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Research paper

Exploring Knowledge Management Drivers in AI Powered CRM: A Conceptual Framework for Marketing Practitioners

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Abstract

Purpose: This study investigates the knowledge management (KM) drivers of Artificial Intelligence-powered Customer Relationship Management (AI-CRM) systems. It explores how organisational culture, learning processes, and individual characteristics affect knowledge seekers and marketer's conduct in acquiring or using knowledge and marketing practices.
Design/methodology/approach: The study used KM, Social Cognitive Theory, and the Technology Acceptance Model. This study provides a conceptual framework for KM and AI-CRM. Data were collected from a sample of 302 marketing professionals (94% response rate) across the IT, retail, healthcare, education, and e-commerce sectors in India using a structured questionnaire. A purposive sampling approach was used, and Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to examine the direct and moderating effects.
Findings: The results indicate that learning mechanisms and individual characteristics have significant impacts on marketing KM practices in AI-CRM environments. In contrast, organisational culture alone cannot directly influence KM, but it can when moderated by individual characteristics. These results indicate that factors related to structured training and individual adaptability, rather than cultural factors, play a more decisive role in promoting AI-CRM adoption.
Research limitations/implications: This study has several limitations, including its cross-sectional design, geographic setting (North India), and reliance on self-reports. Future research should consider longitudinal designs and include more industries and regions to improve generalizability.
Practical implications: Managers and policymakers should focus on targeted training, experiential learning, mentorship schemes, and the creation of psychologically safe spaces for knowledge sharing. Investments in technological and human capacity are key to fully exploiting AI-CRM results.
Originality/value: This study contributes to the existing literature on AI-CRM by generalizing the (Jamil et al., 2025; Nonaka et al., 2000) SECI model to AI-enabled customer relationship management environments, which in turn integrates the knowledge creation process with generative automation. The study empirically validated the PLS SEM framework, providing substantive evidence to support marketers' decision-making in emerging markets. The study also emphasizes the role of individual readiness as a moderating construct in increasing the effectiveness of AI adoption.

Keywords: *Knowledge Management; Artificial Intelligence; Customer Relationship Management; Online Communities; Organisational Culture and Learning Behaviour.*

1. Introduction

The marketing landscape has undergone a significant transformation with the introduction of Artificial Intelligence (AI). The mechanism of Customer Relationship Management (CRM) systems has also been rapidly integrated into AI capabilities (Chatterjee et al., 2022). Such capabilities offer marketers a powerful set of tools for understanding, engaging, and retaining customers, thereby gaining a competitive advantage. However, the effective utilisation of AI-powered CRM is only possible when marketers have substantial knowledge of this evolving technology (Marvi et al., 2024). In this view, the current study explores the drivers of Knowledge Management (KM) in AI-powered CRM. The motivation that delves into the idea for the study states that there is limited research on how marketers acquire and adapt knowledge in AI-CRM environments. With the rapid advancement of AI, understanding knowledge-seeking and sharing behaviour is essential for optimising AI-CRM adoption (Hu et al., 2025). Contemporary KM practices in AI-CRM systems consist of scalable technologies that focus on detailing cognitive-based data and various analytical approaches (Harlow, 2018). In this context, knowledge modelling techniques in AI-CRM are based on two approaches: theoretical and practical (Chatterjee, Ghosh, & Chaudhuri, 2020; Devedzic, 2001). The results of these studies highlight the importance of intelligent systems and ontologies. However, it is difficult to identify scalable parameters for KM (Devedzic, 2001). This study aims to explain the process and technology implementation of AI-enabled platforms to facilitate the acquisition of new knowledge (Zhang et al., 2025) for the distribution and maintenance of knowledge creation, codification, and transfer in organisations (Maras et al., 2022). The current progress in generative AI has significantly revolutionised the fields of customer relationship management systems through conversational agents (Kumar & Shankar, 2025), predictive personalisation, and ROI (return on investment)-based automation (Moro-Visconti, 2024). These developments also require re-evaluation of the impact of KM drivers on the effectiveness of AI-enabled CRM in the post era of 'ChatGPT'.

The CRM system adopted by firms facilitates gaining knowledge about customers and reporting knowledge adaptability to the organisation (Allur et al., 2025). Thus, knowledge provides a substantial basis for effective work design in AI-integrated CRM organisations. However, organisations should also consider return on investment, as funds or investments are required to set up an AI-CRM system. In contrast, marketer's knowledge of AI-CRM has been explored less in the current context. Hence, this study examines the extent to which KM contributes to the establishment of effective AI-CRM systems. Many individuals and marketers benefit from advanced technology. This study outlines concepts related to knowledge adaptability in AI-integrated CRM. Individual improvised behaviour enhances the adaptability of KM in AI-based systems and can motivate others to participate (Wiig, 2012). This study aims to explore two aspects: the first is related to the target and identifies the factors that impact the knowledge of an individual (Kumar & Shankar, 2025), and the second is to examine the impact of KM on organisational marketing practices (Marvi et al., 2024). This understanding is important, particularly in terms of the adaptability of KM to AI-CRM users. Thus, KM adoption among marketers provides benefits in the form of learner's benefits and helps in recognising online community practices. Furthermore, an examination of trend analysis for online communities provides marketers with insights into how to locate the target paradigm for future trends in the marketplace.

1.1. Present status of AI-CRM

The integration of AI into CRM systems has driven the rapid transformation of marketing and customer management. Currently, AI-CRM platforms process large quantities of structured and unstructured data using advanced analytical capabilities. These platforms enable the extraction of new patterns, consumer preferences, and market trends from sources beyond conventional systems (Ledro et al., 2023). Recent research indicates that the implementation of AI-CRM systems has expanded across organisations. The supporting infrastructure for KM and continuous learning practices within companies remains underdeveloped supporting infrastructure for KM and continuous learning practices within companies remains underdeveloped (Singh et al., 2025). This section reviews the current understanding of AI-CRM, identifies existing knowledge gaps, and emphasises the growing importance of continuous learning by marketers (Chatterjee, Nguyen, et al., 2020; Leuba & Piricz, 2025). An overall command of AI-integrated tools and techniques enables marketers to conduct comprehensive analytical reviews, categorise customers, personalise campaigns, and predict consumer needs (Allil, 2024) in accordance with contemporary marketing strategies. Consequently, cultivating knowledge-seeking behaviour not only equips individuals for AI-CRM adoption (Aman & Yusof, 2022) but also opens opportunities for organisations to promote a fearless, innovation-driven work culture. Despite the increasing relevance of AI-CRM, contemporary literature remains limited in its exploration of the organisational knowledge context specific to AI-enabled CRM. As Forsgren et al. (2018) observed, knowledge exchange is often shaped by an individual's perception of and willingness to share and seek information (Chan et al., 2023; Forsgren & Byström, 2018). Thus, the present state of research on AI-CRM in marketing reveals significant opportunities for further exploration, particularly in addressing how organisational knowledge systems can support marketers in adapting to this rapidly advancing environment.

1.2. Knowledge management process for marketing domain

Marketing practices play a vital role in shaping individual knowledge and sharing behaviour in an organisation, and they seem more important, particularly when practices facilitate knowledge acquisition about AI-CRM (Simba-Herrera et al., 2025). Targeted training programs, readily available knowledge, and supportive AI content creation are potential practices (Chen, 2024). The targeted training programs were designed to provide hands-on practice to employees. Social training consists of training group members through several processes. Training organisers monitor specific parameters, such as health, performance, skill development, and training time (Guan, 2021). An application-based AI system automatically provides targeted customer feedback to marketers (Haleem et al., 2022). These feedback stories were presented as large chunks of data in virtual and physical demographic details (Ozay et al., 2025). Such data are beneficial to marketers for executing both supervised and unsupervised machine learning to support active decision-making (Campbell et al., 2020).

2. Study Objectives

Hence, the present study consists of the following objectives-

1) To examine the influence of organisational culture and the learning behaviour of marketers on AI-CRM.
2) To examine the importance of marketing functions that incentivise continuous learning about AI-CRM and knowledge-sharing in marketing practices.
3) To propose a conceptual framework for KM in AI-powered CRM for competitive advantage.

The current study includes section 1, explaining the problem, the introduction of the study, and the research gap. Section 2 consists of a literature review and hypothesis development, along with a theoretical foundation of the framework. Section 3 describes the research methodology used to obtain the results. Section 4 includes the results, followed by a discussion, implications, and limitations of the study.

3. Literature Review and Hypotheses Development

The literature highlights knowledge-based systems in AI-powered CRM and explains the important activities related to distinct levels that indicate the role of cognitive psychology in mental activities while designing the AI-CRM process (Ozay et al., 2024; Visser, 1992). KM also allows individuals to understand how psychological connectivity is required to develop design-based support systems (Sheth et al., 2024; Smithers et al., 1992). In this regard, technology enhancement has shifted from manual operations to automated CRM systems within the last two decades (Ozay et al., 2024). Hence, the integration of AI into CRM systems builds automative functions that make the processes faster, smoother, and prompt commands for the functioning of Chatbot (a B2B model to increase personalised customer experiences) (De Keyser et al., 2025; Isabella et al., 2025). The literature presented in this study reveals the importance of AI integration, which has resulted in the emergence of AI functionalities in the marketing domain and its future aspects for B2C (business-to-consumer) and B2B (business-to-business) marketing (De Keyser et al., 2025; Roy et al., 2025). The literature review in the hypothesis development section used essential analysis to establish solid theoretical connections between the assumptions (Kim & Lee, 2025). The current study has created research assumptions through an extensive survey of knowledge management, organisational learning, and technology adoption research philosophies (Shi et al., 2025). According to social cognitive theory, environmental elements, such as organisational culture, influence human behaviour, as explained in the literature (Nie et al., 2025). According to the Technology Acceptance Model (Davis, 1989), learning mechanisms determine user perceptions of the usefulness and ease of use with new technological systems (Sakib et al., 2025).

3.1. Relationship between organisational culture and marketing practices in AI-CRM

This literature review examines how organisational practices and culture affect marketers seeking knowledge about AI-CRM functionalities (Hughes et al., 2026). From this perspective, organisational culture encourages the promotion of a growth mindset for continuous learning with the aim of making working individuals more comfortable exploring new functionalities within the AI-CRM system (Leonardi & Neeley, 2017). Hence, collaborative learning is facilitated through knowledge-sharing sessions in the working environment (Aslan et al., 2025; Heredia & Viggiani, 2025). The AI-CRM-based tool and applications can balance the 'knowledge growth' and enable estimates of how online communities work to obtain 'perceived social benefits' (Chia-An Tsai & Kang, 2019). Thus, it motivates marketers to learn from each other's experiences, reduces fear, and fosters a sense of shared responsibility (Gaczek et al., 2025). Higher-level management and co-workers enable supervisors in a firm to manage the working environment and encourage marketers to explore AI functionalities to promote a learning culture in a firm. In this way, the following hypothesis is designed:
H1: Organisational culture has a significant effect on marketing practices in an AI-CRM system.

3.2. Relationship between organisational learning and AI-CRM

Organisations implement specific learning mechanisms to encourage knowledge-based systems for AI-CRM (Han et al., 2025). These systems use advanced technology in general, and for the marketing domain in particular. In this regard, targeted training programs should be formulated to build individual knowledge and skills to effectively utilise technology (Redding, 2021). This training mechanism encompasses the structural processes of training programs, feedback loops, experimentation, and reflective practice. Such practices facilitate continuous knowledge acquisition and behavioural adaptation (Crossan et al., 1999). In the context of AI-CRM, marketers need to interpret complex data analytics, automate customer interactions, and personalise campaigns (Truong & Toan, 2025). With these capabilities, AI-CRM is able to build capacity among marketers to learn and adapt to changing strategic necessities. The first step involves hands-on practice, allowing individuals to solve real-life problems similar to those in organisational marketing functions (Dabaieh et al., 2017; Rosário & Dias, 2024). Hence, several firms around the world already use guides, supervisors, tutorials, and solving technologies of knowledge-based systems for AI-CRM (Wamba-Taguimdje et al., 2020). Moreover, this organisational learning facilitates marketing professionals to acknowledge the value of new information (Mena & Chabowski, 2015), assimilate it, and apply it effectively within the context of AI-CRM (Zahra & George, 2002). This new adaptability enables businesses to sustain in times of crises (Chaudhuri et al., 2022). In this way, the following hypothesis is expressed:
H2: Organisational learning mechanism has a significant effect on marketing practices in AI-CRM.

3.3. Moderating role of individual characteristic

Previous studies on 'individual characteristics' in marketing for technology awareness have highlighted the impact of individual characteristics on the implementation of AI-CRM (Chatterjee, Ghosh, Chaudhuri, et al., 2020; Chatterjee, Rana, et al., 2021). Hence, we can say that 'individual capabilities' fall under the category of institutional factors (Chatterjee, Chaudhuri, et al., 2021). In any top management, leadership influences employees to share their knowledge, experience, and other information to build strong B2B relationships (Donate & Guadamillas, 2011; Sheng & Saide, 2024). A significant impact on individual 'service quality' and 'customer satisfaction' was observed for knowledge sharing in the industry (Wang et al., 2025). The moderating aspect of AI has been studied to examine the relationship between 'service quality' and 'customer satisfaction' (Nguyen & Malik, 2022). In this way, individual differences are usually considered a distrust factor (s) towards adopting AI systems (Molina & Sundar, 2022).
The moderating role of AI-integrated human-centric collaboration explains customer acceptance of AI services (Peng et al., 2022) and reveals a low 'perceived fit.' Individual characteristics also explain the gender effect with individual 'satisfaction' and AI 'knowledge' exploring self-regulated learning to estimate the relationship between satisfaction and gender (Xia et al., 2023). Organisational culture plays a critical role in shaping knowledge behaviour. However, its effectiveness often depends on the characteristics of individuals within the organisation. Research indicates that individual traits include openness to experience, cognitive flexibility, and self-motivation (Rienda-Gómez et al., 2025). These traits can significantly influence how employees perceive and respond to cultural signals (Bashir et al., 2025). In the context of KM, individuals with a strong orientation toward knowledge creation and sharing are more likely to leverage a supportive organisational culture to enhance their work practices (Ajmal et al., 2025; Bock et al., 2005).
Furthermore, the contingency theory of organisational behaviour suggests that personal attributes can strengthen or weaken the impact of organisational variables (Ginsberg & Venkatraman, 1985; Wei et al., 2025). Specifically, in AI-CRM environments, where rapid innovation and data-driven strategies are central, individuals who are innovative and proactive are better able to utilise cultural enablers to adopt AI-integrated marketing practices (Chaturvedi et al., 2025). Thus, individual characteristics may amplify the role of knowledge-centric culture in shaping effective marketing knowledge use. In this way, the following hypothesis is expressed:
H3: Individual characteristics have a moderating effect on the relationship between organisational culture KM, and marketing practices KM.

3.4. Moderating role of individual characteristics on the relationship between organisational learning and marketing practices

Learning mechanisms, such as training, mentorship, and continuous professional development, are widely acknowledged as critical components of KM (Chatti et al., 2012; Procacci et al., 2025). However, the ability to absorb, apply, and retain new knowledge often varies among individuals, depending on personal traits such as learning orientation, self-efficacy, and adaptability (Thomas & Gupta, 2021; Yuan et al., 2025). These traits determine how employees internalise organisational learning practices and apply them to their professional roles. A study conducted by Škerlavaj (2007), emphasised that individual learning styles and motivation significantly shape the translation of organisational learning into practical knowledge use (Dehkordi et al., 2025; Škerlavaj et al., 2007). Also, in AI-augmented marketing

contexts, tools and platforms evolve rapidly. Individuals with higher cognitive agility and intrinsic motivation are more likely to turn institutional learning initiatives into marketing innovations (Alaskar, 2025). Hence, individual characteristics are expected to moderate the relationship between learning KM and its practical application in marketing. Thus, the following hypothesis is proposed:
H4: Individual characteristics have a moderating effect on the relationship between Organisational Learning KM and marketing practices KM.

3.5. Relationship between individual characteristic and marketing practices

The direct role of individual characteristics in influencing knowledge behaviour is well-documented across the knowledge management literature (Salehzadeh et al., 2025). Traits such as knowledge self-efficacy, willingness to share, personal innovativeness, and absorptive capacity are consistently linked to higher levels of knowledge application (Juan, 2025; Wang et al., 2017). Particularly in AI-driven marketing ecosystems, individual initiative becomes essential, as the effective utilisation of CRM insights depends not only on technical systems but also on users' proactive behaviour (Mehta et al., 2025). According to another study, individuals who perceive themselves as competent and motivated are more likely to contribute to and draw from organisational knowledge systems (Karsikas et al., 2025). In AI-CRM environments, these individuals are often at the forefront of leveraging predictive analytics (Ozay et al., 2025), customer segmentation (Ozay et al., 2024), and intelligent automation to inform marketing decisions (Jabeen, 2025). Thus, individual-level KM competencies directly contribute to the depth and effectiveness of marketing knowledge (Rani & Devi, 2024). In this way, the following hypotheses are as follows:
H5: Individual characteristics have a direct effect on marketing practices KM.

4. Method and Materials

4.1. Conceptual framework

The present conceptual framework is an extension and adaptation of Knowledge Creation Theory (KCT) proposed by (Nonaka et al., 2014). Organisational KM reflects the socialisation dimension of the socialisation, externalisation, combination, and internalisation model (SECI) (Zhang et al., 2025). Learning KM aligns with the combination and internalisation process highlighted to establish the relationship for the marketing domain (Ceptureanu & Ceptureanu, 2025). The inclusion of individual characteristics as both direct and moderating factors explains the role of individuals in knowledge creation (Karsoo et al., 2025). The alignment of these constructs is applied strategically to improve employee insights and effectiveness. The study tries to establish a theoretical approach in order to determine the relationship between organisational culture (OC), learning, individual (LI) (Abdelrahman et al., 2025), individual characteristics KM (ICKM) (Ma et al., 2025), and marketing practices KM (MPKM) (Kumar, 2024). The theoretical model proposed for the current study is shown in Figure 1.

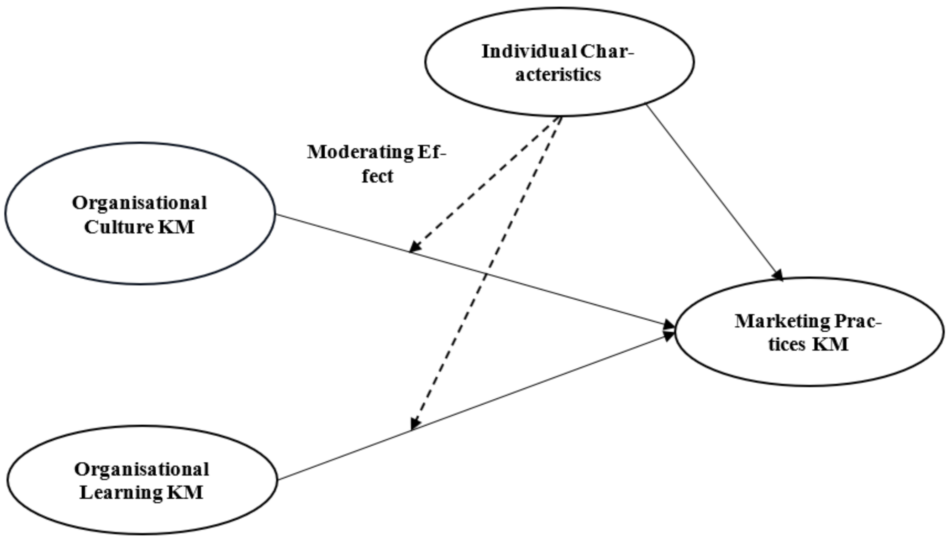

Fig. 1: Proposed Conceptual Framework.

Source: Author owns work.

4.2. Sample design process and statistical approach

Purposive sampling was used in this study, and PLS PLS-SEM approach was applied to explore the factors influencing a marketer's motivation to learn new technologies (Soliman et al., 2025). The study includes various segments of knowledge-seeking behaviour, emphasising the need for necessary skills and expertise to drive an AI-powered marketing environment for marketers (Paschen et al., 2019). The target population for the study was identified as marketers related to IT, retail, healthcare, education, and the digital sector at all distinct levels, from junior, and middle to upper level. The criteria for selecting these marketers were based on (McKensy 2019 and 2022 reports), as these sectors are highly utilising and adapting AI usage for their marketing purposes in the future (Menzies et al., 2024). The respondents were identified from the smart cities of Punjab, Delhi NCR, and North-West UP. The data collection was executed through an offline questionnaire filled out by the respondents. The study surveyed a total of 320 marketers, out of which 302 questionnaires were properly filled (response rate was 94 per cent). The demographic distribution included 302 marketers who participated in the empirical analysis. The data were collected from August 2024 to March 2025. The sample proportion distribution based on industry is shown in Table 1.

Table 1: Sample Distribution

Industry type	No. of respondents	Response percentage
B2B (Business to Business)	120	39.7
B2C (Business to Consumer)	80	26.5
E-commerce	35	11.6
Non-profit	20	6.6
Others	47	15.6
Total	302	100

Source(s): Author's own work.

4.3. Measuring instrument

The study used a structured questionnaire with a 5-point Likert scale. According to the study of (Conchado et al., 2015), the knowledge management scale is used to measure interpersonal, knowledge management, and organisational development, which enables the understanding of why there is a need to design informal and formal training for an individual by the organisation. The construct organisation culture KM was adapted from the study of (Chia-An Tsai & Kang, 2019; Leonardi & Neeley, 2017), and leaning KM was adapted from (Hanaysha & Al-Shaikh, 2022; Jalkala & Salminen, 2010; Wamba-Taguimdje et al., 2020). The moderating aspect of individual characteristics was adapted from the study of (Compeau & Higgins, 1995). Finally, the independent variable marketing KM was adapted from (Ipe, 2003). All of these constructs were reflective constructs, showing that each construct causes the observed variable. The descriptive analysis was carried out by using SPSS-24, and structural relations were examined using PLS-SEM.

5. Results

The results presented here are empirical findings that have been derived from PLS-SEM estimations. These results also include measurement model diagnostics, evaluation of structural paths, and model fit measurements.

5.1. Demographic profile

The demographic profiles of the samples are presented in Table 2. Out of which, 302 respondents included 162 males and 140 females. This indicates a fair balance of the gender distribution in the sample. The majority of participants belonged to the age group of 26-35 years, followed by the age bracket of below 25 years (88) and 36-45 years (58), and a very small proportion of 32 respondents were found to be in the age group of 5 years and above.

Table 2: Demographic Profile

Demographics	Category	Frequency (n)	Percentage (%)
Gender	Male	162	53.60
	Female	140	46.40
Age	Below 25 years	88	29.10
	26–35 years	124	41.10
	36–45 years	58	19.20
	Above 45 years	32	10.60
Discipline	Marketing	112	37.10
	Business Administration	96	31.80
	Information Systems/IT	54	17.90
	Other (e.g., KM, Communication)	40	13.20
Experience	Less than 2 years	66	21.90
	2–5 years	112	37.10
	6–10 years	74	24.50
	More than 10 years	50	16.60

Source(s): Author's own work.

5.2. Assessment of multicollinearity and normality

The evaluation of normality and multicollinearity was examined to ensure the suitability for further data analysis before validation of the proposed theoretical model (Olaluwoye et al., 2025). Table 3 presents the kurtosis and skewness values of each construct along with the Variance Inflation Factor (VIF). The values of skewness and kurtosis should fall within the recommended range of -2 to +2 (Hair et al., 2019), confirming the assumption of univariate normality for the dataset. The value of skewness ranges from -0.575 to 0.690, while kurtosis values vary between -0.120 and 3.625, as shown in Table 3. Even though a few kurtosis values slightly exceeded the conventional threshold of ±2, it remain within the acceptable limits for SEM-based analysis (Iacobucci et al., 2025). While using Partial Least Squares (PLS-SEM), which is relatively robust to minor deviations from normality (Hair et al., 2019). Multicollinearity was assessed by examining the VIF value. All stated VIF values were observed below the accepted threshold of 5.0 (Hair et al., 2019). This indicates the absence of problematic multicollinearity among the indicators. The values of VIF ranged from 1.183 to 4.672, confirming that no significant redundancy existed within the outer measurement model. Therefore, it supports the adequacy of the data for further model estimation and testing of hypotheses using PLS-SEM.

Table 3: Measurement of Skewness and Kurtosis

Item indicator	Excess kurtosis	Skewness	VIF
IKM1	2.080	-0.028	2.152
IKM2	1.442	-0.004	2.776
IKM3	3.625	-0.074	3.156
LKM1	2.327	-0.374	1.466
LKM2	3.137	-0.481	4.672
LKM3	2.754	0.350	4.670
MKM1	2.192	-0.575	3.061

MKM2	0.918	0.142	1.183
MKM3	2.888	0.224	3.114
MKM4	2.787	-0.195	4.433
OCKM1	1.811	0.690	2.279
OCKM2	1.826	0.121	3.872
OCKM3	-0.120	-0.303	4.110
OCKM4	0.531	0.496	2.118

Source(s): Author's own work.

Table 4: Outer Loading Indicator Scores

Indicators	IKM	LKM	MKM	OCKM
IKM1←KM	0.876			
IKM2←KM	0.910			
IKM3←KM	0.920			
LKM1←LMK		0.802		
LKM2←LMK		0.918		
LKM3←LMK		0.917		
MKM1←MKM			0.808	
MKM2←MKM			0.713	
MKM3←MKM			0.851	
MKM4←MKM			0.887	
OCKM1←OCKM				0.874
OCKM2←OCKM				0.889
OCKM3←OCKM				0.902
OCKM4←OCKM				0.848

Source(s): Author's own work.

4.3. Assessment of measurement model

The outer loading values indicate that the scores were assessed to examine the reflective indicators in the measurement model, as shown in Table 4. The highest value of the loading score appeared for IKM3 (0.920), whereas the lowest score was observed for MKM2 (0.713). The lowest value of MKM2 was observed among the four indicator variables. All the values of the loading score were observed to be more than 0.7, which is acceptable for reflective indicator loading scores, as explained by (Hair et al., 2010).

Table 5: Measures of Reliability and Validity

Constructs	Cα	CR (rho_a)	CR (rho_c)	AVE
IKM	0.886	0.889	0.929	0.814
LKM	0.720	0.768	0.839	0.638
MKM	0.777	0.801	0.856	0.600
OCKM	0.931	0.933	0.951	0.830

Source(s): Author's own work.

As Cronbach's α (Cα) values for all constructs were in the acceptable range (0.70-0.95) (Adamson & Prion, 2013). Hence, internal consistency for all constructs was confirmed for the outer model. A composite reliability (CR) was also examined, and its values were observed above the minimum threshold of 0.70 (Table 5). The construct OCKM was observed to have high reliability and strong internal consistency, as indicated by (Hair et al., 2019). The indicators are reliable and valid, which states that the measures capture all the related constructs of KM. However, the AVE values were found above the recommended threshold (0.5) for all constructs (Cheung et al., 2024). Hence, no issues pertained to convergent validity, as shown in Table 5.

The criteria for Fornell and Larcker are based on AVE square roots, which approximate the discriminant validity of a model as shown in Table 6 (Cheung et al., 2024). The values shown diagonally in Table 6 are the estimated square roots of the average variance. The estimated square root of the AVE for each construct was greater than the inter-construct correlations, which established discriminant validity. The study provides Table 7, which shows that the heterotrait-monotrait (HTMT) ratio explains the correlations among the explained constructs. All constructs act as distinct because HTMT explains the ratio of the correlation observed within the threshold value of 0.85.

Table 6: Fornell-Larcker Criterion

Constructs	IKM	LKM	MKM	OCKM
IKM	0.902			
LKM	0.409	0.799		
MKM	0.466	0.569	0.774	
OCKM	0.642	0.581	0.510	0.911

Source(s): Author's own work.

Table 7: Heterotrait- Monotrait (HTMT) Ratio

Constructs	IKM	LKM	MKM	OCKM
IKM				
LKM	0.501			
MKM	0.549	0.727		
OCKM	0.703	0.694	0.582	
IKM x LKM	0.143	0.134	0.051	0.057
IKM x OCKM	0.154	0.085	0.093	0.060

Source(s): Author's own work.

4.3. Assessment of structural model

4.3.1. Testing of hypotheses

This study attempts to establish a structural model to define the relationship between the defined constructs for the proposed research model (Bajjou & Chafi, 2023). The importance of direct effects is explained through different hypotheses, which were assessed by the analysis of the path coefficient (β), t-statistics, and p-values (Aggarwal & Kapoor, 2020). The analysis of the data was done with the help of Smart PLS software. Bootstrapping was performed through 5,000 subsamples to test the hypothesis to ensure that there is stability and no variation in the outcome (Heng & Lange, 2024). Table 8 provides an explanation of the results related to the hypothesis that tests each construct. The path coefficient values signify the effectiveness of the relationship between the defined constructs through PLS-SEM. The first relationship is significant, as the values ($t=3.782$, $p<0.05$) show a positive correlation between individual characteristics and marketing practices for knowledge sharing. This relation has been supported by earlier study that explains that leadership qualities are empowered through knowledge sharing as individual attributes bolster it (Khatoon et al., 2022; Truong & Toan, 2025). The next values ($t=7.492$, $p<0.05$) show a positive correlation between learning and marketing practices for knowledge sharing. However, the values ($t=1.589$, $p=0.112$) signify that organisational culture has no significant impact on marketing practices for knowledge-sharing. The earlier literature states that organisational learning has an influence on knowledge sharing and innovative marketing practices (Patwary et al., 2022). While analysing the moderating role of individual characteristics, it implies that only one aspect is accepted. The values ($t=1.998$, $p<0.05$) explain that individual characteristics have a significant moderating impact on the relationship between organisational culture and marketing practices for knowledge-sharing (Budur et al., 2023). Other aspects of relation values ($t=1.378$, $p=0.168$) signify that the moderating role of individual characteristics has no significant impact on the relationship between learning and marketing practices for knowledge-sharing. This moderating relation of individual characteristics explains that quality of work is important for general satisfaction, and knowledge sharing is driving innovation among academicians (Budur et al., 2023). The value explanation is based on (Hair et al., 2016), which highlights what criteria should be accepted for hypothesis acceptance.

Table 8: Assessment of Hypotheses and the Moderation Effect

Relation based on PLS	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values	Hypothesised Relation
IKM->MKM	0.230	0.232	0.061	3.782	0.000	Supported
LKM-> MKM	0.416	0.418	0.056	7.492	0.000	Supported
OCKM-> MKM	0.122	0.123	0.076	1.589	0.112	Not Supported
IKM x LKM -> MKM	-0.090	-0.085	0.065	1.378	0.168	Not Supported
IKM x OCKM -> MKM	0.157	0.152	0.078	1.998	0.046	Supported

Source(s): Author's own work.

Table 9 shows results regarding model accuracy by explaining the R-square and adjusted R-square values of marketing practices for knowledge-sharing (Marketing KM). The R-square represents the total variance explained by all independent variables, whereas the adjusted R-square estimate suggests that 73 % of the variance can be attributed to independent variables (Hair et al., 2019) after accounting for model complexity. The model has good explanatory power of marketing practices for Knowledge-Sharing.

Table 9: Adjusted R-Squared

Construct	R-square adjusted
MKM	0.725

Source(s): Author's own work.

The SRMR values for both the saturated and estimated models are (0.068). Ideally, SRMR should be less than (0.08) (Hair et al., 2019). This suggests a reasonable fit between the model and data. The d_ULS values for the models are (0.484 and 0.483). This clearly established the benchmark for d_ULS, but lower values generally indicate a better fit (Hair et al., 2019). The smaller difference between the saturated and estimated model values suggests that the model had an acceptable fit. Similar to d_ULS, the d_G values for both models were identical (0.200). Therefore, there is no benchmark. However, chi-square is not directly used for evaluating fit in PLS-SEM, as it is sensitive to the sample size. Some software packages may not report this. The difference between the chi-square values here is minimal, which aligns with the other fit indices, suggesting an acceptable fit. The NFI value was above the 0.80 criterion, indicating a good fit (Table 10).

Table 10: Model Fit Criteria

Measures	Saturated model	Estimated model
SRMR	0.068	0.068
d_ULS	0.484	0.483
d_G	0.200	0.200
Chi-square	368.761	367.557
NFI	0.863	0.864

Source(s): Author's own work.

4.3.2. Moderation effect

This study found a moderating correlation between individual characteristics and KM learning. This study also suggests that individuals with strong marketing-related characteristics are more likely to participate in learning activities (Budur et al., 2023). These learning activities are related to marketing knowledge, and companies with strong marketing knowledge management practices are more likely to have relevant employees (Table 10).

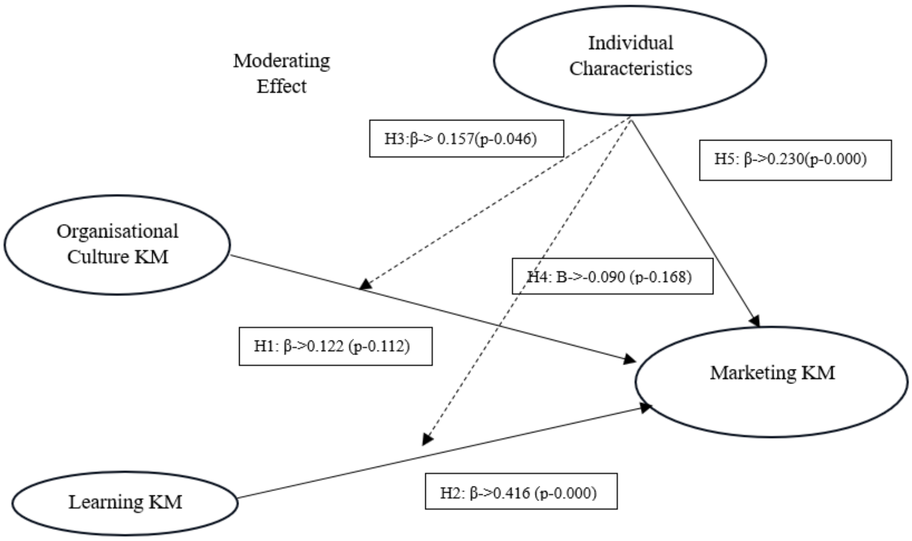

Fig. 2: PLS-SEM Diagram of the Model.

Source(s): Author's own work.

6. Discussion

The aim of this study was to learn about the role of such critical factors as knowledge management (KM) drivers within the context of artificial intelligence (AI)-powered systems based on customer relationship management (CRM) technologies (Chatterjee, Ghosh, & Chaudhuri, 2020). The present study examines the factors that influence organisational and individual factors (Alzahrani, 2025). These factors have an influence on the successful integration and adoption of such advanced technologies for marketing practices, with the aim of departure (Frambach & Schillewaert, 2002). The quantitative findings provide the insight that there is a significant impact of the organisational culture, learning mechanism (Veeravalli et al., 2019), and individual characteristics in shaping marketers' knowledge-seeking behaviour. This study aimed to determine the role of individual characteristics, learning mechanisms, and organisational culture as three significant elements in the construct of knowledge management (KM). It also explains how KM has an impact on marketing knowledge applications in systems such as AI-CRM (Marvi et al., 2024). In terms of research, during the explanation of the conducted research, not only were a number of theory-based relationships confirmed. However, it was also able to provide some surprisingly researched findings and expand the currently known foundations of KM dynamics in AI-driven marketing setups. Furthermore, these findings bring attention to the concerns surrounding AI-driven environments. Mainly, the difficulties are related to data privacy, algorithmic bias, and potential job displacements. These changes occur due to automation that becomes more embedded in CRM workflow.

First, the analysis confirmed that individual characteristics are significantly related to KM and how they affect marketing KM. This supports the premise that marketers who express certain characteristics, including adaptability, intrinsic motivation, and self-directed learning, have a greater chance of engaging meaningfully in AI-enabled systems. In relation to emotion, prior research has stressed the value of individual-level issues of knowledge behaviours (Becerra-Fernandez & Sabherwal, 2010). In the AI-CRM context, such characteristics could facilitate the implementation of intelligent tools towards data-driven decision-making and campaign personalisation as key actors involved in the execution of successful KM (Intezari & Gressel, 2017). Further, these development initiatives involve economic trade-offs like increased cost of AI technologies, training, and integration processes against uncertain returns on investment (ROI), particularly for resources related to constrained environments.

Second, it was found that learning KM had the strongest positive effect on marketing KM, which affirms the critical role of structured organisational culture learning. This finding is consistent with those outlined by (Chatti et al., 2014), who emphasised that it is necessary to learn continuously and in a systematised way to encourage knowledge application in technology-enhanced realities. The study also suggests that AI-CRM tools need constant upskilling as well as understanding the context. Organisations that invest in frameworks for training and knowledge sharing among their teams help develop their marketing teams to obtain the actual strategic value from these tools.

The study found that organisational culture KM did not have a significant direct effect on marketing KM (Lee & Wen-Jung, 2005). This challenges some conventional assumptions because, in prior models, the concepts of culture and knowledge-sharing were frequently identified as one of the main enablers of knowledge sharing. A possible reason is the growing complexity of AI systems, in which informal elements of the company culture may not adequately support the learning and exchange of knowledge unless embedded in actionable learning mechanisms and the digital infrastructure. Thus, it follows that culture needs to be operationalised in a framework of formal structures, not to assume it as an implicit driver (Nguyen & Malik, 2022).

Further insights were derived from moderation analyses. While individual characteristics were not found to significantly moderate the relationship between learning KM and marketing KM, they were found to make an important difference in the impact of organisational culture on marketing KM. This nuanced finding implies that marketers with sound KM orientation could better transform cultural support into tangible results in terms of knowledge. This makes sense within the nucleus of the contingency approach to organisational behaviour (Ginsberg & Venkatraman, 1985), in which the capacity of an individual comes as a key mediator in producing performance as an outcome of cultural or contextual inputs. In contrast to the expected positive interaction, no significant interaction effect was found between individual characteristics and KM learning (Lin et al., 2015). It seems that a structured learning context presents an experience that may not differ significantly depending on individual differences. When these AI-CRM learning systems are designed with inclusivity and simplicity, they make learning outcomes more homogenous across the workforce by having the potential to minimise the influence of personal traits. In summary, this study provides an interconnected understanding of the ways in which knowledge enablers work in an AI-CRM context. It provides a reaffirmation of the importance of individual initiative and structured learning, while also a warning against relying on organisational culture as the only way to learn. These findings add to the growing discourse on how firms can create AI-capable knowledge systems that are human-centred and technologically robust.

7. Theoretical Contribution of The Study

This study presents a critical breakthrough in theoretical conversation. This theoretical direction connects knowledge management (KM) with AI-enabled customer relationship management (AI-CRM) in the marketing field. The study tries to bridge a multidimensional approach to streamline the various earlier literature gaps highlighted that this assessment needs to be studied (Ozay et al., 2024). The analysis is guided by the formulated theoretical constructs defining Knowledge Creation Theory (Nonaka & Toyama, 2003), Social Cognitive Theory (Wood & Bandura, 1989), and the Technology Acceptance Model (Davis, 1989). In order to facilitate analytical research that would combine the interdisciplinary literature in the effort of providing insight into the means through which marketers acquire, transform, and utilise the knowledge in the state-of-the-art CRM systems. The study offers a distilled understanding of how organisational, individual, and technological determinants work together to define knowledge-seeking behaviour within AI-integrated marketing environments. The fact that the authors have elaborated and empirically tested a multidimensional model according to which the relations between organisational culture, learning mechanisms, and individual and marketing KM practices are characterised is also an outstanding theoretical contribution. However, unlike previous models of thinking, which generally isolated such variables, this study will contribute to a holistic approach to the issue, which states that these variables are profoundly intertwined with each other and support one another. The moderating nature of personal traits on the interface between organisational and learning settings and on the interface between settings and KM implementation presents an emerging depth to the theory on KM actions in AI-driven settings. This shows that individual traits, such as confidence, technological appeal, and collaborative willingness, are crucial for enhancing or limiting KM efficiency. Another theoretical contribution is the modification of the SECI model (Nonaka et al., 2000) to the AI-CRM marketing area. The study redefines such components as socialisation, externalisation, combination, and internalisation, and traces them to AI-CRM practices. As an example, mechanisms of learning in organisations provide a combination of internalisation by transforming explicit knowledge into usable intelligence via focused AI-CRM training. Simultaneously, collaborative platforms and feedback mechanisms facilitate both the processes of socialisation and externalisation, for example, in the form of collectively shared user experiences as well as data information. This situational adjustment supports the idea of flexibility in the SECI model and expands its use to digital marketing ecosystems, which are AI-driven, making this study contribute to the body of literature in the fields of KM in AI-driven contexts.

8. Practical Implications

This study has several practical and actionable implications that can be used by marketing practitioners, organisational leaders, and policymakers. These people aim to enhance the effectiveness of AI-powered CRM systems through knowledge management (KM) initiatives. The beginning starts with a research illustration of a strong association between learning behaviours and the knowledge-seeking inclination of employees. Their ability to utilise AI-CRM platforms substantiates the necessity of the concept of an ongoing culture of learning. This also means that marketers need an understanding of technology and flexibility to evolve along with new versions of AI-powered tools. This study provides suggestions for incorporating these capacities through systematic experiential training programs, knowledge-exchange platforms, and systematic mentorship schemes. This action is required to promote the sharing of pertinent expertise among marketing units. Second, the empirical data indicate that organisational culture cannot exist in isolation but requires integration with proactive individual characteristics and resilient learning processes. To obtain this synergy, organisations are encouraged to develop a psychologically safe space where experimentation will be possible, where the fear of AI technologies will be reduced, and where more knowledge-sharing habits should be encouraged. In turn, leadership has to manifest its curiosity and openness to these developing tools to allow harmonious attitudes towards employees. At the same time, these leaders also need to consider broader risks related to AI adoption, data privacy, and algorithmic bias in customer profiling. There is a possibility that automation may displace or downgrade certain marketing roles.

Finally, the findings underscore the need to align KM with the strategic objectives of the marketing procedure. However, when other aspects, such as AI feedback mechanisms, customer input, and community-created learning systems, are integrated into regular marketing operations, more personalised and targeted projects that would strengthen customer satisfaction and retention could be developed. This study presents a prescriptive course for organisations that are in an emergent environment like India, where the use of AI-CRM is still immature. Investments in human and technological infrastructure should make firms realise that the competencies of the workforce should be both technical and cognitive to allow them to exploit competitive advantages in AI-CRM. This means that KM should not be framed as an accessory supporting role but as the basis behind the digital marketing prowess in the era of AI.

9. Limitations of Study

Despite these informative views, the current research provides insights into the determinants of knowledge management (KM) in AI-driven CRM systems. The number of limitations should be addressed by scholars to have a balanced evaluation of the findings and contribute to future studies. First, it was cross-sectional in design, and only data were collected in one instance. The study, therefore, was not able to document the time-contingent nature of knowledge-sharing behaviour, learning, or technological adaptation. It is thus advisable that longitudinal designs be used to study the changing nature of KM practices and their effects on marketing performance in the context of AI-CRM (Chaudhuri et al., 2022). Second, the sample included marketers gathered within a limited range of industries in North India, that is, information technology, retail, healthcare, and education. Although these sectors are aggressively exploring the potential of AI use, the results may not apply to other sectors or regions with varying levels of technological maturity, organisational structures, or a culture that has an inclusive or friendly mindset toward sharing knowledge. It is expected that by extending future research to more general and diverse populations, the external validity can be improved. Third, the study was based on self-reporting. Even though anonymity was established to alleviate the social desirability and overestimation biases, there is a possibility that the respondents still provided the resulting idealised reports on their KM experiences or their trust in AI-CRM tools. Mixed-methods approaches, such as qualitative interviews and observational measures, would also be able to give more detailed, less general answers to actual versus perceived behaviour. Fourth, although variables such as organisational culture, learning, and individual characteristics were covered, different factors that were yet to play a central role, such as technological infrastructure, leadership style, digital literacy, or psychological safety, were not investigated. Such variables can moderate or mediate KM practices in AI environments and are valuable in future research models (Venkatesh et al., 2003). Fifth, despite the fact that PLS-SEM was appropriate for the exploratory network of the study and a complex hierarchical structure, it is still a variance-based method. When a covariance-based SEM validated method is of priority, by playing up the credibility of a finding, this approach will be helpful in cases where inferential soundness is the main target. Being aware of these limitations will provide a basis to streamline future studies, increase methodological rigor, and develop a theoretical and practical manifestation of AI-integrated KM systems in the sphere of marketing. As there also a comprehensive understanding of both the opportunities and risk related to AI adoption. Such understanding ensures that the future KM and AI-CRM research remain relevant, ethical, and resilient to technological disruptions.

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