients (Fiiwe et al., 2023; Wibowo et al., 2020). This phenomenon is particularly evident in the services sector, where success is greatly influenced by customer relationship management (CRM). Over the past few decades, there have been remarkable technological advancements that have facilitated dynamic transformations and enhanced connectivity among people, even across long distances, creating a global community often referred to as a "world village" (Al-Suraihi et al., 2020). Contemporary clients possess a greater amount of information, hence compelling organisations to adapt their customer interactions. Ensuring customer loyalty is not a certainty, and for businesses to endure, they must comprehend the evolving wants and wishes of their customers, along with other relevant facts. In order to be successful, a corporation must actively anticipate and address the needs and wishes of potential customers (Srivastava, Chandra, & Srivastava, 2019); Customers are prioritised and given utmost importance in its marketing approach. If a firm lacks the adaptability to accommodate changes in client behaviour, it runs the danger of losing income and experiencing failure in its marketing activities (Ozuem et al., 2021). The behaviour of customers is crucial for the performance of any firm (Wei et al., 2023). Customer satisfaction fosters brand loyalty (Imran et al., 2019).

Technology has had a profound impact on the behaviours of customers, organisations, and sectors. The market has clearly shifted from being reliant on manual labour to being heavily dependent on technology (Fayyaz & Qasim, 2021). Put simply, the profitability that was mostly derived from human resources now encompasses technology. Technological advancements and the growing influence of information technology (IT) have impacted every industry, including the services sector. Technology has facilitated the enhancement of customer relationship management (CRM) in the hospitality business by increasing performance and productivity (Chan & Chiu, 2022). Knowledge management (KM) and data mining (DM) have enhanced CRM efficiencies to satisfy customers and achieve success in the services sector. Both enable companies to save expenses by keeping consumers, increasing revenue, and enhancing customer relationships (Srivastava et al., 2019).

Innovation capability (IC) refers to a company's inherent capacity to foster innovation, generate novel ideas, and effectively execute those ideas to create innovative solutions (Hatamlah et al., 2023). Several variables contribute to this, such as flexibility, adaptability, and fostering a culture that promotes and incentivizes innovation and novel concepts. This notion is crucial in the realm of business as it enables organisations to adapt to evolving market conditions, sustain their competitive edge, and capitalise on emerging opportunities. The ability of a company to innovate is essential for its sustained success since it enables the creation of revolutionary products and services and enhances the company's ability to meet customers' needs (Al-Rawashdeh, Jawabreh, & Ali, 2023; Alananzeh et al., 2023; Hayek et al., 2023; Kanan, 2020).

This research investigated the impact of DM and KM on CRM in Saudi Arabian industrial companies, while examining the moderating influence of IC. A questionnaire was distributed to 196 IT managers and supervisors. Advanced statistical methodologies, including path coefficients, means, standard deviations, T statistics, and p-values, were employed using the Smart PLS program for rigorous analysis. The study revealed significant positive effects of data mining techniques on CRM and a noteworthy relationship between knowledge management and CRM. Additionally, innovation capability was found to positively moderate the relationships between data mining and CRM, as well as between knowledge management and CRM, emphasizing the importance of fostering an innovative culture in organizations.

2. Literature Review and Hypothesis Development

This section examines relevant theoretical and practical research on CRM, KM, and DM. Research hypotheses have been created based on this review.

2.1 Customer Relationship Management

CRM entails an organization's capacity to provide personalized services to individual customers. This capability relies on the organization's consistent engagement with customers and its systematic collection and retention of customer-related information (Kumar & Misra, 2021). According to Ofosu-Boateng (2020), CRM represents the strategic approach adopted by organizations to comprehend and influence customer behaviour through meaningful communication with the aim of acquiring, retaining, and fostering customer loyalty, consequently augmenting revenue streams. CRM facilitates the provision of personalized services tailored to individual customers, fostering a deeper and more intimate relationship between the organization and its clientele. By accommodating customers' tastes, preferences, likes, and dislikes, the organization cultivates a sense of belonging and care among its customer bases. Concurrently, the organization stands to gain increased revenue by fostering more efficient interactions with customers (Srivastava et al., 2019). Through the integration of human resources, business processes, and technology, CRM endeavours to fulfil customer expectations and enhance relationships with customers. CRM fosters a customer-centric approach, wherein organizational activities are oriented towards meeting customer needs comprehensively. Given the cost-effectiveness of customer retention over customer acquisition, organizations are increasingly prioritizing customer-focused services to satisfy and retain their customer base (Bakar et al., 2021).

2.2 Data Mining

Recent IT advancements have sparked significant transformations in business organizations, particularly in the service sector, emphasizing the long-term provision of hospitable services to customers (Stalmachova, Chinoracky, & Strenitzerova, 2021). Virtually all enterprises utilize IT systems, facilitating the management of expansive databases within organizations. The efficacy of databases is optimized when organizations establish a systematic procedure for the collection, storage, and analysis of data (Alawadhi et al., 2022; Alqaraleh et al., 2022; Hatamlah et al., 2023).

The utilization of computational technology to investigate and scrutinize extensive datasets with the aim of uncovering valuable insights, patterns, and rules encapsulates the broad concept of DM (Yan et al., 2020). It employs statistical methodologies and pertinent techniques to facilitate the development of models elucidating customer behaviour (Kanan et al., 2022). By scrutinizing factors that forecast comparable purchasing behaviours, potential market segments can be discerned. Hence, DM proves advantageous in identifying and engaging potential clientele (Yoseph et al., 2020).

Through the utilization of DM to analyse customer needs, preferences, tastes, and dislikes, organizations can tailor their products and services to align with customer preferences effectively. These inputs should be available in the database (Lai et al., 2022). The inputs also serve to identify new customers and provide guidance on retention strategies (Payne & Frow, 2016). Furthermore, they facilitate upselling, allowing for the provision of customized services to customers and resulting in increased revenue generation. Moreover, services can be adjusted to accommodate evolving customer needs (Kaarnavaara-Puutio, 2021). Consequently, it is suggested that:

H1: *DM positively influences CRM.*

H2: *IC moderates the relationship between DM and CRM.*

2.3 Knowledge management

Given that CRM is predicated on technology-driven approaches, it comprises two integral components: KM and DM. These elements are instrumental in enhancing the efficacy of CRM (Kruger, 2012). The integration of KM with CRM is prevalent in the services sector due to the recognition of customer data as a pivotal determinant of its success (Bratianu, Stănescu, & Mocanu, 2022). Customer-related knowledge constitutes an intrinsic facet of CRM, serving as a means to fulfil customer satisfaction (Kumar & Misra, 2021). An organization gathers this knowledge through diverse channels and touchpoints, employing it to formulate strategies aimed at enhancing service delivery (Akter et al., 2020; Al Shraah et al., 2022). Srivastava et al. (2019) It is posited that organizational performance is contingent upon both customer knowledge and KM. This entails the collection, storage, and dissemination of knowledge, along with the extraction of insights to develop knowledge-based services (Ayatollahi & Zeraatkar, 2020). Within the contemporary marketing landscape characterized by a customer-centric paradigm, KM is deemed indispensable (Sindakis, Depeige, & Anoyrkati, 2015). KM encompasses the structured organization of information and knowledge to enhance managerial decision-making capabilities (Gupta et al., 2021). The integration of a KM system with CRM can enhance both customer satisfaction levels and revenue outcomes (Ramesh & Sivakumar, 2021). The importance of KM within CRM is evident. Its incorporation into CRM enables a service-oriented organization to establish, cultivate, and sustain relationships with its clientele, thereby conferring a competitive edge (Daengs et al., 2020). When an organization adeptly converts customer information into actionable customer knowledge, the efficacy and success of CRM are heightened. Through effective KM, organizations can enhance CRM practices and achieve elevated performance levels (Chatterjee, Ghosh, & Chaudhuri, 2020). Cultivating customer relationships holds greater significance within the services sector, and KM can aid organizations in this sector in attaining competitive advantages. Empirical evidence substantiates the beneficial impact of KM on enhancing customer satisfaction. Consequently, it is suggested that:

H3: *KM positively influences CRM.*

H4: *IC moderates the relationship between KM and CRM.*

3. Research Methodology

This descriptive study endeavours to elucidate a phenomenon or condition to facilitate decision-making. It assesses the impact of KM and DM on CRM through the testing of two formulated hypotheses. Sufficient data was gathered utilizing a questionnaire consisting of four sections and 22 items. The questionnaire addresses socio-demographic characteristics, CRM, KM, and DM, employing a five-point Likert scale for measurement.

The questionnaire's validity and reliability were confirmed through two methods. Initially, feedback from academics was incorporated to refine the items. Subsequently, Cronbach's alpha was computed for each construct, demonstrating strong internal consistency with values exceeding 0.7: CRM (0.900), KM (0.881), and DM (0.913). Thus, the questionnaire was deemed valid and reliable. The study collected 196 responses from IT managers and supervisors in industrial companies in Saudi Arabia, all possessing comprehensive knowledge of their roles. Table 1 outlines the variables, items, and their sources.

Table 1: Items on the Questionnaire.

No	Variable Name	Number of Item	Source
1	Customer Relationship Management	8	(Al-Suraihi et al., 2020; Chan & Chiu, 2022)
2	Knowledge Management	9	(Al Shraah et al., 2022; Bratianu et al., 2022)
3	Data Mining	8	(Yan et al., 2020; Yoseph et al., 2020)
4	Innovation Capability	7	(Saunila & Ukko, 2014)

3.1 Theoretical Framework

The foundational structure of this study comprises a theoretical framework incorporating two distinct independent variables and one dependent variable. Additionally, a moderating variable is incorporated within this research framework. Illustrated in Figure 1 is the theoretical framework delineating the impact of KM & DM on CRM. Moreover, the moderating function of IC is elucidated within this framework.

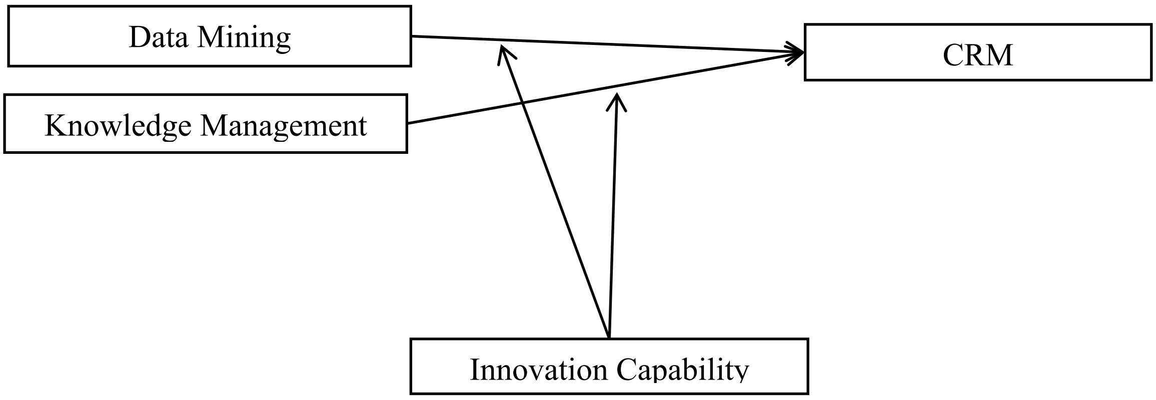

Figure 1. Theoretical Framework.

4. Data Analysis and Findings

Within the framework of Smart PLS, DM is considered an inactive concept. Several indicators are employed to implement it, including tools for collecting data, methodologies for analysing data, and the implementation of initiatives motivated by data. The aforementioned variables are connected to the idea of DM by pathways that show their measuring correlation. KM is an underlying concept in the model that is evaluated by observing various indicators associated with behaviours, such as sharing, storing, retrieving, and distributing knowledge. The picture illustrates the pathways that demonstrate the connections between KM and its corresponding indicators.

IC is evaluated as a latent variable that signifies an organization's capacity to engage in creative endeavours. The construct is connected to IC components that encompass characteristics like innovation culture and innovative solutions, which have been identified and linked by pathways. CRM, or Customer Relationship Management, refers to the underlying notion that is assessed through tangible measures like customer pleasure, loyalty, and the organization's capacity to fulfil client requirements. The aforementioned indicators are interconnected with CRM through various channels, signifying their significance in assessing CRM. The measurement model employed in this investigation is depicted in Figure 2 and was analysed using Smart PLS. The measuring model plays a crucial role in assessing the underlying components of DM, KM, IC, and CRM by utilising observable indicator.

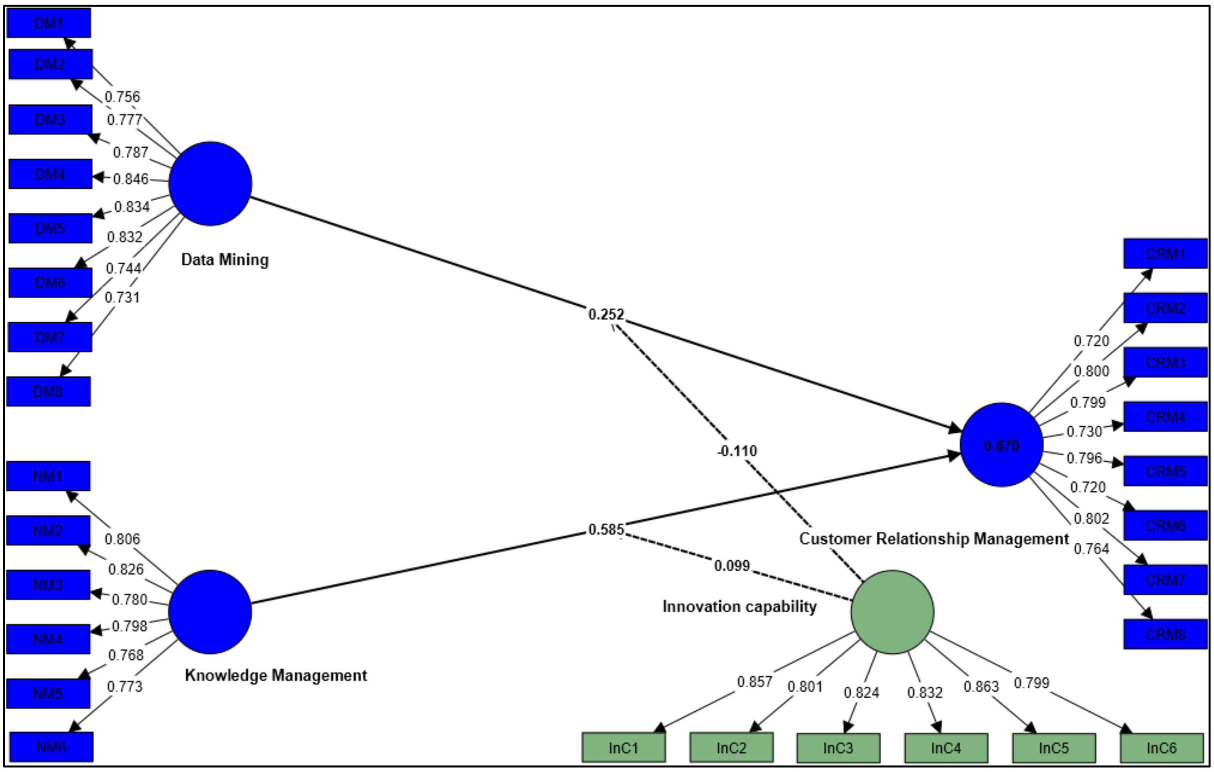

Figure 2: Measurement Model.

The measurement model plays a crucial role in Smart PLS research as it determines the validity and reliability of latent constructs and their associations with observable variables. The model aids researchers in assessing whether the selected observable variables accurately represent the underlying latent components. Smart PLS utilises statistical analysis to assess the accuracy and reliability of the measurement model. This involves analysing the loadings, cross-loadings, and construct reliability of indicators. The measurement model plays a crucial role in establishing a solid basis for future structural modelling endeavours. Figure 2 illustrates the connections between hidden variables and their corresponding indicators. It serves as a visual depiction of how Smart PLS assesses the measurement aspect of the study to verify the reliability and credibility of the research model. Figure 2 provides a visual depiction of the measuring model and offers a comprehensive description of the concepts represented by Smart PLS. This model highlights the significance of employing observable indicators to evaluate latent components within the study's environment.

The structural model analysis, depicted in Figure 3, is a crucial element of the Smart PLS analytical approach employed in this study. The aim of the structural model analysis is to assess the statistical significance and magnitude of these relationships and moderations using the Smart PLS programme. This phase is employed by researchers to evaluate the postulated connections and acquire understanding of the impacts of the independent variables "DM and KM" on the dependent variable "CRM", as well as the influence of the moderator variable "IC" on these links. Figure 3 depicts the analysis of the structural model, which visually represents the connections between different components in the research model. This study facilitates researchers in gaining a more profound comprehension of the complex dynamics inherent in the system being studied. This stage is crucial for evaluating the significance and strength of the projected connections. It offers valuable insights into understanding the impacts of decision-making, knowledge management, and intellectual capital on customer relationship management inside industrial firms in Saudi Arabia. Figure 3 provides a visual representation of the correlations and moderations analysed in the structural model analysis conducted with Smart PLS. This study provides significant information about the relationships between hidden factors and their impact on CRM in the specific context of the research.

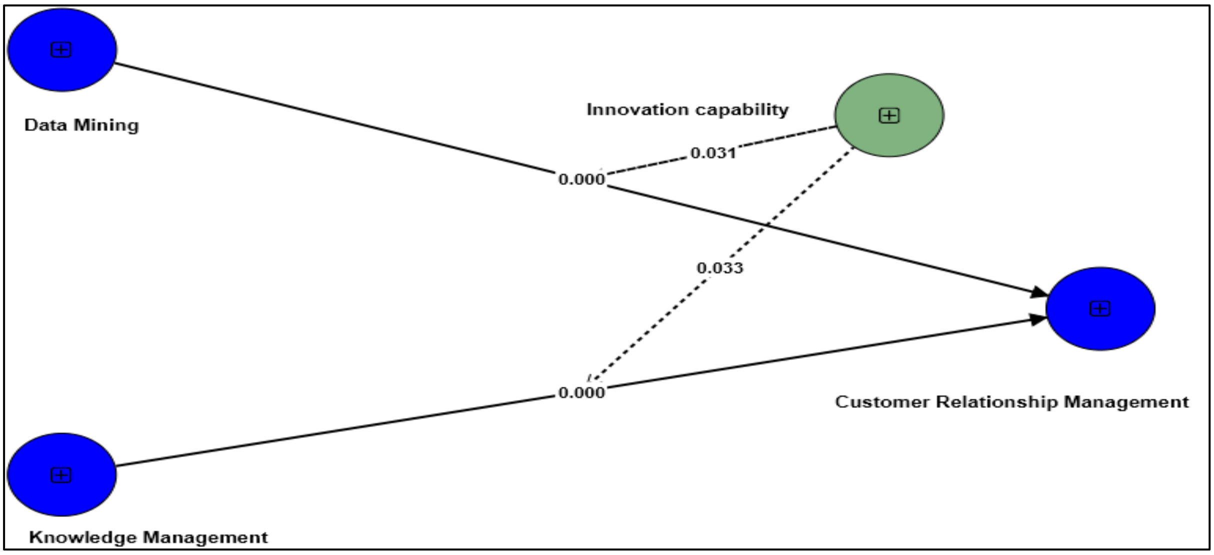

Figure 3: Structural Model Analysis.

Table 2 presents three essential metrics utilised for assessing the soundness and consistency of the construction: Cronbach's alpha, composite reliability, and average variance extracted (AVE). These measures are crucial for ensuring the dependability and accuracy of a measuring instrument within the framework of a study. Cronbach's alpha is a statistical measure that quantifies the degree of internal consistency inside a scale or construct. It assesses the strength of the relationship between the different components of the scale or construct (Cronbach, 1949). All structures in this table, namely CRM, DM, IC, and KM, have robust internal consistency, as indicated by Cronbach's alpha values over 0.88. This indicates that there is a strong correlation between the items within each construct, which is a positive indication of the accuracy and reliability of the instrument used to evaluate them.

Composite reliability is a measure of internal consistency that is analogous to the widely recognised metric of alpha reliability. In essence, it assesses the degree to which a set of items measures the same fundamental concept within a framework (Henseler, 2015). Table 2 demonstrates a significant level of internal consistency among all structures, with values ranging from 0.882 to 0.922. This further substantiates the notion that the individual components of each construct are effectively assessing their intended concepts, and that the overall measurement tool is reliable.

The AVE assesses the extent to which the idea captures the variation compared to the extent of variance attributed to measurement error (Fornell & Larcker, 1981). The AVE values in this table range from 0.589 to 0.689, suggesting that a substantial amount of variance in each construct is accounted for by its elements, thereby supporting the construct's validity. In conclusion, Table 2 exhibits robust validity and reliability metrics for the structure being examined, indicating the trustworthiness of the measuring instrument and the suitability of these constructs for further exploration and analysis.

Table 2: Validity and Reliability of the Construction.

	Cronbach's Alpha	**Composite Reliability:**	**AVE**
CRM	0.900	0.904	0.589
DM	0.913	0.922	0.623
IC	0.909	0.911	0.689
KM	0.881	0.882	0.628

Table 3 displays the external loadings for four separate constructs: CRM, DM, IC, and KM. The size of outer loadings indicates the strength of the relationships between observed variables (items) and their corresponding constructs. The table presents the external loadings of each item at the individual level for each build. The loadings for CRM range from 0.720 to 0.802. The loadings for DM range from 0.731 to 0.846. The loadings for IC are between 0.800 and 0.863. Lastly, the loadings for KM range from 0.768 to 0.826. The strong correlations between items and their corresponding variables adhere to the acceptability standards set by Hair et al. (2017). The outer loadings of Table 3, which are crucial for assessing the validity of the measurement model in Smart PLS, offer valuable information about the extent to which each item accurately measures its intended construct. These loading values fulfil the acceptable standards set by Hair et al. (2017).

Table 3: Outer Loadings.

	CRM	**Data Mining**	**Innovation Capability**	**Knowledge Management**
CRM1	0.720			
CRM2	0.800			
CRM3	0.799			
CRM4	0.730			
CRM5	0.796			
CRM6	0.720			
CRM7	0.802			
CRM8	0.764			
DM1		0.756		
DM2		0.777		
DM3		0.787		
DM4		0.846		
DM5		0.834		
DM6		0.832		
DM7		0.744		
DM8		0.731		
InC1			0.857	
InC2			0.801	
InC3			0.824	
InC4			0.832	
InC5			0.863	
InC6			0.799	
NM1				0.806
NM2				0.826
NM3				0.780
NM4				0.798
NM5				0.768
NM6				0.773

Table 4 presents a concise overview of the findings from the matrix HTMT ratio study, which is employed in structural equation modelling (SEM) to examine the extent to which different components demonstrate discriminant validity. Discriminant validity guarantees that various conceptions evaluate separate underlying notions and are not too interconnected. The diagonal values in this table indicate the connections between elements within the same construct, sometimes referred to as "Monotrait" connections. These values are anticipated to be elevated as they demonstrate the internal coherence of each construction. Conversely, off-diagonal values indicate "Heterotrait" connections that evaluate the relationship between one concept and items from many concepts. Values approaching one indicate possible problems with discriminant validity, suggesting that the concepts are not adequately different. The data presented in Table 4 indicates that all HTMT values are below one, which suggests a favourable relationship. This indicates that the constructs being studied possess satisfactory discriminant validity, as the correlations between items within the same construct consistently exhibit greater strength compared to the correlations between items from different constructs (Henseler et al., 2015).

Table 4: Matrix Heterotrait-Monotrait Ratio (HTMT).

	CRM	**DM**	**IC**	**KM**	**IC x DM**	**IC x KM**
CRM						
DM	0.677					
IC	0.642	0.800				
KM	0.848	0.576	0.602			
IC x DM	0.405	0.455	0.461	0.325		
IC x KM	0.223	0.360	0.304	0.239	0.730	

Table 5, known as the Fornell-Larcker criterion, is a crucial tool used in the field of SEM to evaluate the discriminant validity among different constructs. Discriminant validity guarantees that each construct measures a unique concept without any significant overlap with other constructs. The table provided crucial data regarding many collinearity problems. The diagonal elements of the matrix correspond to the square root of the AVE for each construct, which indicates the degree of internal consistency. Furthermore, the non-diagonal elements in the matrix exhibit correlations between pairs of constructs, so identifying possible intersections.

Moreover, within the realm of CRM, it is evident that the square root of the AVE, which has a value of 0.767, has superior performance when compared to all inter-construct correlations. This establishes its discriminant validity. The discriminant validity of the DM is demonstrated by the consistent observation that the square root of the AVE (0.790) consistently surpasses correlation coefficients. Furthermore, the construct of IC demonstrates robust discriminant validity, seen from its square root of AVE value of 0.830, which regularly exceeds correlation coefficients. Similarly, the KM also demonstrates discriminant validity since the square root of the AVE (0.792) constantly surpasses the correlations. In summary, the results from Table 5 indicate that each construct accurately represents separate concepts, hence strengthening the reliability and validity of the measurement model in the SEM.

Table 5: The Fornell-Larcker Criterion.

	CRM	**DM**	**IC**	**KM**
CRM	0.767			
DM	0.624	0.790		
IC	0.584	0.737	0.830	
KM	0.766	0.531	0.543	0.792

A statistically significant and positive association has been found between the application of CRM and the practice of DM, according to the analysis of Hypothesis 1. The measured path coefficient of 0.252 indicates that the rise in CRM and the growth in DM activities are positively correlated. This finding suggests that companies who engage in DM initiatives are more likely to get improved CRM results. The exceptionally low p-value of 0.000, which denotes a high degree of confidence in the acquired results, supports the statistical significance of the observed association. Practically speaking, it may be concluded that there is a valid link rather than chance for the influence of DM on CRM.

Moreover, hypothesis 2 investigates IC's possible role as a moderating element in the relationship between DM and CRM. The results show that innovation potential is unquestionably moderating the connection, and that this moderation is positively statistically significant. The measured route coefficient of 0.585 indicates that the beneficial effects of DM on CRM are amplified with increasing levels of IC. To put it another way, companies with strong innovation capabilities benefit even more from their DM efforts than from improved CRM. Strong statistical support for the existence of this moderating effect is shown by the T-statistics value of 9.745 and the p-value of 0.000.

As a result, the results of the investigation into Hypothesis 3 point to a statistically significant correlation between CRM and KM. However, it is imperative to recognise that this correlation is negative, as demonstrated by a path coefficient of -0.110. According to this research, organisations' performance in CRM and their amount of KM investment are negatively correlated. Even though this finding is statistically significant, it still requires careful review and more research. This finding implies the existence of complex dynamics in which a focus on KM may be overly damaging to CRM results. The statistical significance of the observed negative relationship is indicated by the obtained p-value of 0.031. Nonetheless, it is recommended that researchers and professionals look into the underlying causes of this surprising result more thoroughly.

The potential moderating effect of IC on the relationship between KM and CRM is finally examined in hypothesis 4. A path coefficient of 0.099 suggests that IC is positively moderating the connection, according to the data. This implies that companies with strong ICs see an improvement in the positive relationship between KM and CRM. The benefits of effective KM strategies become increasingly apparent in connection to CRM outcomes when the level of IC is raised. The p-value of 0.033 and the derived T-statistics value of 2.127 provide empirical support for the presence of this moderating effect. To sum up, the analysis of these suppositions provides important information about how DM, KM, IC, and CRM are related to one another. The previously mentioned results have the capacity to offer decision-makers in businesses useful information about how important these factors are in affecting CRM results. Furthermore, these results can be a useful point of reference for other studies in this area. Table 6 reports the findings.

Table 6: Calculating Path Coefficients.

Hypotheses	Original Sample	Sample Mean	STDEV	T Value	P Value
H1: DM positively influences CRM.	0.252	0.255	0.061	4.134	0.000
H2: IC moderates the relationship between DM and CRM.	0.585	0.581	0.060	9.745	0.000
H3: KM positively influences CRM.	-0.110	-0.095	0.051	2.162	0.031
H4: IC moderates the relationship between KM and CRM.	0.099	0.089	0.047	2.127	0.033

On the other hand, the model's R-squared values used in the investigation are listed in Table 7. The coefficient of determination, or R-squared, is a statistical metric that's used to assess how much of the variation in a dependent variable may be ascribed to variables that aren't included in the equation that depicts the link between the two. CRM is the dependent variable in this instance. First off, R2 has a starting value of 0.670. This suggests that approximately 67.0% of the variation in CRM can be explained by the independent variables in the model. Just a few of the components in the study, the DM, IC, and KM, are responsible for 67.0% of the observed changes in CRM. This degree of explanatory power indicates how well a model can represent the relationships found in the data.

Second, it has been determined that the second R-squared, also known as the "R-square adjusted," has a value of 0.663. In order to account for the number of independent variables in the model, this value alters the R-squared statistic. Using unnecessary or redundant variables may be penalised as a goodness of fit metric. With an adjusted R-squared of 0.663, the independent factors continue to explain approximately 66.3% of the variance in CRM after adjusting for the number of variables in the model. These R-squared values collectively imply that the examined model performs a respectable job of explaining the observed variation in CRM. Even with the complexity of the model, a sizable amount of the variation in CRM (0.663, adjusted) may be explained by the independent variables that are included. This suggests that the model is a helpful resource for understanding and projecting CRM outcomes depending on the parameters that were looked into.

Table 7: R Square.

	R-Square	R-Square Adjusted
Customer Relationship Management	0.670	0.663

5. Conclusion and implications

The purpose of this study was to investigate the intricate relationships between DM, IC, KM, and CRM within the context of Saudi Arabian industrial organisations. The study's findings provide light on the complex processes at play in this phenomena. Additionally, the study's findings demonstrated a statistically significant favourable link between the application of CRM tactics and DM practice. This implies that companies are likely to observe improvements in CRM outcomes when they use DM operations. The strong evidence supporting this association highlights the strategic importance of enhancing client connections through data-driven techniques. Crucially, the study's conclusions emphasised innovation potential's moderating function in addition to confirming its positive effects. A strong capacity for creativity strengthens the positive relationship between DM and CRM. It was also demonstrated to have a positive moderating influence on the relationship between CRM and KM. This claim emphasises how important it is to develop a creative corporate culture in order to maximise the benefits of DM and KM strategies.

A important finding about the correlation between KM and CRM was made by the study, which showed that KM had a negative but statistically significant impact on CRM. This suggests that companies should be cautious when handling their data to avoid unanticipated consequences for CRM outcomes. More research is required to clarify the underlying complexity of this relationship. To sum up, this study has produced important insights into the intricate relationships that govern IT-related behaviours and how they affect CRM in Saudi Arabia's corporate environment. The conclusions presented above have real-world implications for businesses looking to improve their CRM strategies. The research's findings have significant ramifications for the academic community as well as the business sector.

Essentially, this research offers significant and applicable information that organisations in Saudi Arabia's industrial sector can utilise. Organisations should consider utilising DM approaches to improve CRM outcomes. Moreover, fostering a culture that places a high value on innovation is crucial for maximising the benefits obtained from DM and KM. This study emphasised the importance of adopting a nuanced strategy, as evidenced by the unexpected negative association between KM and CRM in relation to achieving balance. To minimise potential disadvantages, it is crucial for organisations to attain a balanced and harmonious state in their knowledge management efforts. This emphasises the importance of aligning KM procedures with CRM objectives.

6. Further Directions

Additionally, this study offers possible directions for future investigation. Comprehensive analyses of the negative relationship between KM and CRM and the application of longitudinal research to establish causation may lead to further advances in our understanding. Furthermore, qualitative research may be able to offer deeper contextual understandings. To sum up, this research contributes to our understanding of the complex relationships between DM, IC, KM, and CRM inside Saudi Arabian industrial businesses. The findings offer useful suggestions for businesses looking to enhance their CRM plans and general efficacy in the dynamic business environment.

References

Akter, S., Motamarri, S., Hani, U., Shams, R., Fernando, M., Mohiuddin Babu, M., & Ning Shen, K. (2020). Building dynamic service analytics capabilities for the digital marketplace. *Journal of Business Research, 118*, 177-188. https://doi.org/10.1016/j.jbusres.2020.06.016

Al-Rawashdeh, O. M., Jawabreh, O., & Ali, B. J. (2023). Supply Chain Management and Organizational Performance: The Moderating Effect of Supply Chain Complexity. *Information Sciences Letters, 12*(3), 1673-1684. http://dx.doi.org/10.18576/isl/120351

Al-Suraihi, W. A., Al-Suraihi, A.-H. A., Ibrahim, I., Al-Tahitah, A., & Abdulrab, M. (2020). The Effect of Customer Relationship Management on Consumer Behavior: A Case of Retail Industry in Malaysia. *International Journal of Management and Human Science (IJMHS), 4*(3), 32-40. https://ejournal.lucp.net/index.php/ijmhs/article/view/1139

Al Shraah, A., Abu-Rumman, A., Al Madi, F., Alhammad, F. A. F., & AlJboor, A. A. (2022). The impact of quality management practices on knowledge management processes: a study of a social security corporation in Jordan. *The TQM Journal, 34*(4), 605-626. https://doi.org/10.1108/TQM-08-2020-0183

Alananzeh, O. A., Almuhaisen, F., Jawabreh, O., Fahmawee, E., Ali, B. J., & Ali, A. (2023). The Impact of Job Stability, Work Environment, Administration, Salary and Incentives, Functional Justice, and Employee Expectation on the Security Staff's Desire to Continue Working at the Hotel. *Journal of Statistics Applications & Probability, 12*(2), 425-439. http://dx.doi.org/10.18576/jsap/120209

Alawadhi, S. A., Zowayed, A., Abdulla, H., Khder, M. A., & Ali, B. J. A. (2022). Impact of Artificial Intelligence on Information Security in Business. In *2022 ASU International Conference in Emerging Technologies for Sustainability and Intelligent Systems (ICETSIS)* (pp. 437-442). IEEE. https://doi.org/10.1109/ICETSIS55481.2022.9888871

Alqaraleh, M. H., Almari, M. O. S., Ali, B. J., & Oudat, M. S. (2022). The mediating role of organizational culture on the relationship between information technology and internal audit effectiveness. *Corporate Governance and Organizational Behavior Review, 6*(1), 8-18. https://doi.org/10.22495/cgobrv6i1p1

Ayatollahi, H., & Zeraatkar, K. (2020). Factors influencing the success of knowledge management process in health care organisations: a literature review. *Health Information & Libraries Journal, 37*(2), 98-117. https://doi.org/10.1111/hir.12285

Bakar, E. A., Muda, I., Nedelea, A., & Wardhani, M. M. (2021). The Influence Of Using Sap Crm On Increasing Customer Satisfaction Index At Pt. Bank X In Medan, Indonesia. *The USV Annals of Economics and Public Administration, 21*(2 (34)), 78-83. http://annals.seap.usv.ro/index.php/annals/article/viewArticle/1293

Bratianu, C., Stănescu, D. F., & Mocanu, R. (2022). The mediating role of customer knowledge management on the innovative work behavior and product innovation relationship. *Kybernetes, 52*(11), 5353-5384. https://doi.org/10.1108/K-09-2021-0818

Chan, M. M. W., & Chiu, D. K. (2022). Alert-Driven Customer Relationship Management in Online Travel Agencies: Event-Condition-Actions Rules and Key Performance Indicators. In *Building a brand image through electronic customer relationship management* (pp. 286-303). IGI Global. https://doi.org/10.4018/978-1-6684-5386-5.ch012

Chatterjee, S., Ghosh, S. K., & Chaudhuri, R. (2020). Knowledge management in improving business process: an interpretative framework for successful implementation of AI–CRM–KM system in organizations. *Business Process Management Journal, 26*(6), 1261-1281. https://doi.org/10.1108/BPMJ-05-2019-0183

Daengs, G. S., Istanti, E., Negoro, R. M., & Sanusi, R. (2020). The aftermath of management actions on competitive advantage through process attributes at food and beverage industries export import in Perak Harbor of Surabaya. *International Journal of Criminology and Sociology, 9*, 1418-1425. http://eprints.ubhara.ac.id/id/eprint/710

Fayyaz, E., & Qasim, Y. (2021). The Digitalization of Supply Chain Impact on Business Performance: A Study of Multinational Companies. *Business Review of Digital Revolution, 1*(1), 41-49. https://doi.org/10.62019/BRDR.01.01.06

Fiiwe, J. L., Egele, A. E., Ozo, J. U., & Obasiabara, B. O. (2023). Customer Relationship Management and Customers Repeat Purchase Behavior in Nigeria. *Scholars Journal of Economics, Business and Management, 10*(1), 19-28. https://doi.org/10.36347/sjebm.2023.v10i01.002

Gupta, S., Justy, T., Kamboj, S., Kumar, A., & Kristoffersen, E. (2021). Big data and firm marketing performance: Findings from knowledge-based view. *Technological Forecasting and Social Change, 171*, 120986. https://doi.org/10.1016/j.techfore.2021.120986

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., & Thiele, K. O. (2017). Mirror, mirror on the wall: a comparative evaluation of composite-based structural equation modeling methods. *Journal of the Academy of Marketing Science, 45*(5), 616-632. https://doi.org/10.1007/s11747-017-0517-x

Hatamlah, H., Allahham, M., Abu-AlSondos, I., Mushtaha, A., Al-Anati, G., Al-Shaikh, M., & Ali, B. (2023). Assessing the moderating effect of innovation on the relationship between information technology and supply chain management: an empirical examination. *Applied Mathematics & Information Sciences, 17*(5), 889-895. http://dx.doi.org/10.18576/amis/170515

Hayek, A. F., Oudat, M. S., Ali, B. J., Al-Alkawi, T., & El Haija, M. F. A. (2023). Corporate governance and cost of equity: An empirical investigation of the United Arab Emirates stock market. *Corporate & Business Strategy Review, 4*(4), 24-31. https://doi.org/10.22495/cbsrv4i4art3

Imran, M., Hamid, S. N. B. A., Aziz, A., & Hameed, W. (2019). The contributing factors towards e-logistic customer satisfaction: a mediating role of information Technology. *Uncertain Supply Chain Management, 7*(1), 63-72. http://dx.doi.org/10.5267/j.uscm.2018.5.002

Kaarnavaara-Puutio, M. (2021). *Streamlining a Service Process. Optimising Two-way Information Sharing in Product Development: Case Origin by Ocean* (Master's Thesis, Ammattikorkeakoulujen opinnäytetyöt ja julkaisut). https://urn.fi/URN:NBN:fi:amk-2021113022766

Kanan, M. (2020). Assessment of the COPQ due to Poor Maintenance Practices in Saudi Industry. *SSRG International Journal of Engineering Trends and Technology, 68*(11), 163-172. https://doi.org/10.14445/22315381/IJETT-V68I11P222

Kanan, M., Wannassi, B., Barham, A. S., Ben Hassen, M., & Assaf, R. (2022). The Quality of Blended Cotton and Denim Waste Fibres: The Effect of Blend Ratio and Waste Category. *Fibers, 10*(9), 76. https://doi.org/10.3390/fib10090076

Kruger, G. (2012). *Strategic information management in the value chain of a multi-national organization, operating in the vehicle industry* (Doctoral dissertation, North-West University (South Africa), Potchefstroom Campus). http://hdl.handle.net/10394/19143

Kumar, M., & Misra, M. (2021). Evaluating the effects of CRM practices on organizational learning, its antecedents and level of customer satisfaction. *Journal of Business & Industrial Marketing, 36*(1), 164-176. https://doi.org/10.1108/JBIM-11-2019-0502

Lai, X., Zhang, S., Mao, N., Liu, J., & Chen, Q. (2022). Kansei Engineering for New Energy Vehicle Exterior Design: An Internet Big Data Mining Approach. *Computers & Industrial Engineering, 165*, 107913. https://doi.org/10.1016/j.cie.2021.107913

Ofosu-Boateng, I. (2020). Influence of Customer Relationship Management on Customers' Retention in the Insurance Industry in Accra, Ghana. *British Journal of Marketing Studies, 8*(2), 77-95. https://doi.org/10.37745/bjms.2013

Ozuem, W., Ranfagni, S., Willis, M., Rovai, S., & Howell, K. (2021). Exploring customers' responses to online service failure and recovery strategies during Covid-19 pandemic: An actor–network theory perspective. *Psychology & Marketing, 38*(9), 1440-1459. https://doi.org/10.1002/mar.21527

Payne, A., & Frow, P. (2016). Customer relationship management: Strategy and implementation. In *The Marketing Book* (pp. 439-466). Routledge. https://www.taylorfrancis.com/chapters/edit/10.4324/9781315890005-21

Ramesh, S., & Sivakumar, V. J. (2021). Influence of knowledge management system on customer satisfaction index-an application study of CRM by offering performance enhancement for transmission. *International Journal of Knowledge Management Studies, 12*(4), 375-391. https://doi.org/10.1504/IJKMS.2021.118347

Sindakis, S., Depeige, A., & Anoyrkati, E. (2015). Customer-centered knowledge management: challenges and implications for knowledge-based innovation in the public transport sector. *Journal of Knowledge Management, 19*(3), 559-578. https://doi.org/10.1108/JKM-02-2015-0046

Srivastava, S. K., Chandra, B., & Srivastava, P. (2019). The impact of knowledge management and data mining on CRM in the service industry. In *Nanoelectronics, Circuits and Communication Systems: Proceeding of NCCS 2017* (pp. 37-52). Springer. https://doi.org/10.1007/978-981-13-0776-8_4

Stalmachova, K., Chinoracky, R., & Strenitzerova, M. (2021). Changes in business models caused by digital transformation and the COVID-19 pandemic and possibilities of their measurement—case study. *Sustainability, 14*(1), 127. https://doi.org/10.3390/su14010127

Wei, Q., Xiao, W., Yaqub, R. M. S., Irfan, M., Murad, M., & Yaqub, M. Z. (2023). Adoption of digital money (e-wallet) in the post COVID-19 era: The moderating role of low distribution charges and low transit time in impulsive buying: A developing country perspective. *Frontiers in Environmental Science, 10*, 984316. https://doi.org/10.3389/fenvs.2022.984316

Wibowo, A., Chen, S.-C., Wiangin, U., Ma, Y., & Ruangkanjanases, A. (2020). Customer behavior as an outcome of social media marketing: The role of social media marketing activity and customer experience. *Sustainability, 13*(1), 189. https://doi.org/10.3390/su13010189

Yan, H., Yang, N., Peng, Y., & Ren, Y. (2020). Data mining in the construction industry: Present status, opportunities, and future trends. *Automation in Construction, 119*, 103331. https://doi.org/10.1016/j.autcon.2020.103331

Yoseph, F., Ahamed Hassain Malim, N. H., Heikkilä, M., Brezulianu, A., Geman, O., & Paskhal Rostam, N. A. (2020). The impact of big data market segmentation using data mining and clustering techniques. *Journal of Intelligent & Fuzzy Systems, 38*(5), 6159-6173. https://doi.org/10.3233/JIFS-179698