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Implementation Challenges of Affective Computing in Customer Relationship Management (CRM) Platforms: A Systematic and Bibliometric Review

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ABSTRACT

Advancing technologies of affective computing have been prompted by the swift development of Artificial Intelligence (AI) to identify, interpret, and react to customers' feelings using multimodal data in Customer Relationship Management (CRM) systems. In spite of the great potential that affective computing has for improving customer engagement and personalised services, there are technical, ethical and organisational challenges that needs are not thoroughly synthesized in the literature. Based on this, the aim of this study is to systematically investigate the issues associated with implementing affective computing in CRM systems and draw the 'concept' map of this research field from 2023 to 2026. The research was carried out by using 61 peer-reviewed publications collected from the Scopus database and carried out by Systematic Literature Review (SLR) and Bibliometric analysis. To identify publication trends, thematic clusters and knowledge structures, bibliometric techniques such as keyword co-occurrence analysis and bibliographic coupling were used. The findings reveal four major research themes: (1) multimodal emotion recognition and technical architectures, (2) CRM integration, customer engagement, and personalization, (3) ethical governance, privacy, and responsible artificial intelligence, and (4) emerging technologies, including Large Language Models (LLMs) and Generative AI. The review also reveals that four theories are dominate this research domain: Technology Acceptance Model (TAM), Privacy Calculus Theory (PCT), Explainable Artificial Intelligence (XAI) and Trust Theory. One of the conclusions was the continued duality of technical and ethics that needs to be addressed in order to make technology a bit more transparent, to protect the privacy user, to be fair, and build trust. This study adds value by offering the first comprehensive Biblio-Metric mapping of Affective Computing implementation challenges in CRM in from 2023 to 2026, and provides practical insights for researchers, CRM practitioners and decision makers in building emotion-aware CRM systems trustworthy, explainable, and privacy-preserving.

Keywords: Affective computing, Customer relationship management (CRM), Multimodal emotion recognition, Explainable AI, Bibliometric analysis.

INTRODUCTION

In the past decade we've witnessed a great convergence of affective computing and enterprise technology systems, one of the most commercially significant being Customer Relationship Management (CRM) platforms. The ability to recognize, interpret, simulate and reply to human emotions between 2023-2026, which is a broader concept known as affective computing, is now being put into practice by identifying people's emotions, interpreting the meaning of their facial expression, simulating human emotions, and reacting to them. Customer Relationship Management (CRM) systems are the backbone of a company's technological operations, interacting with customers, and these are now being enhanced by emotion-aware systems as a way to differentiate from the competition. A qualitative change in how organizations understand and react to their users when they call a service desk, chat with a chatbot, or read through an email, is the ability to pick up on cues of frustration when a customer calls a service desk, understand the cues of satisfaction when a customer chats with a chatbot, or discern whether they are bored or feeling frustrated when reading through an email. Pei et al. (2024) make an exhaustive review of the current state-of-the-art in affective computing, highlighting the swift development of emotion recognition in deep learning applied to various modalities. The authors demonstrate the measurable impact of embedding multimodal emotion analysis in CRM systems on measures of communication quality and customer satisfaction. In this vein, Kumar & Shankar (2025) further explore the organizational context and conclude that using Generative AI CRM systems with emotional intelligence is an important factor in achieving organizational agility in competitive markets.

Emotionally intelligent CRM is the promise of a CRM that can provide context and real-time personalisation throughout the entire customer engagement space. An affective CRM system could alert agents in a call center to when a customer's emotion is increasing, and take steps to de-escalate the situation before an unrepairable service failure occurs. Emotion-aware NLP can help regulate tone and content in chatbots and virtual assistants to align with the emotional state of the customer, ultimately providing more empathetic and effective customer service. Sentiment-based Segmentation can be used to determine the optimal time, tone, and messaging of the individual's email marketing, based on inferred emotion. In their article, Shaikh et al. (2024) illustrate the impact of AI on the CRM transformation being witnessed in the e-commerce sector, which is helping to revolutionize personalization efforts at a level and pace which human employees are not able to achieve without assistance. Leelavathi et al. (2024) provide a systematic review of the latest developments in the use of AI tools and techniques in CRM systems, and document the trend of the organizations towards using emotion-aware tools and techniques in their CRM systems. The study conducted by Gaidhani et al. (2025) shows that the inclusion of affective data in addition to transactional and behavioural data in predicting customer future purchase intent can significantly improve customer retention, increase the accuracy of the prediction of personalization, and increase the quality of managerial decisions. One of the recent technical breakthroughs that makes this vision possible is Guan et al.'s (2026) solution on making RAGE-Fusion, a framework for real-time multimodal emotion processing in interactive CRM interfaces, reliable in the context of noisy data and limited information, which are common in operational deployments.

However, the challenge of introducing affective computing in CRM settings is much more significant than just the technical performance indicators. According to Morales et al. (2026), the central challenge is a 'technical-ethical duality', that is, the need for the high-performance emotion recognition systems, which are also transparent, fair, privacy-preserving, and culturally sensitive. The technical challenge is enormous: In the case of multimodal data fusion, different modalities—such as audio, video and textual modalities—must be merged together in real time, and those modalities that are missing or corrupted must be dealt with gracefully. In this survey paper, Hazmoune and Bougamouza (2024) critically examine the current state of the art of transformer-based multimodal EW and the substantial gap between the accuracy achieved in the lab and the accuracy of real-world deployments, which is due to the natural occurring data in noisy operational environments. Huan et al. (2024) specifically tackle the missing modality problem, where for example a customer call may occur via text only without audio or video, which is a typical problem in real CRM deployments: they propose the UniMF framework for unified multimodal processing in the face of missing modalities. In this regard, Zhan et al. (2025) contribute specific and invariant feature learning strategies to tackle missing modalities in sentiment analysis. There's a lot of technical complexity involved in real-time multimodal processing at enterprise scale, however, because it requires more computing resources, infrastructure investments, and architectural innovation.

Ethics of affective computing in CRM is also complicated and it has become more relevant in the regulatory aspect in the last few years (2023-2026). The collection of emotional and biometric data (facial expressions, tone of voice and physiological data) from the customers, without them being clearly instructed on what is being collected, raises serious privacy concerns under the GDPR and CCPA regulatory regimes. One of the other key challenges is algorithmic bias – emotion recognition algorithms trained primarily on Western white, English speaking users, have systemic poor performance and/or discriminatory results for multilingual and multicultural customer bases. The data privacy and ethical concerns in AI-powered CRM are essential for meeting regulatory needs, a foundation of customer trust, and ultimately the success of affective CRM, as discussed by Kumar et al. (2025). Ortiz-Clavijo et al. (2023) focus on the more far-reaching social ramifications of emotion recognition technology, advocating for the establishment of strong governance mechanisms that will enable to strike a balance between the socio-economic advantages of using affective CRM and the customers' privacy rights and dignity interests. Goel and Gendron (2024) prove this statistically, and show that demographic bias in affective computing systems leads to different outcomes for population groups, encouraging the need for culturally sensitive model development and independent bias auditing.

However, the challenges of affective CRM at the operational level are unique, stemming from organizational behavior, change management, and human-AI collaboration dynamics. The integration of emotion-aware systems in customer service settings transforms the nature of customer service agents and introduces new issues related to surveillance, autonomy, and professional identity. Gaczek et al. (2023) in their pioneering research on B2B marketing contexts, examine one of the most significant hurdles to affective CRM adoption on the organizational level, namely managers' resistance to emotionally embracing CRM solutions supported by AI recommendations, which is driven by lack of transparency and lack of trust and perceived threat of losing professional control. Whatever the technical complexity, this discovery reveals a key element for CRM systems to overcome humans over time: the ability to explain why a system recommends a particular service is important, and the ability to explain that which is understandable and believable to humans is essential. The integration of both human and artificial intelligence (AI) in service design is still a greater challenge, and Rana et al (2024) argue that affective CRM should be thought of as a partnership between humans and AI, rather than a replacement. According to Verma et al. (2024), the attitudes and emotions of employees caused by the technical capabilities of AI-CRM mediated the relationship between the technologic anxiety and intention to implement it in the retail business.

The current knowledge base for affective CRM is not cohesive; no systematic cross-fertilisation has occurred among the fields of affective computing, CRM systems, explainable AI and privacy governance. Perez-Bertozzi and Palos-Sanchez (2026) trace the bibliometric development of eCRM, but do not systematically explore affective computing as a domain of capabilities; meanwhile, Chen et al. (2026) provide a technical synthesis of HCI, without considering CRM implementation contexts in detail. This study fills the gap by providing a structured bibliometric review of the challenges of implementation of affective computing in CRM from technical, ethical and emerging technology perspectives.

New technologies are changing the course of affective CRM. The remarkable progress of LLM and Generative AI has ushered in a new era of emotionally intelligent chatbots, significantly outperforming their predecessors, with Zhang et al. (2026) achieving nearly human levels of nuance detection in text-based interactions, and Yang et al. (2026) achieving better personalisation using emotion-aware recommendation logic. Another important area of governance concern in affective CRM is privacy, and federated learning provides a way to achieve this at scale.

There are three contributions to this study. First, it brings together disparate research streams and presents an integrated framework that charts the challenges of implementation in terms of technology, ethics, organization, and emerging technology. Second, it uses systematic literature review and bibliometric analysis (keyword co-occurrence and bibliographic coupling) to better describe the intellectual structure of the field than either approach alone. Third, it converts the cluster-level results into actionable advice for CRM practitioners, platform developers and regulators.

This study is guided by three research questions:

> *Q1: What are the primary implementation challenges of affective computing in CRM platforms, as revealed through systematic and bibliometric analysis of 2023–2026 literature?*
>
> *Q2: What is the intellectual structure of affective computing in CRM as mapped through keyword co-occurrence and bibliographic coupling analysis?*
>
> *Q3: What emerging technological trends and future research directions are shaping the next generation of emotionally intelligent CRM systems?*

The time window between 2023 and 2026 was crucial for this study, as it covered a period when the capabilities of AI were converging with the development of CRM platforms.The time window for this study (2023-2026) was chosen because it overlapped the time during which the capabilities of AI were converging with the development of CRM platforms. This will bring the value of being up-to-date and relevant, and of having depth in conducting a proper bibliometric analysis. The methodology is described in Section 2, descriptive statistics and results are given in Section 3 (including theoretical frames, keyword networks, bibliographic clusters and collaboration networks), findings by cluster in Section 4, theoretical and practical implications, future research directions and overall conclusions in Section 5.

METHODOLOGY

The methodological framework adopted in this work is Systematic Literature Review (SLR) which is in line with the best practices on conducting a Systematic Literature Review in the field of business and management (Donthu et al., 2021). The SLR approach is well understood and accepted as a systematic, transparent, replicable process to determine the status of scholarly knowledge within a specific field, which is especially appropriate when researching digital domains with growing body of knowledge and a need to support the development of theory (Tranfield et al., 2003; Snyder, 2019). To minimize selection bias, the evidence included in the SLR has been selected according to a specific criterion of inclusion and exclusion so that the evidence synthesized is not only the subjectivity of one researcher, but represents all available evidence.

The bibliometric analysis used for the enhancement of SLR includes bibliographic coupling and keyword co-occurrence analysis, which detect and highlight thematic clusters, intellectual foundations and research fronts, respectively. There are, however, instances where the analyses are better suited to bibliometry methods, such as the ones emerging from interdisciplinary research fields where there are several research traditions, and where interconnections and dynamics are not always clear and straightforward, like in the case of this example, affective computing, Explainable AI, CRM research, and privacy governance. The analysis of keyword co-occurrence generates sets of concepts that are often found in close association, thus showing the conceptual structure of the field. The bibliographic coupling analysis highlights relationships between papers based on their shared reference lists, and demonstrates intellectual kinship and common themes in theory even if there is no direct citation between them. All of these methods provide a more complete, multidimensional description of the field than citation analysis provides.

Given the proven reliability, extensive interdisciplinary coverage, and the academic acceptance of Scopus as a bibliographical database for the field of AI and technology management, it was selected as the primary bibliographic database. The engineering, business and psychology, computer science and social sciences literature of affective CRM are well represented in Scopus, where more than 12,850 peer-reviewed journals are covered. The metadata it has is well organized and can be analyzed through the use of strong bibliometric tools, sometimes not available in other databases such as Web of Science or Google Scholar. There are also previous systematic reviews in related areas that have consistently singled out Scopus as the best database for technology management and AI governance studies.

The search string was designed to be broad but still focus on the topic area while trying to balance terminological variation (due to multiple synonyms in the various disciplinary communities) with precision (so that retrieved documents actually will be relevant to the topic of affective CRM). The following Boolean search string was used:

> *("affective computing" OR "emotion recognition" OR "emotion AI" OR "sentiment analysis" OR "multimodal emotion" OR "emotional intelligence") AND ("customer relationship management" OR "CRM" OR "customer experience" OR "customer engagement" OR "customer service").*

This string is a combination of the affective computing area and the CRM/customer management area, giving a coverage of both the technical aspects and the applied aspects of research in this field.

The PRISMA 2020 framework was followed to structure the identification, screening and inclusion of documents. Total of 89 records were returned from the first search in Scopus.

Overall, 12 duplicate records were excluded, 8 non-peer-reviewed materials (conference abstracts, editorials and book reviews) were excluded and 8 non-English language publications were excluded resulting in a final corpus of 61 peer-reviewed articles that were analysed. Eligibility for documents was as follows: (a) documents were published from January 2023 to early 2026 when the search was performed; (b) documents dealt with the combined themes of affective computing and emotion AI/sentiment analysis in the context of CRM, customer engagement or customer service; (c) documents were only in English language; and (d) documents were published in peer-reviewed journals, conference proceedings, or edited academic volumes indexed in Scopus. Documents that did not contain affective computing in a CRM context (e.g., studies focused on healthcare only), documents that were not published in the last 20 years (from 2023 to the present) and documents that were not provided with complete metadata unless they were the background documents for affective computing were excluded. The overall process of study selection is summarized in Figure 1.

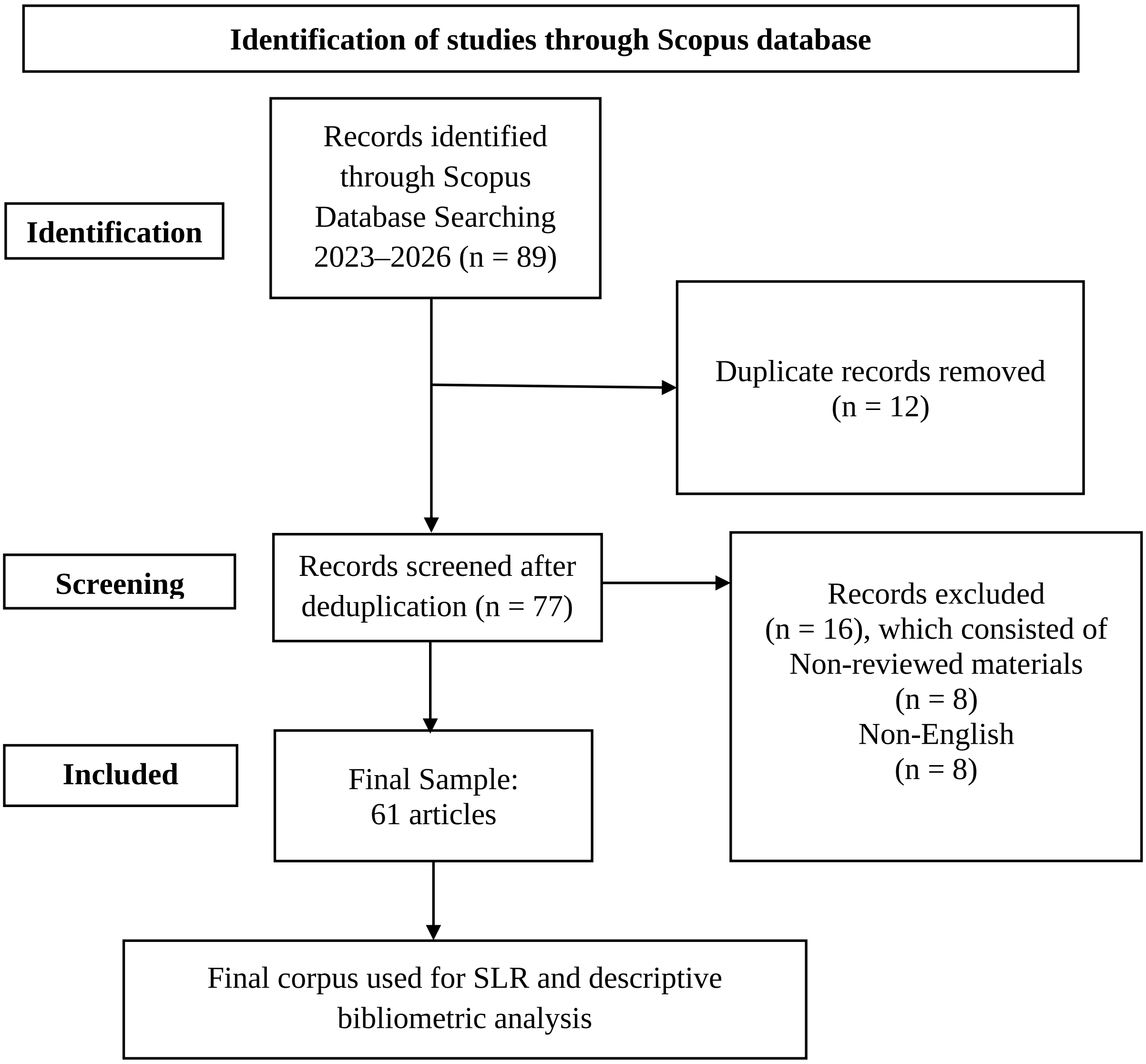

Figure 1. Design of Study Selection Process

For network visualization and cluster identification, co-occurrence matrix analysis with Python software packages performed and bibliometric analysis carried out in the software package VOSviewer (van Eck and Waltman, 2010). A threshold of 3 was used to define the occurrence of the keywords, so that 34 high importance keywords are found in the full corpus. Bibliographic coupling was calculated using the minimum value of three common references, resulting in 28 documents in clusters from 38 documents. They are comparable with the thresholds used in the normal practice of bibliometrics for the size of the corpora.

Table 1. Inclusion and exclusion criteria of the bibliometric analysis

Topic	Inclusion criteria	Exclusion criteria
Affective computing in CRM platforms (2023–2026)	Studies 2023–2026; documents related to affective computing, emotion recognition, sentiment analysis, CRM, emotion AI; English-language; empirical, theoretical, review papers; peer-reviewed journals, conference proceedings, or edited volumes indexed in Scopus	Pre-2023 publications (except seminal theoretical works); non-CRM affective computing studies; duplicate documents; non-English publications; incomplete metadata; non-peer-reviewed materials (abstracts, editorials)

Source(s): Authors' own work

The 61 articles included in the analysis were full-text reviewed, then coded on the following aspects: year of publication, country of the corresponding author, research methodology (empirical/non-empirical; qualitative/quantitative/mixed), outlet of publication, theoretical model(s) used, main thematic area and findings. This coding system was applied in the analysis of the descriptive statistics given in the Descriptive Analysis subsection and in the theory mapping given in the Prominent Theories subsection. The results are presented in the subsequent parts in a methodologically sound basis due to the systematic review rigor and bibliometric visualization.

RESULTS AND DATA ANALYSIS

The findings of the descriptive statistical analysis and the bibliometric mapping of the corpus of 61 papers are presented in this section. The descriptive analysis records the number of publications over time, as well as by geographical region, methodology and outlet. On a map, the most suitable theoretical approaches of the corpus are represented in the Prominent Theories subsection. A new term, co-occurrence network, is presented in the Keyword Co-occurrence Networks subsection, followed by the bibliographic coupling clusters in the Bibliographic Coupling subsection. The Current Collaborations subsection discusses the relationships between authors, between keywords and between publication outlets in terms of collaboration.

Descriptive Analysis

The descriptive analysis of the 61 papers in the corpus shows the unique structural features of the research production on affective computing in the field of CRM in the period 2023-2026. These features are a high empirical emphasis and quantitative dominance, a high spatial concentration (Asia and North America), a very high publication frequency and a scattered group of preferred publication outlets grouped in the engineering and computer science and business management disciplines. These descriptive patterns will help to interpret the bibliometric mapping shown in subsequent sections.

Yearly Publications

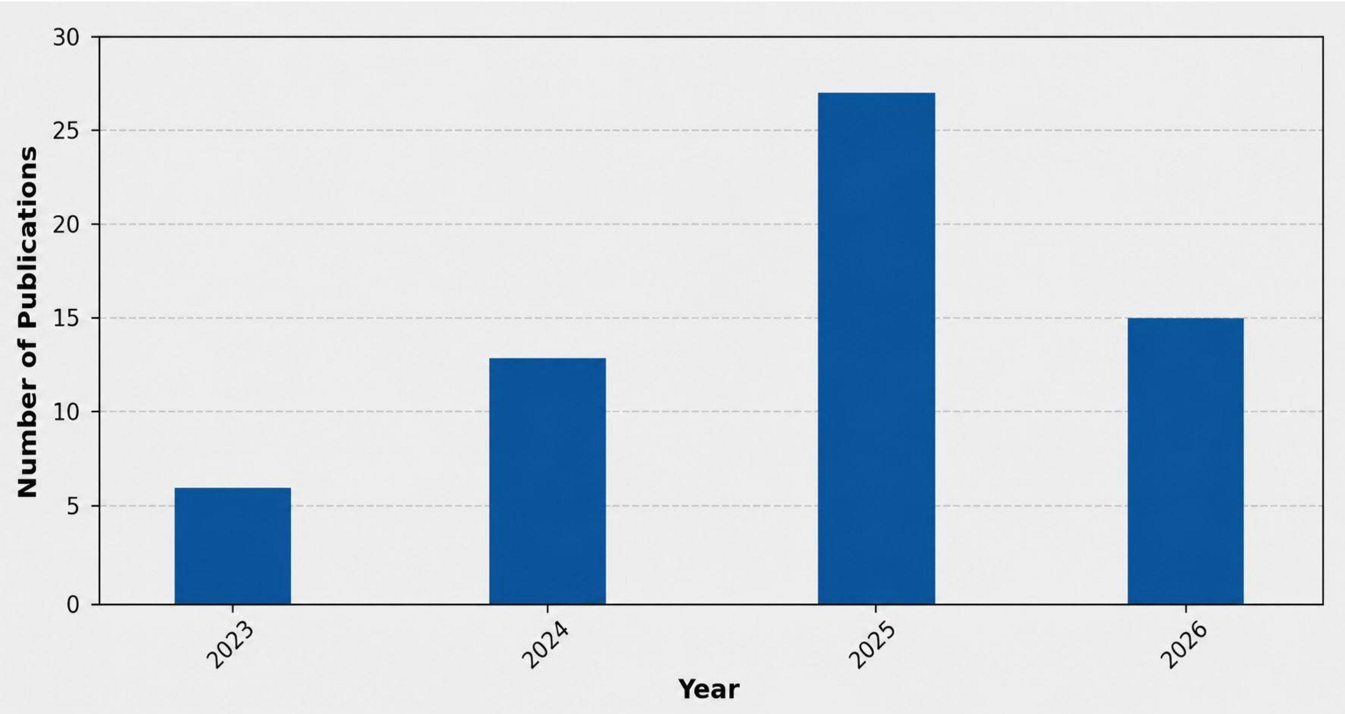

Figure 2. Yearly Publications on Affective Computing in CRM Platforms, 2023–2026

As shown in Figure 2, publication output grew rapidly: from 6 papers in 2023 to 13 in 2024 (a 117% increase), 27 in 2025 (44.3% of the entire corpus), and 15 in the partial year of 2026. The 2023 cohort was mostly conceptual, laying the groundwork for the definitional and taxonomic aspects of the field. The commercialization of AI chatbot platforms and multimodal sentiment analysis tools were the major contributors to growth in 2024,

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as noted by Hazmoune and Bougamouza (2024) and Cortinas-Lorenzo and Lacey (2024), respectively. This increase in 2025 coincided with the general integration of LLMs into customer service, the growing focus on AI governance due to the EU AI Act, and the maturation of methods to mixed methods and qualitative approaches. Although from a partial year, the 2026 papers indicate persistent growth in federated learning for privacy-preserving affective CRM, cross-cultural bias correction, and LLM-native multimodal architectures. Table 2 presents the overall annual distribution of publications.

Table 2. Types of publications by year

Sr.No	Year	Total publications	Non-empirical	Empirical	Qualitative	Quantitative	Mixed
1	2023	6	2	4	1	2	1
2	2024	13	4	9	1	6	2
3	2025	27	7	20	2	14	4
4	2026	15	5	10	1	7	2
Total		61	18	43	5	29	9

Source(s): Authors' own work

Country-wise Publications

Figure 3. Country-level distribution of research on affective computing in CRM platforms

The geographical distribution of publications on affective computing in CRM platforms is presented in Figure 3, based on the final corpus of 61 publications found in Scopus, with the majority of publications coming from China, India and the United States.

Geographical distribution of publications indicates that publications are concentrated in technologically advanced economies, where research activity in AI exists and enterprise software deployment bases are large. The country has the most publications on the corpus, with around 18 publications, mainly owing to the high levels of investment in emotion recognition and deep learning research in China as well as the massive implementation of AI for CRM applications across e-commerce and financial services. The Chinese community also shows a strong presence in the areas of the deployment of real-time processing systems, applied AI engineering in multimodal fusion architectures, and emotion recognition through deep learning approaches.

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India has about 12 publications, growing academic and industry research labs and facilities in AI and machine learning and a massive enterprise software and IT solutions industry, where CRM implementation is a vital business enterprise. Indian papers are on a wider methodological track than those published in China, ranging from technical architecture papers to CRM adoption and implementation studies. There are approximately 8 publications that address explainable AI frameworks, the ethics of affective systems, and organizational issues relating to the integration of AI into CRM systems in the U.S., influenced by the regulatory environment of the U.S. (CCPA, HIPAA), as well as academic traditions in technology management and business ethics (Goel and Gendron, 2024; Chochlakis et al., 2025).

The institutions in Iberia have robust traditions of HCI and marketing technology research, with their total publications being 7, of which important works have been done in the fields of multimodal sentiment analysis for marketing purposes, responsible AI in CRM contexts, and bibliometric reviews of the evolution of CRM (Cesar et al., 2024; Vaz et al., 2025; Perez-Bertozzi and Palos-Sanchez, 2026; Ortiz-Clavijo et al., 2023). Table 3 shows that other countries in the top ten are South Korea (3 publications), Turkey (3) and Poland (3). The majority of the contributions (almost half of the corpus) are written by scholars who are not from the West, showing that “affectionate” CRM research is not only rooted in Western academic and regulatory traditions, but is also diffused internationally.

Table 3. Top ten countries by number of publications

Ranking	Country	Publications	% Publications
1	China	18	29.5%
2	India	12	19.7%
3	United States	8	13.1%
4	Portugal	4	6.6%
5	Spain	3	4.9%
6	South Korea	3	4.9%
7	Turkey	3	4.9%
8	Poland	3	4.9%
9	Saudi Arabia	2	3.3%
10	Malaysia	2	3.3%

Source(s): Authors' own work

Types of Publications

The technology management classification system of Donthu et al. (2021) in their previous bibliometric study was followed for classification of the publications in the corpus. Papers in the technology management field were classified as either empirical or non-empirical articles.To classify the articles in the corpus, the technology management classification scheme proposed by Donthu et al. (2021) in their previous bibliometric review was used, and 61 articles were grouped as empirical or non-empirical. The non-empirical publications comprised conceptual reviews, theoretical frameworks, systematic literature reviews, position papers, and comprised 18 papers (29.5% of the corpus). At the present moment this ratio reflects the constant need for conceptual consolidation that is characteristic of the field: affective CRM is still very new and working on definitional matters, taxonomic clarifications, and the development of theoretical frameworks are still active scholarly endeavors. It seems that the majority of non-empirical papers are in the ethical governance and emerging technology clusters, suggesting that there is a high degree of conceptual uncertainty in these two areas, and a need for theoretical foundations in these two areas.

The remaining papers (43, 70.5%) were empirical. Some of the 5 papers that applied qualitative methods (11.6%) applied case studies or interviews, and others conducted ethnographic observations of the implementation processes of affective CRM in organisations, bringing into focus the growing awareness that affective CRM adoption in organisations is a social and cultural process, beyond the reach of quantitative measurements. Most empirical studies used quantitative methods (29, 67.4%), such as survey research, computational experiments, model benchmarking and statistical analysis of archival CRM data. Nine empirical papers (20.9%) used a combination of quantitative measures of performance and qualitative organizational analysis (mixed methods). This distribution shows that empirical testing (quantitative methodology) is still the dominant approach, and at the same time it shows that the variety of methodology needed to address the range of complexity in the application of affective approaches to CRM is needed and is emerging.

Publication by Journals

The field is interdisciplinary, and publications cover engineering, computer science and business management journals. The IEEE Access' three publications and IGI Global's Emotion AI/CRM book series' five chapters on operational, ethical, and relational aspects make it the single-source output. IEEE Transactions on Multimedia and IEEE Transactions on Engineering Applications of AI address technical architectures, while Industrial Marketing Management and Journal of Business and Industrial Marketing address business adoption perspectives. The inclusion of Scientific Reports and Knowledge-Based Systems in this list of IEEE conference proceedings further indicates that affective CRM is not an easy subject to classify in a single discipline. Full outlet distribution is shown in Table 4.

Table 4. Top publication outlets by number of publications

Outlet	Type	Publications	Key topics covered
IEEE Access	Journal	3	Multimodal emotion recognition, sentiment analysis, gesture recognition
IGI Global Book Series (Emotion AI/CRM)	Book chapters	5	Ethics, CRM adoption, emotional empathy, privacy
Engineering Applications of AI	Journal	2	Transformer-based multimodal emotion recognition
IEEE Transactions on Multimedia	Journal	2	Multimodal fusion, missing modalities
Knowledge-Based Systems	Journal	2	LLM-based affective computing, XAI for CRM
Scientific Reports	Journal	2	Multimodal CRM emotion analysis, chatbot trust
Industrial Marketing Management	Journal	1	Manager aversion to AI-CRM
Journal of Business and Industrial Marketing	Journal	1	Generative AI-enabled CRM agility
Journal of Relationship Marketing	Journal	1	E-CRM bibliometric evolution
Lecture Notes in Networks and Systems	Proceedings	2	Multimodal emotion recognition reviews
IEEE Conference Proceedings (various)	Proceedings	8	Technical architectures, real-time systems
Cluster Computing	Journal	1	Multi-task emotion/sentiment for customer service

Source(s): Authors' own work

Prominent Theories

The 12 most important theoretical approaches that could be identified from the systematic coding of the 61-paper corpus are shown in Table 5. Theories presented in the corpus vary in scope to mirror the interdisciplinary nature of the field of affective CRM, which has equally interdisciplinary roots in technology management, the study of human-computer interaction, organizational behaviour, marketing science and computer ethics. This is the most widely used model, known as the Technology Acceptance Model (TAM), which is available in various forms for studies on the individual and organisational level of adoption of a CRM system. The most frequently used models were Theory of Privacy Calculus (2nd) and Trust Theory (3rd), indicating that the field has shifted its focus to aspects of governance and quality of relationships. As Explainable AI architectures and Privacy by Design increasingly gain momentum, social science-based governance models are increasingly being seen in the engineering community's analysis of affective CRM.

Table 5. Prominent theoretical frameworks in affective computing CRM research (2023–2026)

Theory	Core proposition	Key studies in corpus
Technology Acceptance Model (TAM)	Perceived usefulness and ease of use drive technology adoption	Verma et al. (2024); Alyousuf et al. (2025); Al-Shuridah (2025)
Stimulus-Organism-Response (SOR)	Environmental stimuli shape internal states and behavioral responses	Khoa and Thanh (2025); Wang et al. (2026)
Privacy Calculus Theory	Individuals weigh privacy risks against perceived benefits of data sharing	Kumar et al. (2025); Hasani et al. (2023); Morales et al. (2026)
Trust Theory	Cognitive and affective trust dimensions mediate technology adoption and relationship quality	Wang et al. (2026); Gaczek et al. (2023); Prakash et al. (2026)
Self-Determination Theory (SDT)	Autonomy, competence, and relatedness drive human motivation and adoption	Kumar and Shankar (2025)
Explainable AI (XAI) Framework	AI systems must produce human-interpretable outputs to support trust and adoption	Cortinas-Lorenzo and Lacey (2024); Ayaz et al. (2024); Maqbool and Qureshi (2026)
Innovation Resistance Theory (IRT)	Functional, usage, and value barriers generate resistance to innovation adoption	Kumar and Shankar (2025); Ferreira et al. (2023)
Social Cognitive Theory (SCT)	Observational learning and self-efficacy drive behavioral adoption	Verma et al. (2024); Chochlakis et al. (2025)
Cognitive Load Theory (CLT)	Working memory capacity limits shape system design and usability	Wei and Chen (2025); Guan et al. (2026)
Privacy by Design (PbD)	Privacy protections embedded in system design from inception	Morales et al. (2026); Maheen et al. (2025); Kumar et al. (2025)
Human-Computer Interaction (HCI) Theory	Design, evaluation, and implementation of interactive systems for human use	Chen et al. (2026); Verma et al. (2025)
Persuasion Knowledge Model (PKM)	Awareness of persuasion attempts shapes consumer response to commercial messages	Reza et al. (2025); Ida Evangeline (2025)

Source(s): Authors' own work

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) (Davis, 1989) is a lens through which to understand how perceived usefulness and ease of use affect the individual's intention to adopt a technology, and the dominant one used in understanding individual and organizational adoption of emotion-aware CRM systems. The original TAM model assumes that external factors affect perceived usefulness and perceived ease of use which then affect the intention to use a technology. In more intricate organizational settings, the model has been extended to incorporate additional factors related to social influence, facilitating conditions, and hedonic motivation, including the Unified Theory of Acceptance and Use of Technology (UTAUT), the TAM2 and the TAM3 extensions. Verma et al. (2024) surveyed 487 respondents from the retail industry to evaluate their intention to adopt AI, and they found that perceived usefulness is a significant predictor of the intention to adopt the technology, while the feeling of techno-anxiety has a negative moderating effect on the relationship between perceived usefulness and intention to adopt the technology, suggesting that emotional responses to AI technology are not only impacts of adoption but also precursors to it. To analyze the use of AI in purchasing green products, Alyousuf et al. (2025) added social influence factors to TAM, and found that the core variables of TAM were clearly enhanced by the factors of peer influence and normative pressure in younger consumers. In a cross-national study, conducted across Saudi Arabia and Australia, Al-Shuridah (2025) found that in both countries system quality and customer perception act as the mediating factors in the relationship between CRM adoption and ease of use and usefulness, and also illustrated that the relative importance of ease of use and usefulness vary across the countries. As a whole, these studies support the idea that perceived value and usability are still fundamental factors affecting the decision of ACRM adoption, while trust, transparency and culture become more and more important factors to act as moderators or boundary conditions.

Stimulus-Organism-Response (SOR) Theory

This is called SOR (Mehrabian and Russell, 1974) theory, which states that the influence of environmental stimuli on internal psychological states (organism) which in turn produce effects (responses). The tripartite concept has been used extensively in retail marketing and consumer research for the purposes of understanding the relationship between the physical and digital design of environments and the thoughts, feelings and actions of consumers. Khoa and Thanh (2025) investigated the relationship between perceived surveillance and data collection stimuli, trust as a psychological state and behavior intentions for data sharing and channel involvement in the context of omnichannel retailing and found that the perceived surveillance and data collection stimuli have a positive impact on consumers' trust, which in turn positively influences their behavior intentions regarding data sharing and channel involvement. In the case of affective CRM, where all the system elements are affective (such as the responses of a chatbot, the characteristics of the interface, the recommendations made by the service agent), this can be a stimulus that affects the customer's cognitive and affective state, such as creating trust, satisfaction and the emotional involvement of the customer. These internal states, in turn, affect downstream behaviors like purchase intention, loyalty behaviors and complaints escalation. Wang et al. (2026) indirectly use SOR logic when they show how human like features in AI chatbots (stimuli) affect the ratings of perceived reliability and warmth (organism) that boost user trust and maintain their engagement in the chatbot (response). In terms of affective CRM research SOR has great potential as a means of linking the chain of causation from technical system design to customer behavioural outcome measurable, thus it provides a strong linkage between the technical and marketing science literature.

Privacy Calculus Theory

A model of the privacy calculus theory (Laufer, Wolfe 1977) is used to discuss the process people go through when they decide to share their personal data, what they think they benefit from, what they think they lose, and their feeling of informational control. These are particularly relevant to affective CRM, since emotion recognition technologies involve the collection of sensitive behavioural and physiological data (voice tone, facial expressions, heart rate variability etc) beyond that typically collected by a CRM system. This information can be highly sensitive, and the collection of affective information can be very implicit and invisible during the actual interaction with CRM, so that the customer's calculation about his/her privacy might not be sufficiently informed. The GDPR and CCPA compliance frameworks formalize the privacy calculus in the principles of privacy, such as data minimisation and consent and purpose limitation, that serve to establish the institutional setting in which affective CRM data collection could be considered legitimate.The principles of privacy calculus have been formalised in compliance frameworks including GDPR or CCPA, which specify a range of formal conditions on data minimisation, consent and purpose limitation that help define the institutional context in which affective CRM practices can be said to be legitimate. Hasani et al. (2023) present empirical findings supporting the beneficial role of Privacy Enhancing Technology (PET) on SME performance in terms of managing the tensions of privacy and benefit constructively: when organizations provide tangible privacy protection, they can provide more personalized benefits to their customers without causing a defensive reaction. In the dynamics of privacy calculations, as suggested by Morales et al. (2026) and Maheen et al. (2025), the privacy-by-design approach is a new way of thinking, as a system that is designed to be privacy is more likely to be attractive for customers to share their data.

Trust Theory

Based on Trust Theory (McKnight and Chervany, 2001), this theory suggests that both cognitive and affective dimensions of trust are significant in technology adoption, technology use, and the relationship quality in digital commerce. Cognitive trust is a attitude of a trustee's competence, reliability, and integrity. Affective trust is related to the emotional sense of security and goodwill of the trustee. Affective CRM systems rely on trust in three relational dyads: trust between the customer and the service systems that rely on AI, trust between the employees, managers and the AI-driven recommendations, and trust between the organization and the emotion detection systems offered by the vendor. These trust relationships are unique and vulnerable to various aspects that designers of affective CRM systems need to consider. Through a qualitative analysis, Wang et al. (2026) conclude that the combination of conversational warmth, emotional state recognition, empathy expression and perceived system reliability leads to user trust in AI customer service interactions. In institutional trust environments like B2B marketing to institutional decision makers, Gaczek et al. (2023) demonstrate that there is a general rejection of the AI-CRM recommendation when the reasoning behind the recommendation is not transparent.Gaczek et al. (2023) determine that in institutional trust situations such as B2B marketing to organizational decision makers, aversion is significant overall when the "how" of the recommendations is not communicated clearly. Prakash et al. (2026) also show that AI transparency tools and organisational accountability tools, like audit trails, Humans in the loop, or explicit decision accountability, aid in the process of forming trust in managerial decision making systems. The results as a whole give a multi-level view of trust as a construct which needs to be developed across different dimensions of system design, the quality of explanations and organisational governance.

Self-Determination Theory (SDT)

According to Self-Determination Theory (Deci and Ryan, 1985), the motivation of humans is basically composed of three psychological needs: autonomy (the need to act as an agent of one's own actions), competence (the need to succeed at performing challenging tasks and feel effective), and relatedness (the need to feel connected to others). The features of technology systems are effective in supporting the intrinsic motivation to adopt and sustain technology use when they match or don't interfere with these needs. Kumar and Shankar (2025) leverage SDT to explain why human empowerment CRM systems integrating Generative AI to extend employee decisions using AI-generated data meet autonomy and competence needs, leading to decreased resistance in adoption. An affective CRM can provide service agents with actionable and interpretable recommendations that can be evaluated, modified and rejected by the service agents, satisfying the service agents' need for self-determination without being threatened by an automated response. The SDT framework also sheds light on the customers' side in affective CRM relationships. When customers hear their needs for relatedness validated by a related, contextually-appropriate response, they are more likely to be emotionally understood and relationally valued during their interactions with the service, and thus more likely to engage in a meaningful, lasting relationship with the service. In contrast, customers who perceive that AI emotion monitoring is overly invasive or controlling may feel it is encroaching on their autonomy need, leading to privacy concerns and reactions. Thus, SDT offers a theoretically sound explanation as to why affective CRM's effectiveness relies not only on technical accuracy of identification of emotions but on relational quality of delivering emotionally-informed service.

Explainable AI (XAI) Framework

The Explainable AI framework (Gunning and Aha, 2019) tackles the core opacity issue of today's machine learning architectures, which demands that AI generated data should be accompanied with human-understandable explanations to help stakeholders gauze, trust and act on AI recommendations accordingly. The black-box nature of the deep learning models with their high accuracy of prediction, complex non-linear transformation of the high dimensional input data and difficulty in explaining the model, are particularly problematic in the context of accountabilities, fairness and explainabilities not only being desirable features of a model, but required and a condition for organizational trust in a CRM deployment. Cortinas-Lorenzo & Lacey (2024) find that, although the transformer model is an intuitive class of multi-modal emotion recognition systems, it is inherently ambiguous and only becomes useable and credible when applied in practice with the implementation of XAI tools, like SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-agnostic Explanations), and attention visualization mechanisms. Giving the marketing managers the reasons for selecting the customers in which the model would like to contact using XAI, Ayaz et al. (2024) show empirically that it results in measurable increases in conversion rates without compromising the trust of stakeholders in the model's recommendations. Even when the black-box models outperform the explainable ones in predictive accuracy, Maqbool and Qureshi (2026) provide an overview of the advantages of explainable models in churn prediction and customer segmentation and its likelihood of being accepted within and integrated into organization's decision workflows. Finally, Gaczek et al. (2023) draw the institutional relevance of these implications the most clearly. They discover that the managers' resistance to using AI-CRM is directly and significantly connected to the lack of satisfactory explanations, making the significance of XAI more than a technical flourish, it is a fundamental institutional aspect.

Innovation Resistance Theory (IRT)

Organisational and consumer resistance to new technologies is illustrated by Innovation Resistance Theory (Ram, 1987) which focuses on functional, usage, value and psychological barriers. Resistance to affective CRM comes from legacy integration, lack of clarity on regulatory compliance, and questions about how customers will respond to emotion monitoring. According to Kumar and Shankar (2025), functional complexity and learning-curve barriers are the most prominent barriers to the adoption of GenAI in CRM, and Ferreira et al. (2023) validate that learning-curve barriers are independent reasons for CRM interface adoption failure. The utility of IRT is that it offers a theoretically informed taxonomy of types of resistance that can be used to guide targeted adoption strategies other than simply investing in technology.

Social Cognitive Theory (SCT)

Social Cognitive Theory (Bandura, 1986) contends that behaviour happens by way of observational learning and self-efficacy, meaning that agents are more likely to adopt the use of emotion-aware CRM tools when they see others successfully using them. On the other hand, when AI-CRM systems fail in public, it can quickly lead to a loss of confidence in the system, affecting the organization's ability to accept it.However, if the AI-CRM system has problems in public, it can quickly reduce organisation self-efficacy and hinder the acceptance of the system. Verma et al. (2024) statistically validate that social influence is a predictor of AI-CRM adoption intent in retail, and Chochlakis et al. (2025) demonstrate that the use of modality-agnostic systems decreases the operators' mental effort and increases their perceived competence. The managerial champions who visibly use successful affective CRM are identified as the critical accelerators for the whole organisation to use SCT.

Cognitive Load Theory (CLT)

In terms of cognitive load theory (Sweller, 1988), the design of a system should aim to reduce the extraneous cognitive load to allow for meaningful decisions to be made in working memory. Real-time affective CRM requires agents to multi-task between AI-generated emotional responses, customer interactions, and navigating CRM systems, leading to high levels of cognitive load. Wei and Chen (2025) show that using context-aware fusion architectures can decrease the interpretive difficulty of the multimodal sentiment output, and Guan et al. (2026) propose a reliability-aware gating mechanism that eliminates the requirement for manual assessment of output confidence levels by agents. CLT-based systems enable agents to focus their mental resources on the interpersonal aspects of customer service instead of interpretation of output.

Privacy by Design (PbD)

Privacy by Design (Cavoukian, 2009) is a design principle that privacy considerations must be integrated into the design of systems, rather than subject to compliance measures as an after-thought. Affective CRM is realized through the framework of emoAIsec proposed by Maheen et al. (2025) that incorporates data security protocols as architectural components, and GDPR/CCPA-compliant architecture which deals with data minimisation, purpose limitation and consent as proposed by Kumar et al. (2025). Another important aspect of federated learning is its ability to train models from a variety of sources without compromising individual privacy, as shown by Morales et al. (2026), which addresses another critical balance between the volume of training data and privacy concerns. Businesses with a privacy-first mindset put privacy on the front lines and make it a competitive differentiator, not a compliance challenge.

Human-Computer Interaction (HCI) Theory

When considering interactive systems, Human-Computer Interaction theory (Dix et al., 1998) takes into account the measures of usability, the quality of user experience and human-machine communication. The key HCI problem for affective CRM is to create systems that are able to identify subtle emotional signals in noisy, culturally diverse, real-world settings and react in an empathetic way. The evolution of the field from facial expression recognition to LLM-based multimodal perception is traced by Chen et al. (2026), and Verma et al. (2025) show emotion recognition and response generation in real time in enterprise multimodal interfaces. The HCI lens ensures that the design of the interface, the quality of the interaction, and the authenticity of the emotions are not set aside, but are always at the heart of the evaluation of affective CRM.

Persuasion Knowledge Model (PKM)

The Persuasion Knowledge Model (Friestad and Wright, 1994) accounts for the activation of coping responses (skepticism, counter-argumentation, or avoidance) that consumers may engage in when they become aware of a commercial persuasion attempt. The influence mechanism of emotion-based personalisation in affective CRM is complex and often not visible, and when customers discover it, they might feel manipulated instead of served, resulting in protecting themselves which can hinder the effectiveness of the system. This ambivalence is echoed by Reza et al. (2025), who showed that the awareness of GenAI within commercial communication results in positive perceptions of service quality and negative perceptions of emotional manipulation. Ida Evangeline (2025) goes so far as to argue that transparency in the disclosure of affective data collection is crucial to ensure that services enhance while respecting the legitimate interests of customers in maintaining their autonomy.

Keyword Co-occurrence Networks

The 61-paper corpus was analysed with respect to author assigned and Scopus indexed keywords, using a threshold of three occurrences, to achieve 34 high-frequency keywords that formed a connected network. All four clusters contain the conceptual core—'emotion recognition,' 'affective computing,' 'multimodal fusion,' 'CRM,' 'sentiment analysis,' and 'deep learning'—which is used as common technical terminology across disciplines. From 2023 to 2026, there has been a significant increase in the number of 'privacy,' 'GDPR,' 'explainability,' 'XAI,' 'trust,' and 'algorithmic bias' terms, forming a second cluster of concepts.The terms 'privacy,' 'GDPR,' 'explainability,' 'XAI,' 'trust,' and 'algorithmic bias' have also increased significantly from 2023 to 2026, and 'explainability' is a conceptual bridge between the technical and ethical clusters. Another cluster that emerged after 2024 focused on ‘LLM’, ‘generative AI’, ‘NLP’, ‘personalization’, and ‘chatbot’, with ‘LLM’ not standing alone, but rather co-occurring with ‘multimodal fusion'. Recurring co-occuring pairs like 'real-time processing' and 'customer service,' 'cultural sensitivity' and 'algorithmic bias,' and 'privacy-preserving' and 'federated learning' indicate that latency, fairness, and privacy architecture are now fundamental design tenets. The patterns follow the four bibliographic coupling clusters found in the Bibliographic Coupling subsection, which supports the convergent validity of the thematic structure of the field.

Clusters Identified Through Bibliographic Coupling

The bibliographic coupling analysis was used to detect the clusters of papers that share common ideas and research foundations (shared reference lists). Three was used as the minimum threshold, and 38 documents were extracted of the number of documents that meet the criteria; then the isolated documents which lack enough references with the remaining documents in the collection were removed, resulting in 28 documents that were retained. Four main clusters were identified in the analysis, which have a high level of coherence and are clearly differentiated from each other and are accepted by the thematic axes resulting from the keyword co-occurrence analysis in the Keyword Co-occurrence Networks subsection.

Table 6. Top five most influential documents per bibliographic coupling cluster

Cluster	Paper	Citations	Core contribution
Cluster 1 (Red): Multimodal Technical Architectures	Hazmoune and Bougamouza (2024)	102	Taxonomy of transformer-based multimodal emotion recognition
	Pei et al. (2024)	71	Comprehensive survey of affective computing advances
	Cortinas-Lorenzo and Lacey (2024)	41	Explainable affective computing review
	Huan et al. (2024)	39	UniMF: unified multimodal framework for missing modalities
	Pena et al. (2023)	27	Framework for evaluating multimodal fusion methods
Cluster 2 (Green): CRM Integration and Personalization	Gaczek et al. (2023)	36	Manager aversion to AI-CRM and explainability
	Ferreira et al. (2023)	21	CRM UX design and implementation failure

	Chen et al. (2024)	16	Multi-task emotion and sentiment for customer service
	Shaikh et al. (2024)	5	AI-CRM transformation in e-commerce
	Kumar and Shankar (2025)	9	GenAI-enabled CRM and organizational agility
Cluster 3 (Yellow): Ethical Governance and Privacy	Hasani et al. (2023)	40	Privacy Enhancing Technology adoption in SMEs
	Ortiz-Clavijo et al. (2023)	14	Emotion recognition: privacy and public safety implications
	Khoa and Thanh (2025)	8	Consumer privacy and trust in omnichannel retailing
	Kumar et al. (2025)	7	Data privacy, ethics, and AI in CRM
	Maqbool and Qureshi (2026)	1	XAI for churn prediction and customer segmentation
Cluster 4 (Blue): Emerging Technologies	Verma et al. (2024)	2	TAM and AI-CRM adoption in retail
	Yang et al. (2026)	2	LLM-driven context-aware recommendation with NLP
	Wang et al. (2026)	2	Human-like cues and trust in AI chatbots
	Guan et al. (2026)	0	RAGE-Fusion for real-time reliable multimodal emotion
	Zhang et al. (2026)	0	Affective computing in LLM era: NLP survey

Source(s): Authors' own work

Cluster 1 (Red) is the most solid and coherent one, with 12 papers sharing a common basis in research and development of Deep Learning, Transformer Architectures and Multimodal Signals Processing. A significant body of later research is technically grounded by the data of the taxonomy for multimodal emotion recognition systems developed in Hazmoune et al. (2024) that were built by Bougamouza and Hazmoune. The cluster's intellectual heritage is primarily that of computer vision, speech processing and natural language processing, and secondarily, of affective computing and HCI. This cluster has the highest number of citations (102 citations for Hazmoune and Bougamouza (2024) and 71 citations for Pei et al. (2024) respectively), indicating that this cluster is the oldest and most developed one in the corpus.

Cluster 2 (Green): CRM Integration, Customer Engagement and Personalization includes 8 papers with intellectual dimensions that are related to CRM research and the science of marketing and organizational information systems. The cluster centers on the real-world implications of using the affective capabilities within the current CRM system, how the affective capabilities alter the customer engagement process, and how the organizational actors respond to the new emotional data that AI brings to the CRM. The cluster's most cited paper (Gaczek et al., 2023) is located in a middle ground between the technical and organizational papers, and research from the fields of behavioral economics and management science and AI capabilities research.

Cluster 3 (Yellow) – Ethical Governance, Privacy, and Responsible AI – is made up of the 6 papers which have common grounds in privacy law, ethics of computing, and research in regulatory compliance. The cluster's legal origins trace back to the theory around information privacy, the academic research around the compliance of regulations, and the (emerging) literature on AI governance. The cluster stands out in particular because of its interdisciplinary nature: sharing some common underlying papers, there is an intellectual community that could be defined around the governance of affective CRM.

The newest and fastest-growing cluster, Cluster 4 (Blue) – Emerging Technologies and Future Trajectories – shares the concepts of the papers in LLM research and Generative AI and introduces new and next-generation

Affective Computing architectures. The low citation rates for this group of papers do not indicate small impact, because they are papers at the cutting edge of the field, but should start to see significant citations as the literature expands, as they have been recently published. The cluster starts to form an intellectual community as part of the network, explaining the fact that LLM-based affective CRM is not just another technical refinement, but a true revolution.

Current Collaborations

The three areas of core research – affective computing, CRM integration and ethical governance – are also tightly connected in the current literature, both in terms of authorship and co-citation networks, and also in terms of publication media. The bibliographic coupling analysis indicates some intellectual clustering but the present collaborative situation (as reported in Table 7) reveals important bridge figures that have works that bridge different clusters, enabling conceptual cross-fertilization.

There are a number of key authors from these three fields, most notably Pei et al., who conducted an in-depth review of the state of affective computing which links the technical architecture cluster (Cluster 1) with the HCI and deep learning literature that contribute to designing the systems across the other clusters. Cortinas-Lorenzo and Lacey provide the framework of explanation between technical performance and the needs of organizational governance, which serve as a bridge between XAI research and multimodal affective systems. We are lucky to have both Kumar and Kumar et al. (2025, in Cluster 3) and Kumar and Shankar (2025, in Cluster 2) who incorporate both the governance parts of privacy and practical "how to" tips for implementing CRM.

The authors, keywords and journals are arranged in a three-field plot (Table 7) to illustrate the overlap between clusters of technical papers (for example, IEEE Access, Engineering Applications of AI, IEEE Transactions on Multimedia) and business oriented papers (for example, Industrial Marketing Management, Journal of Business and Industrial Marketing) through 'bridge' keywords, for example, 'personalisation,' 'sentiment analysis' and 'customer engagement'. These bridge terms are central to the co-occurrence network of all other terms and they are mentioned in publications from all kinds of outlets and literature lends support to their status as conceptual 'langua franca' for communicating between disciplines in the affective CRM research community. The non-interaction between the authors from the Western regulatory jurisdictions (US, EU) and the Asian research centres (China, India) suggests a room for more international cooperation on research based on the best of technical innovations and governance framework.

Table 7. Three-field collaboration map: Main authors, keywords, and journals

Main Authors (by cluster)	Bridge Keywords	Primary Journals/Outlets
Hazmoune and Bougamouza; Huan et al.; Pei et al.; Cortinas-Lorenzo and Lacey; Pena et al. (Cluster 1)	Multimodal fusion; deep learning; transformer; emotion recognition; missing modality	Engineering Applications of AI; IEEE Transactions on Multimedia; IEEE Access; Intelligent Computing
Gaczek et al.; Ferreira et al.; Kumar and Shankar; Chen et al. (Cluster 2)	Personalization; CRM adoption; customer engagement; sentiment analysis; chatbot	Industrial Marketing Management; Journal of Business and Industrial Marketing; Cluster Computing; Journal of Relationship Marketing
Hasani et al.; Ortiz-Clavijo et al.; Kumar et al.; Khoa and Thanh (Cluster 3)	Privacy; GDPR; XAI; ethical AI; trust; algorithmic bias; privacy-by-design	IEEE Technology and Society; Int. Journal of Engineering Business Management; ACIIW Proceedings; IGI Global book series
Zhang et al.; Yang et al.; Wang et al.; Guan et al.; Verma et al. (Cluster 4)	LLM; generative AI; real-time; reliability; NLP; context-aware personalization	Knowledge-Based Systems; Scientific Reports; Int. Journal of Data Science and Analytics; IEEE Conference Proceedings

Source(s): Authors' own work

DISCUSSION

The results are discussed with regards to the four bibliographic coupling clusters that were identified in the Bibliographic Coupling subsection. The four clusters are a representation of four different but interwoven aspects of the challenge presented by the implementation of CRM: the technical architecture challenge, the challenge of implementing CRM integration, the challenge of ethical governance and the emerging technology opportunity. Together they offer a comprehensive overview of the intellectual landscape and most interesting research questions in the field.

Cluster 1: Multimodal Emotion Recognition and Technical Architectures

The technical core of affective computing in the context of CRM, Cluster 1 deals with deep learning architectures, multimodal fusion and real time emotion recognition systems for interactive customer environments.

The most influential paper in this dataset is Hazmoune and Bougamouza (2024) with 102 citations who present a taxonomy of transformer-based multimodal emotion recognition systems that is able to reach state-of-the-art results on benchmarks such as IEMOCAP, CMU-MOSI and MELD. They claim that their architecture's self-attention mechanism is capable of modelling long-range temporal dependencies and cross-modal relationships, which they show is an incremental step in different tasks over previous CNN-LSTM hybrid architectures. They, however, recognize one important shortcoming between benchmark accuracy and the accuracy needed when deployed in a challenging customer relationship management (CRM) application in which the audio quality may be poor, video streams are obstructed, text data is incomplete or written in non-standard dialects and the customers' cultural and linguistic backgrounds are varied. This gap in the current ability is the main technical hurdle faced by organisations aiming to implement affective CRM at enterprise scale, and is the basis for the work undertaken by Cluster 1 as a whole.

Huan et al. (2024) tackle the missing modality problem as one of the main challenges identified by Hazmoune and Bougamouza as being present in real-world deployments through the use of the UniMF (Unified Multimodal Framework). When one or two of the three traditional modalities (audio, video, text) are missing, UniMF uses a single attention mechanism to learn to fill in the gaps so it can maintain emotion classification accuracy above acceptable levels. This is directly relevant to enterprise CRM deployments: The interaction with the customer service bot could involve only text; the interaction with a customer service phone call is limited to audio but no video; and in the case of a video interaction, the video could occasionally go out of sync with the audio. The ability to deal with these conditions gracefully (without catastrophic errors in accuracy) is an important step toward truly deployable affective CRM systems. This work is complemented by Pena et al (2023), who propose a systematic evaluation framework for comparing fusion strategies under various data conditions, and show that hybrid fusion of multimodal features in early fusion, of unimodal predictions in late fusion, and of cross-modal attention in fusion is consistently outperforming single strategy fusion methods in dynamic and naturalistic settings.

Huan et al. (2024) tackle the missing modality problem as one of the main challenges identified by Hazmoune and Bougamouza as being present in real-world deployments through the use of the UniMF (Unified Multimodal Framework). If only one or two of the three modalities (audio, video, text) are missing, UniMF is able to learn to compensate for the missing information using one attention mechanism, while keeping its emotion classification accuracy above a desired threshold. This is directly relevant to enterprise CRM deployments: The interaction with the customer service bot could involve only text; the interaction with a customer service phone call is limited to audio but no video; and in the case of a video interaction, the video could occasionally go out of sync with the audio. Dealing gracefully with these conditions (without catastrophic errors in the accuracy) is a crucial step towards truly deployable affective CRM systems. This work is complemented by Pena et al (2023), who propose a systematic evaluation framework to compare fusion strategies in different data conditions, and demonstrate that the hybrid fusion of multimodal features in early fusion, unimodal predictions in late fusion, and cross-modal attention in fusion consistently outperforms single strategy fusion methods in dynamic and naturalistic settings.

This trend is further reinforced by the RAGE-Fusion (2026) framework developed by Guan et al., which is more suitable for customer facing CRM systems, in a real-time, interactive interface. RAGE-Fusion adds reliability-aware gating mechanisms which consider the confidence of each modality emotion prediction when deciding which ones to take into the fused result. This will remove any false or incorrect predictions in the weak audio stream (such as a corrupted video stream) from influencing the overall emotion assessment and triggering the unwanted automated CRM response. The reliability-gated fusion as a safety feature is very important for enterprise CRM deployments where a false positive – the misperceived significant confusion in the customer as a neutral “satisfied” – could lead to an automatic response, which, in turn, would cause a bigger service problem. This is one of the key points of RAGE-Fusion's architecture that makes it easy to distinguish it from advertisement oriented techniques that are based on maximum rates for benchmarking under clean laboratory conditions.

The explainability dimension becomes important when it comes to enterprise adoption, as shown by Cortinas-Lorenzo and Lacey (2024), who found that even highly successful affective models are still hard to audit, interpret and explain. They provide a thorough analysis of explainable affective computing techniques and explain why SHAP, LIME, counterfactual explanations, and attention visualization methods are the most promising XAI techniques for multimodal emotion systems, highlighting the key limitations they present in practical applications for high dimensional and complex representations employed by state-of-the-art transformer models. Explainability comes with a tradeoff: It poses big functional risks in regulated CRM applications, like those in the financial sector, health sector, and insurance industry, where companies need to be able to explain precisely what factors (and only legitimate ones) the AI does not discriminate against when evaluating customers. Adding a new dimension, Zhan et al. (2025) present enhanced feature learning strategies for sentiment classification when polarity is missing, showing that modality-invariant features can retain classification accuracy across varying levels of modality availability.

Cluster 1 confirms that, while the technical performance of multimodal deep learning is amazing in controlled environments, translating these achievements to reliable, explainable and operationally robust CRM tools is an ongoing process and is supported by continued investments in three areas: establishing reliable evaluation protocols that reflect the typical data quality and multimodal configuration of CRM in the wild, developing reliability and graceful degradation mechanisms that allow for the model to deliver acceptable results when deployed with the missing modality and data quality common in operational environments, and creating XAI integration approaches that render complex multimodal models interpretable without compromising the accuracy gains that make them practically valuable.

Cluster 2: CRM Integration, Customer Engagement, and Personalization

In Cluster 2, the affective dimension of the computing system is placed in the larger organizational context of the implementation of CRM, where technical skills are not enough: the complexity of integration, the design of human experience, and the dynamics of human-AI collaboration play a role of at least equal importance for the success of the deployment.

One of the most cited papers in this cluster is that of Gaczek et al. (2023) which investigated the responses of B2B marketing managers to the AI generated recommendations for CRM, revealing that the recommendations were very personal and psychological in terms of organizational adoption of AI. When AI-CRM systems cannot explain their reasoning adequately, these findings suggest that negative emotion attitudes towards the AI systems (professional replacement, distrust of AI system opaque recommendation process, threat to managerial expertise and authority) have significant impacts on the adoption and effective use of AI-CRM systems. The takeaway of this finding is that it's a big practical deal: If a CRM system can be successful from a technical standpoint, but cannot effectively communicate to managers why it has recommended a certain thing, then it will meet with resistance, rather than acceptance. In other words, explainability is not just a technical aspect of the capabilities of the CRM system, but it is also a social contract that must be established for AI-CRM systems that are part of complex organizations where human professionals will need to act on (and be held responsible for) the insights generated by the AI.

Under the ensemble framework, which is capable of predicting emotional states and sentiment polarity together, based on customer service conversation text, Chen et al. (2024) present the technical foundation of intelligent customer service conversation analysis. They argue that their multi-task learning approach shows that the joint modelling of emotion and sentiment—two related but distinct constructs that are usually treated separately in the current research—results in predicting more accurately and clarifying the output of the sentiment, which can be beneficial to CRM systems. If you're able to interact with the customer through the embedded email-based CRM or chatbot, knowing that a customer is feeling "negative" is one thing, knowing that a customer is feeling "frustrated" – that is, frustrated by a process – is another: knowing the specific nature of the negativity ("frustrated" vs. "disappointed") can lead to better, automated or agent-based responses, and to a more precise understanding of the customer's specific emotional state.

The study by Ferreira et al. (2023) brings a relatively neglected perspective in the literature of technocentric affective CRM studies – the organisational and user experience context that makes the use of high-tech features possible for users who could potentially use them. The risks of implementing CRM in the real estate sector are still too great, as evidenced by the research they have conducted on the outcomes of the real estate sector's CRM implementation, where the rate of failed projects is always greater than 50% from the CRM literature and serious problems in relation to user experience design and attention to the human dimensions of implementation are among the top reasons for project failure. Even if technically correct the Affective CRM systems that end up with too high a mental effort, too cumbersome set-up processes, too difficult to interpret outputs in the realm of real customers or too cumbersome service processes will be rejected and rejected, simply because they are too difficult to use. Along with the technical architectural requirements identified in Cluster 1, this finding sets forethought on user-centered design as a basic requirement for implementing affective CRM successfully, with a focus on the needs and capabilities of the human service agent rather than the customer.

Kumar and Shankar (2025) discuss how the early adopters have already used the affective capabilities of LLM to transform the CRM, bringing a future perspective to the organizational implications of Generative AI in CRM. They find that GenAI-CRM integration can help reduce their customer response time, offer a dynamic layer of personalization that is not possible with traditional CRM systems, and benefit from the synthesis of knowledge from extremely large customer interaction databases that are impossible to do without AI. They also highlight key integration problems with current CRM offerings as a significant barrier to adoption, including the disconnect between the architecture of today's LLM APIs and legacy CRM database schemas and workflows. The takeaway is that AI readiness is just as much a matter of investment in infrastructure – and an often overlooked one that organizations need to consider in their adoption plans – as it is of investment in AI capability development and adopting the organizational benefits of affective CRM.

For e-commerce, Shaikh et al. (2024) give an example of how AI-CRM can impact customer service by demonstrating that affective AI, which involves adapting the product, when and how to promote it, and the tone of the product messages based on the inferred emotional state of the customers, is a qualitative leap in effective customer service in measurable terms, with increased conversion rates and customer satisfaction scores as proof. They also note that the kind of behavioural changes required in the customer service and marketing teams (for instance, being able to grasp and react to the emotions that the AI systems produce) can't be solved with technology, but with training and change management in the organization.

Cluster 3: Ethical Governance, Privacy, and Responsible AI

Cluster 3 focuses on the ethical aspects of affective computing in CRM, which have come into a new spotlight this year in light of the entry into force of the EU AI Act, more stringent GDPR enforcement procedures on biometric data processing, increasingly stronger provisions of the California Privacy Rights Act (CPRA) and the increasing awareness of the public about the dangers of emotion recognition technologies implemented in commercial environments without adequate governance structures.

The researchers, G. Hasani, N. V. K. Prasad, and C. S. Balasubramanian (2023), provide supporting empirical evidence in Cluster 3: "Privacy investment in technology companies is not just a compliance burden, but a strategic performance lever." Indeed, their research on SME adoption of Privacy Enhancing Technologies shows that businesses with low PET adoption scores significantly underperform those that have high rates of adoption in terms of customer retention, brand trust and revenue growth, making a clear business case for investing in privacy and not just for compliance. In the context of affective CRM adoption the result is significant because it changes the perspective of the "privacy by design" requirement from being an limitation on the affective capabilities to being the basis for the customer trust which would enable the affective capabilities to be effective.

Positive emotions make it easier for customers to communicate their emotions with emotion-aware service systems, which will help to better identify their emotional state, and better respond to it. Therefore, positive emotion can be said to be a good investment for emotion-CRM to be more effective.

Ortiz-Clavijo et al. (2023) provide the most comprehensive discussion about the social implications of emotion recognition technologies, suggesting that the extent to which society has been able to control the use of emotion recognition in customer service environments, like call centres, retail stores, chatbots, and video consultation, is a qualitative step up. These report the state of the art technical challenges of available emotion recognition systems, including the systematic error of these in recognizing non-Western facial expressions and non-English speech, which they claim is actively undermining unregulated commercialization of such systems and is ethically problematic. During the study period, explicit consent frameworks, independent algorithmic auditing, and dedicated regulatory oversight of commercial emotion recognition have become a strong policy component of the policy discourse and are reflected in aspects of the EU AI Act, the classification of emotion recognition applications as part of high-risk AI systems requiring conformity assessment.

The authors of Kumar et al. (2025) offer the most operationalistic directions in Cluster 3 with a thorough examination of GDPR and CCPA compliance needs specifically for AI-based CRM systems that gather and process emotional and behavioral customer data. They also rule that the specific regulations of GDPR of biometric data (which means that it is subject of special handling and can only be used for consenting purposes, and not for mere commercial interests, unless there is a legal basis to do so) also apply to emotion recognition data that is captured through facial analysis, voice print analysis, and physiological monitoring. Technically and ethically, getting real time emotional data—consensually, specifically, freely and revocably—from a customer in the middle of a customer service interaction, where there is clearly a power imbalance involved, is no easy task, especially with affective CRM deployments. Considering all the above, Kumar et al.'s proposed architecture for privacy by design as compliance approach rather than consent management as compliance approach might be regarded as a practicable guideline for organizations that wish to and are able to implement affective CRM in the compliance context.

Goel and Gendron (2024) explore empirically the critical bias dimension and how Affective CRM models perform systematically differently across various demographic sub-groups (e.g., racial, gender, age and cultural sub-groups) that could result in differential outcomes of service in CRM deployment contexts. Their findings are even more disturbing in the context of employment law (affective CRM in the customer facing workforce management world) and consumer protection law (differential treatment based on an inferred emotional state may be considered to be unlawful discrimination). There are systematic ways to counter these biases, with a need for a diverse collection of training data, cross-cultural validation, and continual monitoring of pushback in performance across demographic groups. These concerns are echoed by Morales et al. (2026) who demonstrate the solution to two of Cluster 3's challenges can also be technically sophisticated by training models on geographically-distributed and diverse data sets, while maintaining privacy without transferring sensitive data to a central entity through Federated learning.

Maheen et al. (2025) further explore the cybersecurity aspects of real-time Emotion AI systems by showing how their 'emoAIsec' approach leads to new attack surfaces, such as adversarial emotional signal manipulation (deliberate generation of false emotional signals to trigger inappropriate automated responses), model inversion attacks (reconstructing sensitive biometric features from model outputs), and data poisoning (corrupting training datasets to introduce systematic biases or backdoors into deployed emotion recognition models). These risks call for special cybersecurity procedures different from traditional CRM data security procedures and must be handled from the beginning of building the system as privacy-by-design.

Cluster 4: Emerging Technologies and Future Trajectories

Moving forward with the future of CRM, the current cutting edge (Cluster 4) is the use of Large Language Models (LLMs), Generative AI, federated learning, and next generation of multimodal architectures that now enable the technical possibilities of emotionally intelligent Customer Relationship Management. Papers in this cluster tend to have relatively low citations, because they are newer, not because they have low importance—they show a trajectory in the direction the field in general is going, and are the most indicative of medium-term development in affective CRM.

In the most comprehensive theoretical paper in Cluster 4, Zhang et al. (2026) illustrate that the use of LLMs in affective computing is a paradigm shift, not just a step toward improved performance, in the capabilities of the field. Pre-LLM emotion recognition systems were mostly extractors, meaning they fed raw multimodal signals (such as prosodic information, lexical sentiment scores and facial action units) into a model and then classified them as belonging to one of the discrete emotional categories by relying on the patterns they found in the labeled training data. LLMs, however, have been pre-trained using vast quantities of world knowledge and language reasoning, and can thus understand the semantic and pragmatic context of the emotions conveyed in a message. For instance, a user's comment: "This is exactly what I needed" could mean that they are frustrated, rather than satisfied, or a customer's complaint about an invoice error could be a financial insecurity that would necessitate the LLM's consideration of the emotion behind the complaint as well as the invoice issue. The technological blueprints in this paradigm come from instruction tuning and reinforcement learning from human feedback for creating Emotionally Competent LLMs as surveyed by Zhang et al.

To demonstrate this shift in paradigm, Verma et al. (2025) present a practical case study of emotion recognition and response generation for real-time applications with LLM. They've introduced Graph Convolutional Networks for emotional chain-of-thought reasoning, enabling the system to understand the emotional context of the entire conversation rather than just each turn; they've introduced LLM response generation which can generate contextually appropriate responses that are sensitized to emotions. The system shows that technically it is possible to have real-time operations if it is done in a controlled environment, but if some further optimizations are done then it may be possible to deploy the architecture up to the size of a very large enterprise CRM system.

In terms of recommendation systems, Yang et al. (2026) shed light on the development of LLM-based context-aware recommendation systems, demonstrating that these systems can provide recommendation results that are measurably better than traditional recommendation systems like collaborative filtering or content-based systems. The implications for affective CRM are worth noting as they highlight the importance of integrating emotional context into the recommendation logic, rather than as an additional analytical stream, by showing that it enhances both customer outcomes and the nature of the customer experience. As the research of affective computing and recommender systems is merging, it seems that one possible future trend will be the creation of more complete and integrated emotionally intelligent personalization platforms that will be able to understand the emotional state of a customer, analyse and understand the sentiment of what they are saying, predict their behaviour and then present content to them based on that. All of this within a single unified customer intelligence framework.

The RAGE-Fusion framework by Guan et al. (2026) is the most operationally-ready architecture in Cluster 1 discussed. One major practical hurdle in the deployment of affective CRM is the challenge of maintaining the consistency and reliability of the assessment of emotions in the data streams of real enterprise CRM, which varies in quality. RAGE-Fusion's reliability-aware gating mechanism directly tackles this practical challenge. RAGE-Fusion fits in between the technical aspects of the performance benefits of Cluster 1 and the operational aspects of using the work identified in Cluster 2, and is an exactly those kind of applied engineering research that is needed to accelerate the adoption of affective CRM in an organizational context.

Mariyam and Sadia (2026) present a synthesizing review of the multimodal emotion recognition approaches that confirms that there are emerging common practices in the field such as deep learning based fusion, transformer attention, multi-task learning, and unifies the field around the identified open challenges of cross-cultural validation, robustness in the real world, and efficiency. This systematic review is valuable for CRM practitioners and platform developers who are interested in assessing the current state of deployable affective computing technology, not only because of the distinction between research-ready and validated features, but also because of the systematic and validated process used to conduct this review. Cluster 4's overall result is a picture of fast technological development leading to increasingly capable affective CRM systems that also show new issues, such as computational cost, cross-cultural generalization and LLM safety, which will need ongoing research efforts to overcome.

CONCLUSION

The present paper has conducted a systematic review and bibliometric analysis of the implementation of affective computing in Customer Relationship Management (CRM) application in the period 2023-2026. A corpus of 61 peer-reviewed publications was identified after screening it using strict application of PRISMA principles in the Scopus database and through keyword co-occurrence and bibliographic coupling techniques, 4 main thematic clusters, 12 major theoretical frameworks and characteristics of the publications, geographical origins, method and outlet of this rapidly maturing field were identified. The theoretical implications, the practical implications and future research directions are presented in the following subsections and the overall conclusion of this synthesis.

Theoretical Implications

Theory is advanced in four ways in this review. First, it offers a structured form of embedding the disjointed research streams, uncovering the fact that the challenges of technical, organisational and ethical implementation are not parallel tracks but interconnected elements of a complex problem. The synthesis of these four areas of competencies shows that competencies need to be addressed in tandem to achieve affective CRM and hence organisational value.

Second, the bibliometric coupling analysis aids in the theoretical classification of the field by allowing the identification of four main groups of academic research: multimodal technical architectures, dynamics of CRM integration, ethical governance and emerging technological pathways, which help to explain the theoretical mapping of the intellectual structure of affective CRM studies and which provide a scientific basis for organizing future theoretical development. The clusters emphasize that the engineering and management science, psychology and computer ethics are all equally important and present areas of study in this field and challenge the single-discipline approach used in earlier studies. The bridges between the different clusters that were found in the collaboration analysis are particularly interesting and are authors as well as ideas that can be further explored by future researchers.

Third, this review provides an integrative sociotechnical perspective where Affective CRM implementation is seen as a challenge which is not only theory-rich but also theory-thirsty in nature and in need of a framework other than technology management to be explained. The collective learning from the Technology Acceptance Model, Privacy by Design, Trust Theory and Explainable AI frameworks provide a strong argument that implementation challenges are relational, perceptual, and cannot be addressed purely through technical means – but are rooted in human judgements of safety, control, fairness, explainability and value. The sociotechnical framing has direct implications for theory development: future affective CRM research should be planned (from the start) not to look at organizational factors as boundary conditions for technical performance, but to explicitly account for the "people" and "organizations" aspects.

Fourthly, the review sheds light on the theoretical relevance of the new paradigm shift in LLM-affective computing as a new mode of development and not mere an incremental progress. Emotion recognition was previously done using paradigms that focused on extracting features from isolated, discrete physiological data, and evaluating emotional expression as a pattern recognition problem, which could be solved with algorithm classifiers. LLM-integrated approaches, however, constitute a completely different theoretical perspective of emotion as a semantic and pragmatic phenomenon, which can only be understood within the context of the world, the need for context-dependent reasoning and the appreciation of the culture – a theoretical turn in the way emotion is perceived, as well as in the way it can be processed computationally. The consequences of this paradigm shift for the theories applied to affective CRM research are far-reaching, especially for theories which view emotion recognition as a measurement problem (as, for example, TAM's construct of perceived 'accuracy') as opposed to an interpretive problem.

Practical Implications

For CRM platform developers, technical benchmark performance is not enough, they need to make sure their systems are ready to deploy as a basic requirement, with support features for graceful degradation in the case of missing modality, XAI (eXplainable AI) features for human auditable outputs and embedded consent management and data minimisation features for GDPR/CCPA compliance. Cross-cultural robustness, as measured in technical terms and as required by law as a risk management tool, is validated in demographically diverse data sets. Evaluation benchmarks need to be developed under realistic conditions of operational CRM systems, not in clean laboratory conditions, so that performance may be meaningfully compared and research advances more quickly translated into deployable systems.

The review emphasizes that the value of the affective CRM to marketing practitioners and customer service managers critically relies on the effective human-AI synergy. However, as shown by Gaczek et al. (2023) and Verma et al. (2024), even when the emotional insights generated by AI are correct, they will be rejected and underutilized when they are not transparent, when the explanation is not clear, or if they are perceived as a threat to professional independence. The focus should be on co-design with service agent teams to improve the capacity of the AI infrastructure to communicate in a human-friendly manner, clearly define the capacity to override by an agent, who will have the final say in the decision making process; and have incremental capability rollout to build trust – a "show don't tell mentality" – by proving value before increasing the capacity of the AI to make decisions. The emotional AI literacy (understanding and critical evaluation of emotional assessment generated by AI) should be in the scope of the training programs for managers and agents.

The findings support the importance of paying attention to emotional recognition in commercial use of CRMs and offer a specific area of focus for the regulatory actions of regulators and policymakers beyond the overarching or umbrella rules on AI governance in place. The biometric nature of emotional data, the powers dynamic inherent to the commercial customer service scenarios, the well-known systematic demographic biases in existing emotion recognition models, and the novelty of the commercial risk of manipulated emotions all call for specific regulations like compulsory impact assessment prior to deployment, constant monitoring and public reporting of bias, explicit and detailed consent requirements in respect of biometric emotional data collection, and a need for access to data to be audited independently for regulatory purposes. The EU AI Act has classed some emotion recognition applications as "high risk" and this concept is a good example of a model that other jurisdictions can transfer to their own environments.

This review provides a few suggestions for methodological priorities for researchers. It requires standardized assessment techniques that can accommodate the typical characteristics of CRM data and are not based on data collected in a lab environment where it can be easily "made up to be good". This is because the existing literature on studies of affective CRM effects has been mainly descriptive or cross-sectional, with very little current empirical work focusing on the longitudinal nature of the effects of such a relationship, as trust, adaptation, and relationship quality can change over time as a human-AI relationship unfolds. In order to be able to successfully cross-culturally and linguistically generalize models of emotion recognition, there is an urgent need for cross-cultural validation studies.

Future Research Directions

Cluster 1: Multimodal Emotion Recognition and Technical Architectures. One of the gaps in the cluster is the need for a standard assessment process of affective CRM systems in actual operational environments. Current benchmark datasets (IEMOCAP, CMU-MOSI and MELD) are designed for research purposes only, and do not reflect the quality, modalities, cultural diversity, and interaction types of enterprise CRM deployments. Creating a benchmark sharing ecosystem that would ideally be co-designed with partners from the industry to be ecologically valid, would offer a solid framework for comparing performance and would encourage the quick transfer of new research findings into operational systems. There is a need to investigate low weight edge-based emotion recognition systems that can operate in the limited computational resources and latency times of SME CRM systems to bring affective CRM to the masses as well.

Cluster 2: CRM Integration, Customer Engagement and Personalization. A priority for future research is to study the organizational change management needs for successful integration of affective CRM. Well documented evidence of current implementation failures with CRM projects and specific needs and failure modes with affective CRM projects are further complicated by the need for human interaction with AI, the need for AI to collect affective data and the need to assess and understand emotion from the data. Further research on the adaptations of the role of service agents, team working and performance management that emerge in the longer-term of the affective CRM would be of value. The current literature has no study on the impact of affective CRM on customer lifetime value and long term relationship quality, both of which indicate the trust outcomes of the relationship with emotionally intelligent service.

Cluster 3: The topics of Cluster 3 are Responsible AI, Ethics of Governance, and Privacy. Future research should come with the development and its empirical validation of privacy preserving architectures of affective computing systems designed for CRM contexts. The solutions proposed by Morales et al. (2026) need to be adapted, tested and benchmarked for enterprise deployment of CRM, where there is more data and lower latency. Algorithmic bias auditing frameworks with standardized procedures to measure the emotion recognition performance gaps between the different algorithmic groups and to assess the impact of emotion recognition performance gaps on the quality of services: their mandatory use as part of affective CRM responsible deployment. The customer reactions to the affective data collection disclosures and the consent related behaviors that would be performed in response to the disclosure would support designing consent interfaces.

Cluster 4: The "Emerging Technologies and Future Trajectories" cluster groups together research projects on the evolution of technology and the possibilities for the future. The need for real-world deployment of LLM-powered affective CRM systems in enterprises to be empirically validated is pressing. Almost all literature in the current cluster 4 is proposals for architecture; with virtually all being laboratory controlled demonstration of impact. There are virtually no contributions of impact or adoption, let alone evidence of impacts in live enterprise deployments at scale, in cluster 4. Operational research testing the attributes of latency, reliability and cost of affective CRM systems powered by LLM would play a crucial role in the platform investment decision, in addition to the results from other research. Insights into customer perception of the impact of LLM-affective personalization on customer trust, customer engagement, customer privacy concerns and customer persuasion knowledge activation will be pivotal in driving a successful commercialization of LLM-affective CRM in responsible ways. An emerging frontier area for wearable biometric sensing for CRM, to continuously monitor the affective state of interactions, is however very relevant for both capability and governance and requires pre-competitive research investment.

This paper summarizes systematically and biblio-metrically the challenges for implementing affective computing for CRM platforms from 2023 to 2026 from literature. The results show that affective CRM is not just some additional technology that can be added to the existing CRM system, but a reorientation of the organizational/customer relationship where the emotional aspect becomes the basis for establishing long-term relationship, and not the effectiveness and efficiency of the transaction or the quality of the product. Together, all four of these clusters form a research program, which is conceptually interesting and challenging.

The technical-ethical duality that is at the core of affective CRM – recognising emotions at high performance and at the same time ensuring proper privacy, fairness and accountability – is not some transitional, short-term issue that will be solved as technology progresses. Emotion is a structural aspect of emotionally intelligent commercial systems that must be dedicated to for the long haul—both in institutional oversight and adaptive governance, as well as in investment in responsible AI practice. Sustainable companies in the field of engineering competency and ethical governance with empathy will be the best ones to pursue emotionally intelligent CRM as a sustainable competitive advantage. As long as people who make ethics a rule to follow will not get the respect they deserve, customers will continue to be an elusive target of any affective CRM.

It is up to future scholars to take the next step in this work, crafting rigorous empirical studies that are truly interdisciplinary and concerned with the human experiences that emotion-aware commercial systems ultimately create. Customers are not just a set of data points to be manipulated at the whim of the algorithms for personalisation—they are humans whose dignity, privacy and autonomy must be respected, even if not more, in the spaces in which they experience it, where more and more emotionally intelligent AI is at play.

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ETHICAL CONSIDERATIONS

Ethical Approval

This study was based exclusively on a systematic review and bibliometric analysis of published academic literature and bibliographic metadata retrieved from the Scopus database. It did not involve human participants, animals, experimental interventions, or personally identifiable information. Therefore, formal ethical approval was not required.

Conflict of Interest

The authors declare that there is no conflict of interest.

Data Availability Statement

The bibliographic metadata analysed in this study were retrieved from the Scopus database. The processed dataset and coding framework are available from the corresponding author upon reasonable request, subject to applicable Scopus licensing restrictions.

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APPENDICES

Table A1. Systematic Literature Review Summary of Key Studies (2023–2026)

Year	Author(s)	Title (abbreviated)	Focus	Methodology	Key Findings	Implications
2023	Hasani et al.	Privacy enhancing technology adoption and SME performance	Privacy governance	Quantitative survey	PET adoption improves SME performance significantly	Privacy investment is strategic, not just compliance
2023	Gaczek et al.	Collaboration with machines in B2B marketing	Manager adoption of AI-CRM	Qualitative/Quantitative mixed	Manager aversion to AI-CRM linked to explainability gaps	XAI is critical enabler for B2B AI-CRM adoption
2023	Ortiz-Clavijo et al.	Implications of emotion recognition technologies	Societal/ethical implications	Conceptual review	Emotion recognition requires explicit consent and regulatory oversight	Governance frameworks are needed before wide CRM deployment
2023	Ferreira et al.	Improving real estate CRM user experience	CRM UX and implementation	Case study/qualitative	UX design failures are primary CRM implementation failure driver	User-centered design essential for affective CRM success
2023	Pena et al.	Framework to evaluate fusion methods for multimodal emotion recognition	Technical: multimodal fusion evaluation	Experimental/quantitative	Hybrid fusion strategies outperform single-method approaches	Standardized evaluation critical for comparing affective CRM systems
2024	Hazmoune and Bougamouza	Using transformers for multimodal emotion recognition	Technical: transformer architectures	Systematic review	Transformers state-of-the-art but benchmark-to-deployment gap persists	Real-world robustness is the key unsolved challenge
2024	Huan et al.	UniMF: Unified multimodal framework	Technical: missing modality handling	Experimental	UniMF maintains accuracy under missing modality conditions	Graceful degradation is essential for CRM deployment
2024	Cortinas-Lorenzo and Lacey	Toward explainable affective computing	XAI for affective systems	Review	Multimodal affective models are opaque; XAI tools are insufficient	Explainability R&D is prerequisite for regulated CRM deployment
2024	Cesar et al.	Responsible multimodal sentiment analysis in marketing	Responsible AI in marketing	Systematic review	Privacy-preserving and fair sentiment analysis requires governance	Responsibility frameworks needed for commercial sentiment AI
2024	Shaikh et al.	Transforming CRM with AI in e-commerce	AI-CRM transformation	Conceptual/case-based	AI-driven personalization improves conversion rates and satisfaction	Organizations must invest in data infrastructure alongside AI

2024	Chen et al.	Emotion and sentiment analysis for intelligent customer service	Multi-task emotion/sentiment	Quantitative/experimental	Joint modeling improves accuracy and interpretive richness	Multi-task frameworks better suit CRM deployment than single-task
2024	Verma et al.	Adoption of AI in CRM: TAM perspective	CRM AI adoption	Quantitative survey	Perceived usefulness predicts adoption; techno-anxiety moderates	Organizations must address employee emotional responses to AI
2025	Kumar et al.	Data privacy, ethics, and AI in CRM	Privacy/ethics governance	Conceptual/legal analysis	GDPR/CCPA compliance requires privacy-by-design architecture	Privacy-by-design is both legal requirement and trust strategy
2025	Gracy Theresa et al.	Multi-modal emotional analysis in CRM	Multimodal CRM emotion analysis	Experimental/quantitative	Integrated affective computing improves CRM communication quality	Multimodal integration improves both detection accuracy and outcomes
2025	Kumar and Shankar	Role of GenAI-enabled CRM in achieving agility	GenAI-CRM and organizational agility	Qualitative/conceptual	GenAI-CRM reduces latency and enables at-scale personalization	Legacy integration barriers are the primary adoption constraint
2025	Goel and Gendron	Implications of affective computing for diverse populations	Demographic bias in affective AI	Empirical/quantitative	Emotion recognition shows systematic disparities across groups	Bias auditing and diverse training data are mandatory requirements
2025	Maheen et al.	emoAIsec: Emotion AI and data security	Cybersecurity for affective CRM	Design science	Affective CRM creates novel cybersecurity attack surfaces	PbD security protocols needed from system inception
2026	Zhang et al.	Affective computing in the era of LLMs: NLP survey	LLM-affective computing integration	Survey	LLMs represent paradigm shift; instruction tuning most promising approach	Next-generation affective CRM will be LLM-centered
2026	Guan et al.	RAGE-Fusion: Reliability-aware multimodal emotion fusion	Reliability in real-time affective systems	Experimental	Reliability-gating prevents false signals corrupting CRM responses	Reliability mechanisms are deployment prerequisite for enterprise CRM
2026	Morales et al.	Affective intelligent systems in healthcare: Systematic review	Privacy-preserving affective AI	Systematic review	Federated learning resolves privacy-performance tension	Federated architectures offer model for privacy-by-design affective CRM

Source(s): Authors' own work