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Systematic Review

The Integration of AI in CRM and Its Impact on Online Sales Services Profitability: A Systematic Literature Review

Khaoula Fath El Khair *, Ahmad El Oualfi, Mustapha El Hamzaoui and Miloudi Kobiyh

Laboratory of Studies and Research in Economic Sciences and Management (LERSEM), National School of Business and Management (ENCG), Chouaib Doukkali University, El Jadida 24000, Morocco; eloualfi.ahmad@ucd.ac.ma (A.E.O.); elhamzaoui.m@ucd.ac.ma (M.E.H.); kobiyh.m@ucd.ac.ma (M.K.)
* Correspondence: fathelkhair.k@ucd.ac.ma

Abstract

The rise of e-commerce is leading companies to rethink their customer relationship management (CRM), particularly through the integration of artificial intelligence (AI). AI opens up opportunities for personalization, automation, and optimization of customer interactions, potentially improving sales performance and the profitability of online sales services. This article examines, through a systematic literature review (SLR), the impact of AI integration in CRM on the profitability of online sales services. Following a rigorous selection process using the Scopus and Web of Science databases, and covering the period 2016–2026, 51 studies were selected for analysis. The results show that the integration of AI technologies into CRM functionalities has positive associations or perceived improvements, but causal evidence for profitability remains thin in all the selected studies, regardless of the geographical context, the technologies used, or the performance indicators considered. The limitations identified in the existing literature open several avenues for future research, including a more rigorous measurement of online sales profitability and improved geographical contextualization of studies.

Keywords: AI; CRM; E-commerce; online sales services; performance; profitability; SLR

1. Introduction

Digital transformation, increased competition, and demanding customers are driving e-commerce companies to rethink their management practices to meet these new requirements [1]. The rise of AI is a major driver of innovation in this regard, offering advanced data analytics capabilities, process automation, and personalized customer interactions [2,3]. These developments are gradually leading these companies to shift their CRM, traditionally focused on collecting and using customer data, toward a more intelligent, predictive, and proactive approach.

In this context, AI-driven CRM goes beyond simply adopting new technologies. This reflects a transformation of managerial and commercial practices aimed at optimizing operational processes, improving the quality of decisions, strengthening sales performance, and developing value-creating customer relationships [4]. For companies offering online sales services, this evolution represents a strategic challenge, as their profitability depends on their ability to effectively leverage AI technologies.

However, while research on AI and CRM is experiencing significant growth, knowledge remains fragmented regarding the mechanisms by which AI-based CRM improves the profitability of online sales services. Existing literature generally focuses on specific

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effects, such as improved customer experience, service personalization, and interaction automation, without always offering an integrated understanding that links these innovations to profitability. In addition, no SLR has been conducted on the impact of integrating AI into CRM on the profitability of online sales services. Therefore, our article aims to explore this impact by:

- Identifying the AI technologies most used in CRM;
- Analyzing the effects of this integration on the performance and profitability indicators of online sales services;
- Comparing the empirical results obtained in previous studies;
- Highlighting the limitations of existing research and future directions.

Regarding the contributions of this article, from a theoretical standpoint, it enriches the existing literature by revealing theoretical and methodological gaps that need to be addressed. From a managerial perspective, it offers practitioners in the online sales sector a set of operational benchmarks based on the literature. It enables managers and CRM professionals to identify the technologies best suited to their strategic priorities and to guide their technology investment decisions accordingly.

This article is organized as follows:

✓ The literature review presents the key concepts of the study;
✓ Methodology adopted;
✓ Findings of the SLR;
✓ Discussion;
✓ Conclusion of the study and its limitations.

2. Literature Review

2.1. AI Technologies

Mukhamediev et al. [5] highlight that AI relies on a set of technologies capable of replicating certain human cognitive functions. The first technology is machine learning (ML), defined as a set of computational methods that use data to make accurate and efficient predictions [6]. It combines computer programming and statistics to establish various types of learning processes. The second technology, known as Natural Language Processing (NLP), enables machines to understand, interpret, and manipulate human language in both written and spoken forms [7]. Its primary goal is to develop systems capable of effectively analyzing, understanding, and generating natural language, allowing computers to perform tasks such as translation, question answering, and sentiment analysis in a manner closely resembling human capabilities [8].

Another major technology is computer vision, which aims to equip machines with the ability to automatically acquire, process, and interpret visual information from images or videos [5]. It seeks to replicate human perception by enabling the 3D reconstruction of scenes, the tracking of moving objects, and the detection and recognition of visual features such as faces or clothing items [9].

Meanwhile, expert systems are knowledge-based computer programs designed to replicate the reasoning of human experts in order to solve specific [5]. Unlike traditional software, which is limited to processing raw data, these systems manipulate structured knowledge to draw conclusions or propose solutions. They rely on knowledge bases derived from human expertise and on inference engines capable of applying logical rules to simulate the decision-making process [10].

Robotics represents another important facet of AI. By combining perception, planning, and action, it enables machines to interact directly with their environment [5]. Intelligent

robots and autonomous vehicles are prime examples, as they simultaneously employ multiple AI technologies to make real-time decisions and act autonomously [11].

2.2. Integrating AI into the CRM

AI is playing an increasingly important role in organizational processes and is being integrated into several business services [12], particularly CRM [13]. In this regard, Ledro et al. [13] emphasize that CRM aims not only to attract new customers but also to establish and maintain long-term relationships with them. According to these authors, companies rely on various CRM-related activities, such as the collection, management, and use of customer data, enhanced by the use of technological solutions to achieve these objectives. In this sense, they argue that AI is a promising technology, particularly due to its machine learning (ML) and deep learning (DL) capabilities, which enable learning from data, pattern recognition, and decision-making with limited or even no human intervention.

At this stage of AI integration in CRM, Mullangi et al. [14] highlight that this integration enables:

- The personalization of customer experiences by analyzing large amounts of data from digital interactions, including social media, browsing habits, and purchase history. This analysis generates strategic insights that allow for tailored recommendations to be suggested based on individual needs.
- The promotion of predictive analytics by leveraging past data to anticipate market trends, identify new opportunities, reduce risks, and improve companies' ability to adapt to changes in the competitive landscape.
- The automation and optimization of processes through tools such as chatbots and virtual assistants. These handle repetitive tasks, manage high volumes of requests, and free up sales teams to focus on higher-value activities, such as building trust with customers and prospects.
- The analysis of customer sentiment using NLP techniques involves examining feedback expressed on various platforms (social media, emails, surveys). This analysis provides companies with valuable information to better understand consumer expectations, assess brand perception, and adjust their communication strategies.
- Adherence to ethical and transparent principles helps build lasting trust with customers.

In summary, the integration of AI into CRM results in a wide range of applications, from advanced customer data analysis to chatbots and virtual assistants, personalized recommendations, sentiment analysis, computer vision, speech recognition, and predictive analytics [13].

2.3. Digitalization as a Factor in Profitability

Gbadamassi [15] emphasizes that digitalization is a major strategic lever for improving business profitability. First, he argues that integrating digital technologies increases organizational agility, optimizes internal processes, and enhances adaptability in the face of a dynamic competitive environment. In this regard, McKinsey [16] observes that companies that successfully navigate this transition generally achieve superior financial performance due to improved operational efficiency and increased responsiveness.

Second, Gbadamassi [15] demonstrates that digitalization fosters value creation by expanding revenue generation opportunities. Thus, the development of digital services, the personalization of offerings, and the improvement of the customer experience directly contribute to revenue growth. However, this transformation requires significant investments, both in technology and human resources, as well as an adaptation of organizational structures and management practices, which can pose a challenge for some companies. Third, Brynjolfsson and McAfee [17] emphasize the importance of adopting emerging

technologies such as AI, big data, blockchain, and the Internet of Things in boosting profitability by enabling more efficient data utilization and increased process automation. These tools facilitate reduced operating costs, improved product and service quality, and more informed decision-making. By leveraging these technologies, companies can improve their overall efficiency and support sustainable growth.

2.4. Key Indicators of the Profitability of Online Sales Services

Profitability indicators are ratios used to assess a company's ability to generate profits at a satisfactory level [18]. Within this framework, the literature highlights a set of key indicators commonly used to analyze company profitability. These indicators are applied to the profitability of companies offering online sales services, including the following:

- Net profit margin measures the percentage of revenue remaining after accounting for all expenses incurred by the company, including costs and charges [19]. A high level of this indicator generally reflects better overall performance [20].
- Basic earnings capacity illustrates the company's ability to generate profits from all its assets and is calculated by dividing total profit before interest and taxes by total assets [21]. A high level of this ratio is generally interpreted as a favorable sign for the company [20].
- Return on Assets (ROA) is used to assess the company's ability to generate profits from all of its assets, regardless of its financing structure. It thus evaluates the efficiency of using available resources to generate revenue [22]. A high ROA reflects efficient capital management and greater value creation [23].
- Return on Equity (ROE) assesses the profitability of the capital provided by shareholders; it measures the company's ability to generate profits from invested equity [21]. Furthermore, this indicator is obtained by dividing net income by the average value of shareholders' equity. Therefore, a high ROE reflects enhanced performance, indicating efficient use of owners' capital [21].
- Return on investment (ROI) is a ratio of net income to capital investments. It measures a company's ability to repay long-term investors and its capacity to attract future investors [24].

2.5. Profitability and Performance

According to Issor [25], performance is not an absolute or universal concept; rather, it is generally defined as the degree to which a company achieves its objectives relative to the efforts expended and resources mobilized. It relies primarily on the concepts of effectiveness (referring to the achievement of set results) and efficiency, which measures the ability to optimize resource use in producing those results. In this context, various studies highlight profitability as a key indicator for assessing an organization's overall performance, as it reflects how effectively committed resources are used to generate economic results [26].

Furthermore, performance encompasses several complementary dimensions, including economic aspects (such as competitiveness), financial aspects (profitability), legal aspects (solvency), organizational aspects (efficiency), and social aspects. This perspective underscores the multidimensional nature of performance and confirms that profitability is merely one component among many, closely linked to the company's various forms of performance [25]. From this standpoint, financial performance is reflected notably in the organization's ability to achieve the level of profitability expected by shareholders, while maintaining sufficient revenue and market share to ensure its long-term viability [25].

3. Materials and Methods

Unlike traditional literature reviews [27], SLRs are based on a rigorous methodological approach structured in several steps, highlighting the most relevant ones:

- Definition of objectives and the research question;
- Determination of the literature search;
- Identification of eligibility criteria and selection of studies;
- Data extraction.

To improve the quality, transparency, and reproducibility of this SRL, we followed the PRISMA guidelines.

3.1. Definition of Objectives and the Research Question

Our SRL focuses on the impact of integrating AI into CRM on the profitability of online sales services. Through this study, we aim to:

- Identify the AI technologies most commonly used in CRM;
- Analyze the effects of this integration on the performance and profitability metrics of online sales services;
- Compare the empirical results obtained in previous studies;
- Highlight the limitations of existing research and future directions.

Thus, to meet the objectives of this RSL, the main research question can be formulated using the following PEO (Population, Exposure, and Outcome) framework:

✓ P (Population): online sales services;
✓ E (Exposure/Environment): the integration of AI into CRM;
✓ O (Outcome): profitability and performance.

This PEO framework helps clarify the essential dimensions of the study and structure the formulation of the research question [28]. Consequently, the central question guiding this SRL is: "What does the literature reveal about the integration of AI into CRM and its impact on the profitability and performance of online sales services?"

3.2. Determination of the Literature Search

This phase involves identifying databases relevant to the literature review and defining keywords for searching these sources [29]. Based on this, we chose to conduct our literature review in the Scopus and Web of Science databases because their rigorous evaluation procedures ensure that only high-quality articles are included [30,31].

Regarding the keywords used, our search is based on a search equation constructed from the keywords, using logical operators (AND/OR) to optimize the literature review process. This search equation is formulated exclusively in English as follows: ("Artificial Intelligence" OR AI OR "Machine learning" OR ML OR "predictive analytics" OR NLP) AND ("Customer Relationship Management" OR CRM OR "Customer satisfaction" OR "Customer Analytics") AND (Profitability OR "business performance" OR "Financial performance") AND ("Online sales" OR "E-commerce" OR "Digital sales").

In Scopus, the equation was applied to the TITLE-ABS-KEY field (title, abstract, keywords); in Web of Science, it was applied to the TS/Topic field, its functional equivalent. We applied identical filters to both databases: publication period from 2016 to May 2026, document type restricted to articles and conference proceedings, and English language.

It should be noted that our literature search was conducted between March and May to ensure the reproducibility of the results, given that the databases were being continuously updated during this period.

3.3. Identification of Eligibility Criteria

The robustness of an SRL is closely linked to the quality of the studies examined [32]. For this reason, defining eligibility criteria is essential. These criteria are divided into two types: inclusion and exclusion criteria. Generally, each systematic review is based on specific objectives and research questions; consequently, its inclusion and exclusion criteria are defined specifically to meet these objectives [33]. Table 1 presents the eligibility criteria selected to narrow the scope of the research and ensure its rigor:

Table 1. Eligibility criteria adopted.

	Inclusion Criteria	Exclusion Criteria
Document type	The studies are peer-reviewed and published in journals or conference proceedings indexed in the Scopus or Web of Science databases.	The studies are not peer-reviewed and are not published in journals or conference proceedings indexed in the Scopus or Web of Science databases.
Language	English	Languages other than English.
Time Period	2016–2026 (from January to May of 2026)	Studies outside of this period.

According to this table, we included only peer-reviewed studies published in journals or conference proceedings indexed in the Scopus and/or Web of Science databases, in order to ensure the quality and reliability of the research. Thus, only studies written in English were included, while those published in languages other than English were excluded. The decision to limit inclusion to studies published over the past decade is justified by the fact that the integration of AI into CRM practices and e-commerce began to become widespread starting in 2016 [34,35].

3.4. Selection of Studies

The overall literature selection process is illustrated in Figure 1, outlining the different phases of identification, pre-selection, eligibility, and inclusion of references. This diagram represents the information flow through each stage of the literature review, specifying the number of articles identified, included, and excluded, as well as the reasons justifying these exclusions.

According to this figure, the collection of bibliographic data began with the Scopus database, from which our search yielded a total of 38 results. Applying the pre-selection criteria regarding language of publication, document type, and the time period under consideration allowed us to identify 32 articles deemed potentially relevant.

The same process was carried out using the Web of Science database, which yielded 102 initial results. After applying the same eligibility criteria, 70 articles were retained at the end of this filtering phase. Thus, the preselected corpus, drawn from both databases, consists of 102 articles.

All these articles were imported into the bibliographic management software Mendeley, which automatically identified and removed 24 duplicates between Scopus and Web of Science based on metadata (title, authors, publication year, DOI), resulting in 78 unique articles. The titles and abstracts of these articles were then reviewed by the first author to assess their thematic relevance based on the following exclusion criteria: articles not addressing AI-based CRM, articles focusing exclusively on offline sales, and articles addressing neither profitability nor performance indicators. This screening led to the exclusion of 16 articles, leaving 62 articles selected for full-text reading.

During the full-text reading phase, the eligibility of each article was independently assessed by two authors based on the following criteria: coverage of AI-based CRM, mention of profitability and/or performance indicators, and explicit inclusion within the online sales domain. Failure to meet even one of these criteria resulted in the article's exclusion. Cases of disagreement between the two reviewers were submitted to a third author for arbitration, with the final decision confirmed by a fourth author. At the end of this stage, 11 articles were excluded for failing to meet at least one of the inclusion criteria, resulting in a final corpus of 51 articles selected for analysis.

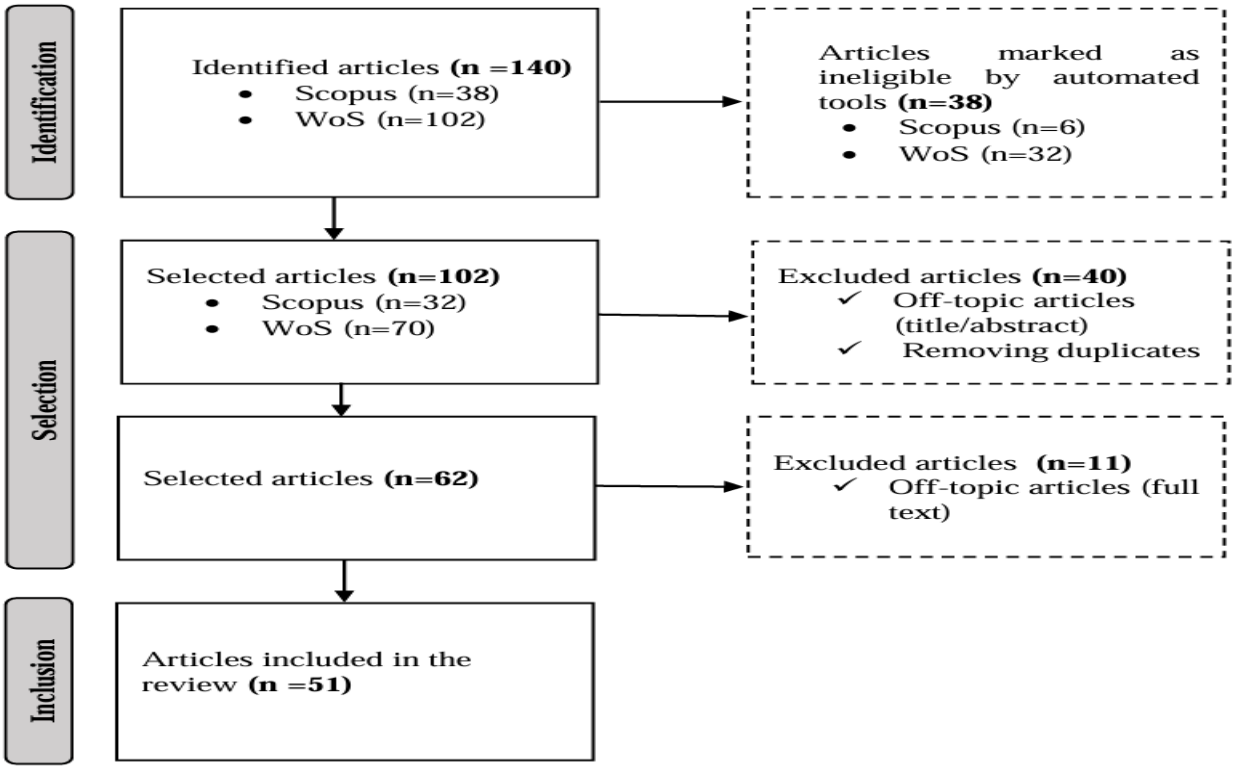


Figure 1. PRISMA Flowchart of the article selection process.

3.5. Data Extraction

Following the selection process, a final corpus of 51 articles was compiled to conduct this review. To rigorously synthesize the contributions of each study and identify the elements necessary to answer the research question, a structured data extraction phase was carried out.

This extraction is based on a pre-defined analytical framework, the dimensions of which were established in accordance with the objectives of this review. The data collected for each selected study relates to the following queries: the authors' identity and year of publication, the publication title, the preferred methodological approach, the geographical area studied, the AI technologies used in the CRM framework, the targeted CRM functionalities, the performance and/or profitability indicators used, as well as the main results obtained and the limitations identified by the authors.

This systematic approach ensures the consistency and comparability of the extracted data across the entire analyzed corpus.

3.6. Quality Assessment

This study employed a modified version of the Mixed Methods Appraisal Tool (MMAT) to assess the methodological quality of the 51 included studies. This tool considered four criteria: the clarity of the research question, the applicability of the methodology,

the comprehensiveness of data collection, and the relevance of the results. Each criterion was evaluated on a three-level scale (high, medium, low) based on factors such as the study design, the precision of the AI techniques employed, the description of data collection procedures, and the clear presentation of results regarding profitability and performance. The overall quality level of each study was determined according to the criteria assessment rules. A study was classified as "low" if all four criteria were rated "high," "medium" if at least one criterion was rated "low," and "medium" otherwise. Based on this classification, 14 studies (27.5%) were considered high-quality, 31 studies (60.8%) medium-quality, and 6 studies (11.8%) low-quality. In accordance with MMAT recommendations [36], this study used the quality score to assess the robustness of the evidence in the narrative analyses rather than as an exclusion criterion. Six studies rated as lower quality were retained because their shortcomings were limited to one or two criteria (primarily inaccuracies regarding AI technologies and a lack of primary data collection in conceptual or review articles), while their research topics were clearly defined and directly relevant to the relationship between AI-based CRM and e-commerce profitability. Consequently, the contributions of these studies were considered conceptual or contextual rather than substantial empirical evidence.

4. Results

Following the data extraction phase, graphical representations are crucial for exploring our corpus and interpreting it according to the defined queries. These representations are processed in Excel, except for word clouds, which are processed in Python 3.6. It should be noted that all the articles selected during the review process focus on the integration of AI into CRM, specifically within the context of online sales services, with particular attention paid to profitability and/or performance.

4.1. Query 1: Structural Characteristics of the Corpus

The first representation concerns the temporal distribution of the publications constituting the corpus, in relation to the problem of this research, namely the integration of AI into CRM in the context of online sales services, with attention paid to profitability and/or performance. Figure 2 illustrates this distribution.

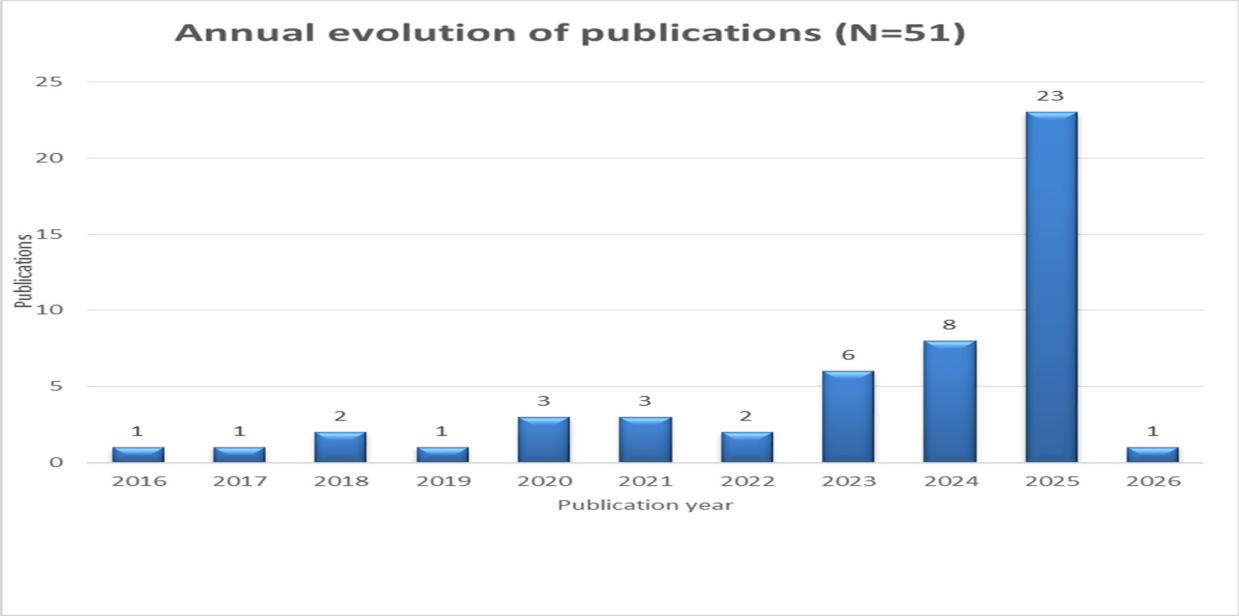


Figure 2. Annual evolution of publications.

Figure 2 shows that scientific output on this topic remained particularly limited between 2016 and 2022. A modest increase is nevertheless observable in the two subsequent years. In contrast, 2025 stands out with a significant growth in the volume of publications, surpassing all previous years. The decline observed in 2026 is attributable to the fact that data collection took place between March and May of that year; the corpus therefore reflects only a portion of the annual scientific output.

The second representation focuses on the typological distribution of the articles constituting the corpus, in order to identify the dominant methodological nature of the selected works. Figure 3 illustrates this distribution.

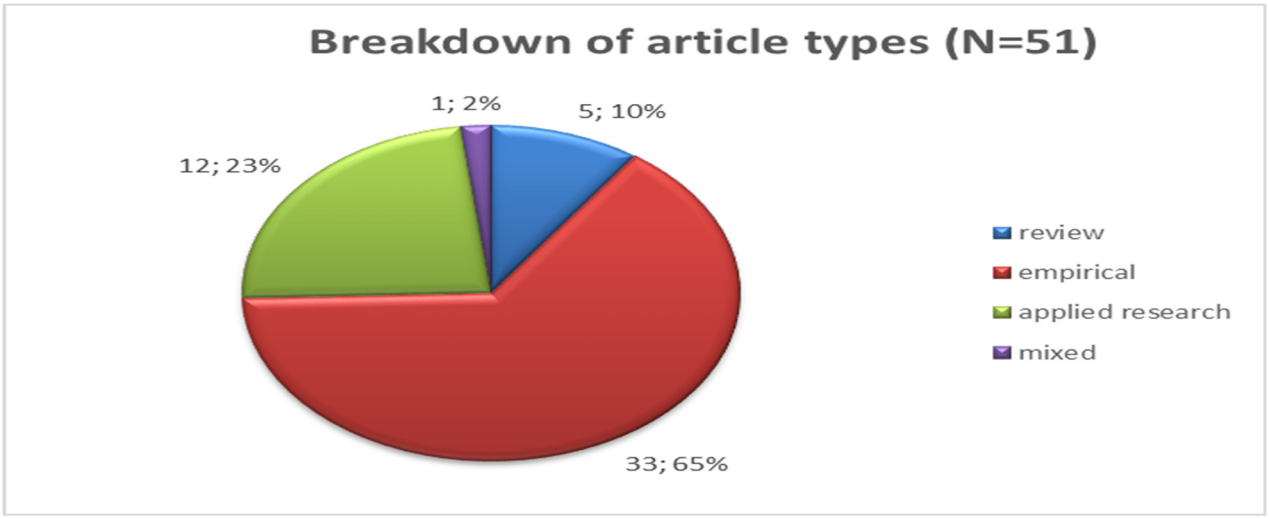


Figure 3. Distribution of selected article types.

According to this figure, empirical studies represent the majority category, comprising 65% of the corpus, followed by applied research at 23%. Review articles remain in the minority at 10%, while mixed-methods articles are almost absent, representing only 2% of all publications included.

The third representation concerns the diversity of geographical areas covered by the studies constituting the corpus. Figure 4 illustrates this distribution.

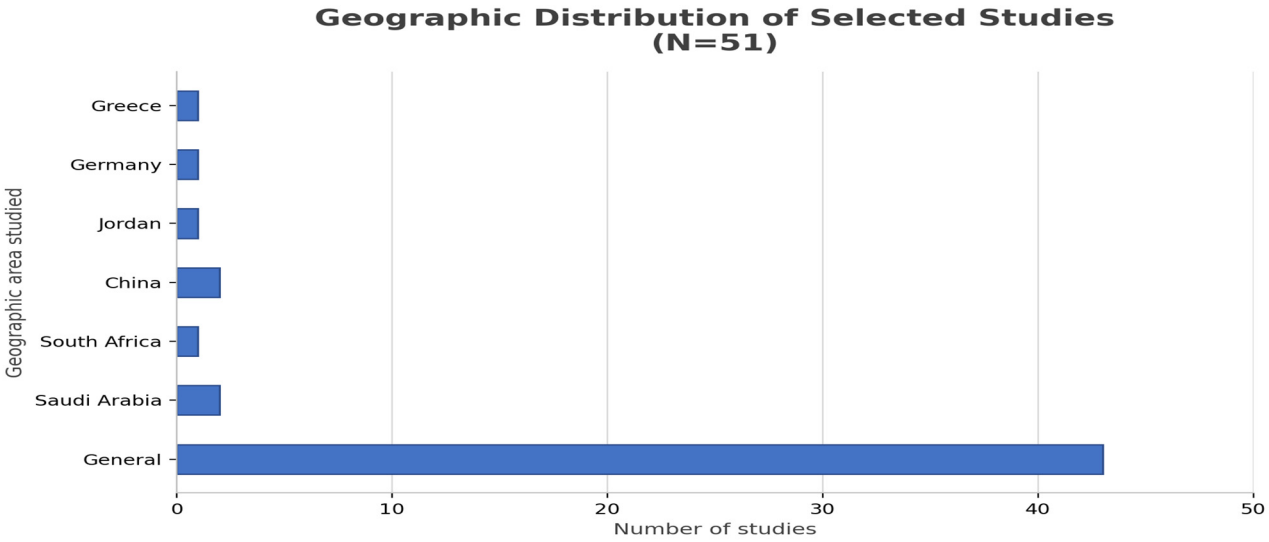


Figure 4. Geographical distribution of the selected studies.

Figure 4 highlights that the majority of the selected studies do not specify an explicit geographical framework, thus adopting a general perspective that is not territorially contextualized. Only a few works explicitly identify their context of investigation, primarily located in Saudi Arabia and China.

4.2. Query 2: AI Technologies Deployed

Since AI is a central element of this issue, analyzing its distribution within the corpus is essential to identifying the AI technologies most frequently used in the selected studies. Figure 5 illustrates this distribution.

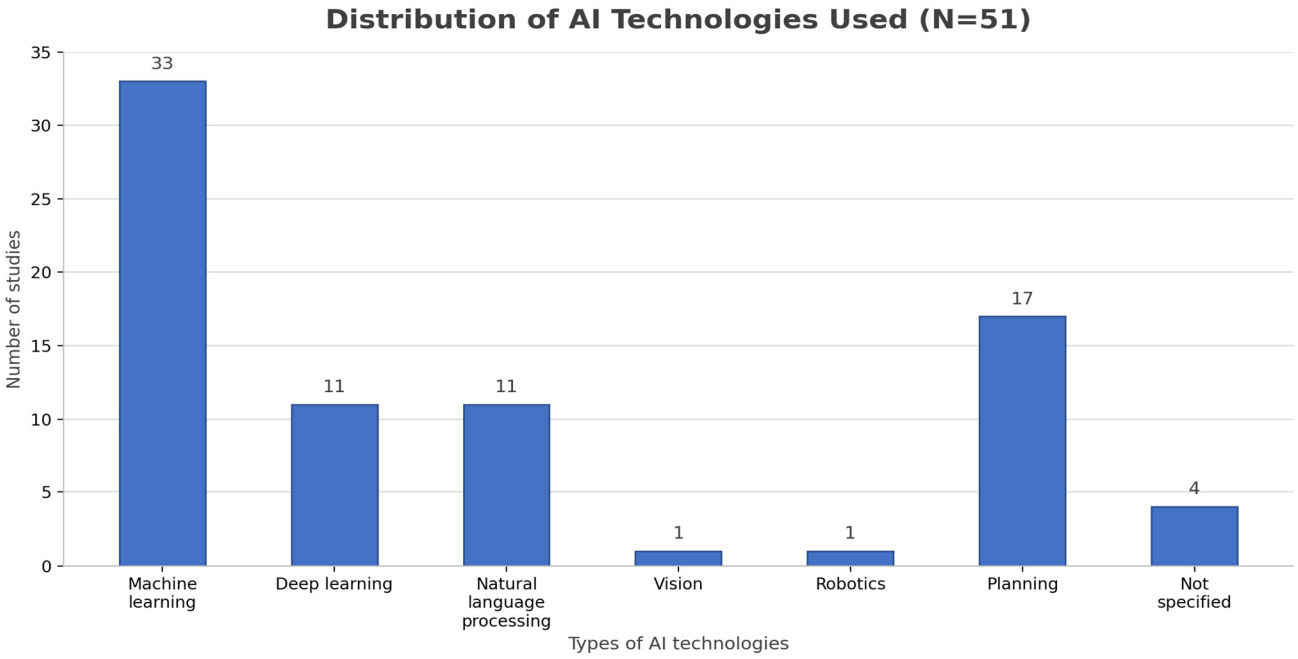


Figure 5. Distribution of AI technologies used in the selected studies.

According to this figure, we observe that ML is the most dominant technology, used in 42.3% of the studies, through various techniques such as clustering, classification, data sheets, association rules, segmentation, and automation. It is followed by planning technology, which encompasses techniques geared towards prediction and dynamic pricing. DL and NLP also occupy a significant place, the former being primarily represented by neural network architectures, and the latter by sentiment analysis, text analysis, and chatbot techniques. In contrast, computer vision and robotics technologies remain underrepresented in the corpus. Furthermore, a portion of the selected studies do not specify the AI technology used, thus treating it as a general term.

4.3. Query 3: Targeted CRM Functionalities

Since CRM is central to this research, exploring the most relevant CRM functionalities within the selected studies is of paramount importance. Figure 6 illustrates the distribution of these functionalities within the chosen corpus.

Figure 6 highlights three particularly dominant functionalities, totaling 52 occurrences, or 41% of all studies: marketing decision support (23), customer behavior analysis (17), and customer segmentation (12). Other functionalities, representing 27% of the corpus with a total of 34 occurrences and an individual distribution ranging approximately from six to eight, include: customer identification, personalized dynamic pricing, customer service automation, offer personalization, and customer data analysis.

Finally, several functionalities remain marginally represented in the selected studies, totaling 32% of the corpus with an individual distribution of five occurrences or fewer. These include, in particular, sales and demand forecasting, identification of at-risk customers, etc.

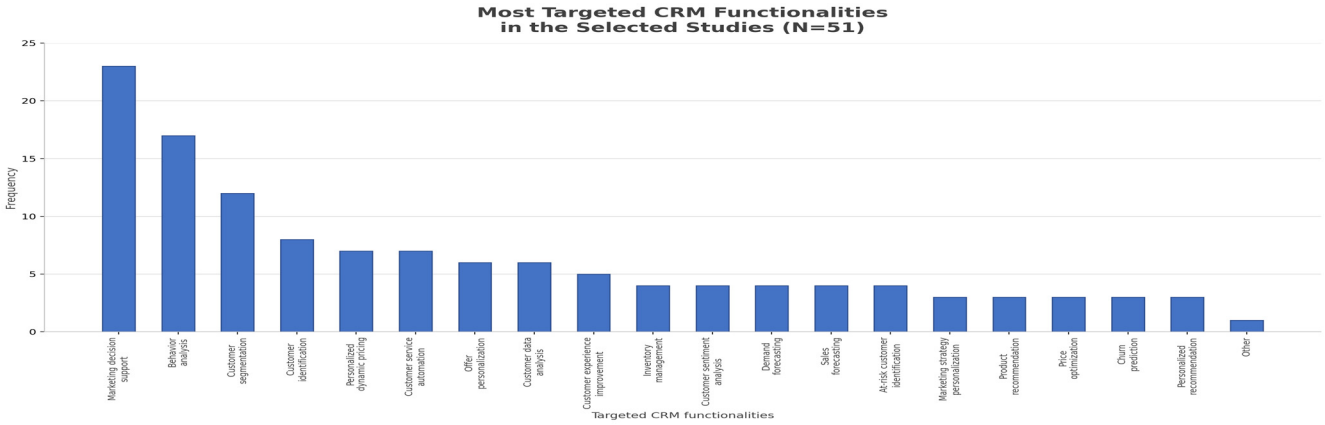


Figure 6. Distribution of CRM functionalities targeted by the selected studies.

4.4. Query 4: Profitability and Performance Indicators

Profitability is the central dependent variable in this research, and its operationalization necessarily relies on the use of measurable indicators. Figure 7 illustrates the distribution of these indicators within the selected studies.

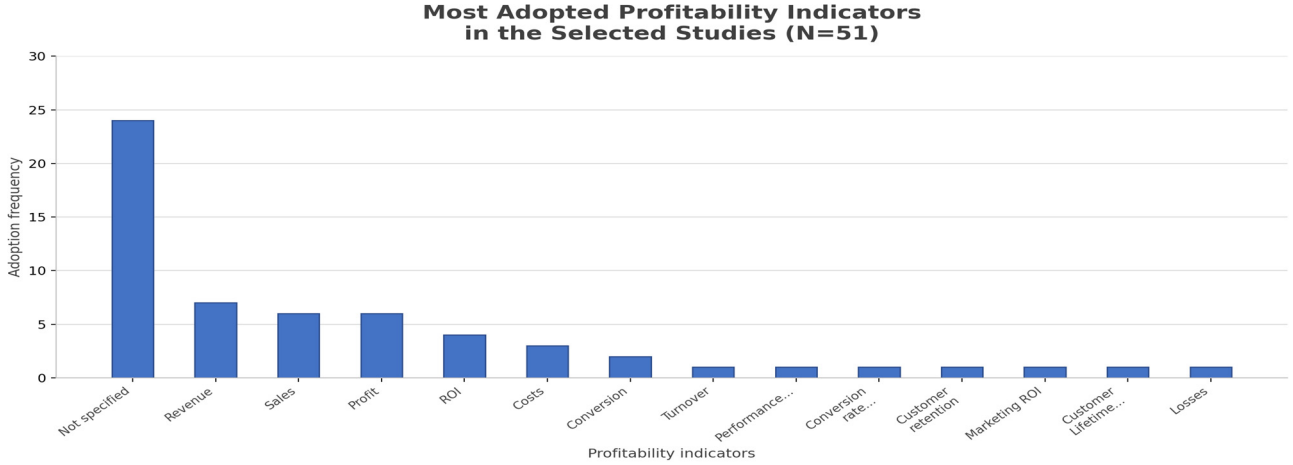


Figure 7. Profitability indicators adopted by the selected studies.

Figure 7 indicates that 41% of the studies do not specify profitability indicators. Nevertheless, among the studies that operationalize this variable, revenue, sales, and profit emerge as the most frequently used indicators within the selected corpus.

Regarding performance indicators, they were integrated into the corpus selection criteria to address the underrepresentation of studies using profitability indicators. Figure 8 illustrates the distribution of these indicators within the selected studies.

This figure reveals that customer satisfaction, loyalty, and engagement are the most frequently adopted performance indicators, representing 71% of the selected studies. Furthermore, the proportion of studies not specifying their performance indicators remains significantly lower than that observed for profitability, not exceeding 3%, compared to 41% for profitability. This finding demonstrates a greater availability and better use of performance indicators in the selected scientific literature, compared to studies focusing specifically on profitability.

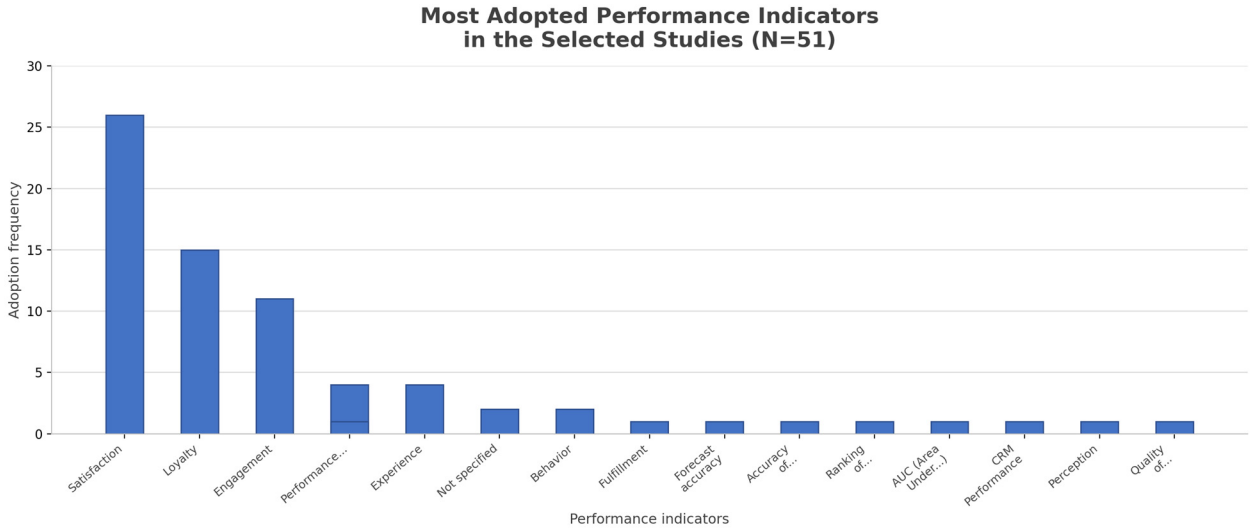


Figure 8. Performance indicators adopted by the selected studies.

4.5. Query 5: Results Found and Limitations Identified

Manual analysis of the results from the selected studies generally reveals a positive associations or perceived improvements, but causal evidence for profitability remains thin. Because these results were extracted in uncoded text format, a word cloud presentation was deemed appropriate, allowing for the identification of the most frequently cited words within the query corresponding to the study results. Figure 9 illustrates this distribution.

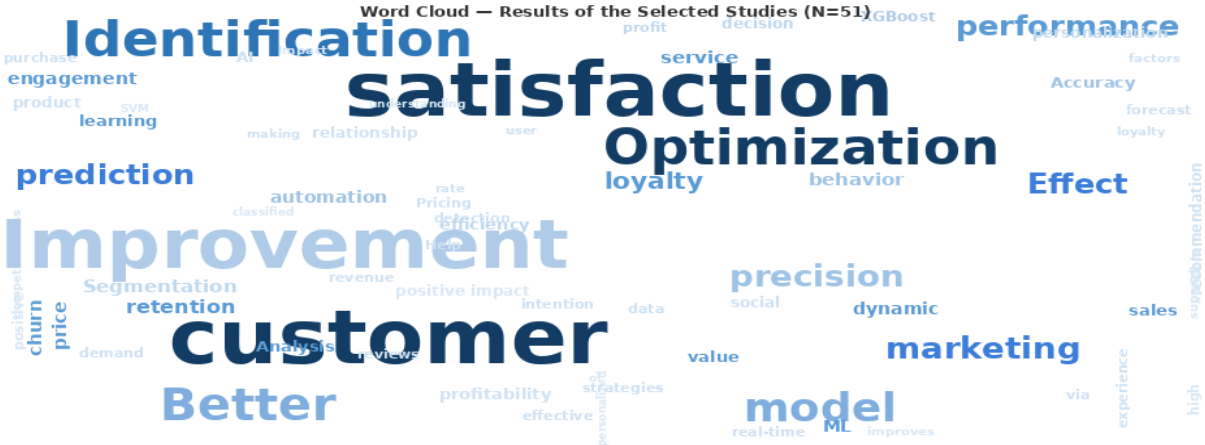


Figure 9. Word cloud of results from the selected studies.

Figure 9 highlights a visual hierarchy of terms based on their frequency of occurrence, reflected in each word's size, color intensity, and position. At the center of the word cloud, the term "Improvement" appears with the largest font size, indicating its lexical predominance within the corpus, while "Positive Impact" appears in smaller type. In the upper part, the terms "satisfaction," "optimization," and "identification" stand out due to their size and color, which are sufficiently visible to demonstrate their significant recurrence. In the lower part, the words "customer," "better," and "marketing" are clearly legible. Furthermore, the term "performance" is more visible than "profitability," confirming the observations made during the interpretation of the indicators. Finally, the terms "precision," "prediction," and "model" appear with a similar size and color, but their legibility remains limited due to their low color intensity.

Thus, a manual review of the limitations declared by the selected studies reveals that a significant proportion of these works do not explicitly mention their limitations. For the

studies that do state limitations, the same word cloud approach was adopted to identify the most frequent occurrences. Figure 10 illustrates this lexical distribution.



Figure 10. Word cloud of limits from the selected studies.

Based on this figure, we observe three major recurring limitations within the corpus:

- The first concerns the data, which manifests itself either through its declarative nature, limited sample size, or issues related to data security and confidentiality.
- The second limitation relates to the context, which is addressed in a general way in the majority of the selected studies, without specific geographical or sectoral focus.
- The third major limitation is the limited generalizability of the results, stemming largely from the two previous constraints.

Furthermore, difficulties related to the technical integration of AI constitute a limitation noted in several studies. Finally, concerns regarding price fairness, as well as the skills of the employees involved, are also identified as constraints affecting the implementation and validity of the results.

5. Discussion

The results presented above cover all the dimensions necessary to answer the central research question of this RSL: "What does the literature reveal about the integration of AI into CRM and its impact on the profitability and performance of online sales services?" The analysis of the corpus queries thus makes it possible to provide structured elements of an answer, which this section proposes to discuss in light of the existing literature.

5.1. Discussion of Query 1

Analyzing structural characteristics is an essential prerequisite for understanding the composition of our corpus.

Regarding the temporal distribution of the 51 selected studies, we observed a predominance of publications in 2025, following a marked scarcity of work before that period. This recent concentration can be explained by the increasing technological maturity of AI, the growing interest of researchers in AI applications for online sales services, the acceleration of scientific production resulting from the democratization of AI tools, and other factors. The single publication identified for 2026 is explained by the fact that the literature search only covered the period between March and May of 2026, as this review itself was still being written at that time. It would therefore be methodologically unsound to conclude the volume of publications for that year.

Regarding the typology of the articles, the corpus presents a diversity of research types, including empirical studies, applied research, literature reviews, and mixed-methods studies, with a predominance of empirical studies. In this context, it is important to emphasize that the articles comprising the corpus do not necessarily establish a causal relationship between the integration of AI in CRM and the profitability of online sales services. However, they are all relevant, insofar as each contributes, directly or indirectly, to highlighting the research question of this review.

As for the geographical distribution of the studies, the analysis reveals a scarcity of works grounded in specific geographical contexts. This suggests that researchers should prioritize studies conducted in a specific geographical area rather than general studies, given that each area has its own cultural, economic, and regulatory specificities that may influence the relationship under investigation.

5.2. Discussion of Query 2 and Query 3

Analysis of the selected corpus reveals that ML is the most frequently used AI technology in studies addressing CRM in the context of online sales. This dominance can be explained by its ability to effectively address key CRM functionalities, particularly classification, clustering, and decision-making process automation techniques, making it a technology particularly well-suited to the operational needs of online sales services [37]. However, robotics and computer vision remain the least integrated technologies in the selected studies, which can be explained by several converging factors. On the one hand, these technologies remain underdeveloped in customer service, despite significant progress in other sectors such as healthcare, and face resistance to acceptance from both customers and staff [38]. On the other hand, the literature on robotics in customer service remains scarce and fragmented. Consequently, its true impact and application methods in customer relations remain largely unknown, which itself constitutes an obstacle to its adoption [39].

Regarding the CRM functionalities targeted by this technological integration, marketing decision support appears to be the most frequently addressed functionality in the selected studies. This finding is not surprising given that CRM is, by origin, structurally oriented towards marketing [40]. This functionality utilizes a variety of AI technologies, including ML, NLP, planning, and DL. Customer behavior analysis is the second most represented functionality in the corpus, primarily implemented through ML techniques. Thus, customer segmentation is well documented and relies on the same technological foundations. These CRM functionalities allow companies to identify, understand, and target their customers more precisely [41], which is a lever for optimizing revenue and, by extension, online sales profitability [42].

In short, the integration of AI into CRM is characterized by the predominant adoption of technologies such as ML, Planning, NLP, and DL, primarily used to support marketing decision-making, behavioral analysis, and customer segmentation. Conversely, robotics and computer vision remain the least represented technologies, as do several CRM functionalities that are still only marginally addressed in the AI literature.

5.3. Discussion of Query 4 and Query 5

According to the selected studies, the integration of AI into CRM is assessed through several profitability and performance indicators to detect its impact on the profitability and/or performance of online sales services.

Although our research question initially focused on the profitability of online sales services, the limited number of studies specifically addressing this variable led us to broaden the scope of the analysis to include performance. This choice is justified by the explicit link between profitability and performance [43,44]. In fact, 41% of the selected

studies do not specify any profitability indicators, which justifies the use of performance indicators to fill this gap in the literature.

In this context, the selected studies primarily utilize profitability indicators such as revenue, sales, and profit, while the literature highlights other indicators considered equally relevant, such as net profit margin, basic profit capacity, ROA, and ROE [19,45,46]. This discrepancy between the results obtained and the literature can be explained by the fact that the majority of indicators adopted by the selected studies are neither precisely measurable nor quantifiable.

Regarding performance indicators, the selected studies frequently use satisfaction, loyalty, and engagement. Other indicators, although considered relevant in the literature, are rarely used in the selected studies, particularly those specific to the online retail sector, such as traffic indicators and operational and financial efficiency [47].

The findings indicate that the majority of the selected studies do not use quantified and measured profitability or performance indicators, but rather treat them either as empirically unverified assertions or as unquantified descriptive observations.

Although none of the selected studies address the causal relationship between AI integration in CRM and the profitability and/or performance of online sales, and although most do not measure the impact of this relationship, all the results show a positive associations or perceived improvements, but causal evidence for profitability remains thin: improvement, satisfaction, loyalty, optimization, performance, profitability, accuracy, or prediction. This result holds true regardless of the type of product, the geographic area studied, the AI technologies integrated, the targeted CRM functionalities, and the profitability and/or performance indicators used. The literature relating to the same online sales context confirms this result [48–50]. However, several studies report limitations primarily related to the data used, the study context, and the generalizability of the results, as well as analytical limitations related to technical integration, employee skills, and price fairness. This finding aligns with that established in the literature, which identifies limitations related to data confidentiality and ethics as the most frequently raised [34,51–54] followed by difficulties in technical integration [34,53], then limitations related to staff skills [51] and the high cost of AI [54].

5.4. Implications and Limitations of Our SLR

This review makes several theoretical contributions to the field of research on the integration of AI in CRM and its impact on the profitability and/or performance of online sales services. First, it provides a structured overview of the state of the art in the AI technologies most commonly used in CRM, the CRM functionalities most targeted by these technologies, and the profitability and performance indicators most frequently adopted to explore this impact. Second, this review highlights several discrepancies between the results of the selected studies and the existing literature, particularly regarding the profitability and performance indicators used. Far from being a limitation, these discrepancies enrich the existing literature by revealing theoretical and methodological gaps that need to be addressed.

From a managerial perspective, this review offers practitioners in the online sales sector a set of operational benchmarks based on the literature. It enables CRM executives and managers to identify the technologies best suited to their strategic priorities and to guide their technology investment decisions accordingly. Furthermore, identifying the most frequently used profitability and performance indicators in the literature provides practitioners with a measurement framework to rigorously assess the impact of AI integration on the profitability of their online sales services. This review also draws decision-makers' attention to the main obstacles to the effective integration of AI in CRM, including data

privacy and ethical issues, technical integration challenges, and the high cost of these technologies. In this regard, it underscores the strategic importance of investing in employee training and developing AI-related skills.

This review has several limitations. First, restricting the search to Scopus and Web of Science and to English-language publications may have introduced selection bias and excluded relevant studies. Second, most included studies address profitability and performance indicators conceptually or descriptively rather than through rigorous quantitative measurement; relatedly, none establish causality, and study quality varies considerably (MMAT: 27.5% high, 60.8% medium, 11.8% low). Third, the categorization of AI technologies remains broad and prone to confusion; future research would benefit from a more granular coding system distinguishing AI techniques, applications, and CRM functions. Finally, no formal assessment of reporting bias or overall evidence certainty (e.g., GRADE) was conducted, and data extraction was performed by a single author without independent double-extraction.

6. Conclusions

To conclude this section, this review set out to answer the following question: what does the literature reveal about the integration of AI into CRM and its impact on the profitability and performance of online sales services? Following a rigorous selection process conducted across Scopus and Web of Science, covering the period from 2016 to May 2026, 51 studies were retained for analysis. The results show that the integration of AI technologies into CRM functionalities is associated with predominantly positive outcomes, or perceived improvements, across most of the reviewed studies, irrespective of geographical context, the AI technologies employed, or the indicators selected. This convergence must, however, be interpreted with caution: the majority of studies do not operationalize profitability or performance indicators in a rigorously quantified or measured manner, and none establish a formal causal relationship between AI-enabled CRM and these outcomes, limitations that considerably temper the robustness of the conclusions that can be drawn. These gaps point to several avenues for future research, notably the development of more rigorous, quantified measures of online sales profitability, greater geographical contextualization of empirical studies, and research designs capable of establishing causal, rather than merely associative, evidence.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
CRM	Customer Relationship Management
DL	Deep Learning
ML	Machine Learning
MMAT	Mixed Methods Appraisal Tool
NLP	Natural Language Processing
PEO	Population, Exposure, and Outcome
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
ROA	Return on Assets
ROE	Return on Equity
ROI	Return on investment
SLR	Systematic Literature Review

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