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Setting B2B digital marketing in artificial intelligence-based CRMs: A review and directions for future research

Jose Ramon Saura [a,*], Domingo Ribeiro-Soriano [b], Daniel Palacios-Marqués [c]

[a] Rey Juan Carlos University, Madrid, Spain
[b] University of Alcalá, Madrid, Spain
[c] Universitat Politècnica de València, Valencia, Spain

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ABSTRACT

The new business challenges in the B2B sector are determined by connected ecosystems, where data-driven decision making is crucial for successful strategies. At the same time, the use of digital marketing as a communication and sales channel has led to the need and use of Customer Relationship Management (CRM) systems to correctly manage company information. The understanding of B2B traditional Marketing strategies that use CRMs that work with Artificial Intelligence (AI) has been studied, however, research focused on the understanding and application of these technologies in B2B digital marketing is scarce. To cover this gap in the literature, this study develops a literature review on the main academic contributions in this area. To visualize the outcomes of the literature review, the results are then analyzed using a statistical approach known as Multiple Correspondence Analysis (MCA) under the homogeneity analysis of variance by means of alternating least squares (HOMALS) framework programmed in the R language. The research results classify the types of CRMs and their typologies and explore the main techniques and uses of AI-based CRMs in B2B digital marketing. In addition, a discussion, directions and propositions for future research are presented.

1. Introduction

The B2B ecosystem has undergone important changes in the last decade linked to the development of new technologies and process automation (Lages, Lancastre, & Lages, 2008). One of the most relevant changes has been the implementation of techniques and software that use Artificial Intelligence (AI) to increase the optimization and efficiency of the processes carried out through intelligent agents or systems (Davenport, Guha, Grewal, & Bressgott, 2019; Martínez-López & Casillas, 2013).

The new business challenges are determined by connected ecosystems (Saura, 2021), where data analysis is crucial for successful strategies and where AI plays a relevant role (Duan, Edwards, & Dwivedi, 2019). In this business context, the importance of a correct implementation and use of Customer Relationship Management (CRMs) is vital for business success, since data-driven decision-making processes are increasingly common (Dwivedi et al., 2021; Grover, Kar, & Dwivedi, 2020).

To date, CRMs have been extensively used to date to organize processes (Kim & Kim, 2009), execute logistical orders (Bull, 2003), obtain inventory product and service information (Rigby & Ledingham, 2004), communicate with suppliers and wholesalers (Hung, Hung, Tsai, & Jiang, 2010), perform automated marketing (Rigby, Reichheld, & Schefter, 2002), or collect data (Ribeiro-Navarrete, Saura, & Palacios-Marqués, 2021).

However, the constant use of tools linked to social networks (Duan et al., 2019), interactions with customers and suppliers in digital ecosystems (Dwivedi, Kapoor, & Chen, 2015) or the identification of new opportunities (Dwivedi, Papazafeiropoulo, Ramdani, Kawalek, & Lorenzo, 2009) has made B2B companies focus their attention on the implementation of artificial intelligence-based CRMs in B2B digital marketing (Zhang, Wang, Cui, & Han, 2020). Furthermore, there is a lack of scientific literature that studies the correct application of these AI strategies when talking about B2B digital marketing and CRMs.

In this way, the increased need for large-scale data processing resulting from the digital marketing strategies that companies carry out in B2B environments (Gordini & Veglio, 2017), and which has boosted the use of AI tools that are added to conventional CRMs, makes it possible to extract insights and create knowledge that companies can use to improve their digital performance and relationship with their

* Corresponding author.
E-mail addresses: joseramon.saura@urjc.es (J.R. Saura), domingo.ribeiro@uah.es (D. Ribeiro-Soriano), dapamar@doe.upv.es (D. Palacios-Marqués).

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customers (Lages et al., 2008; Piñeiro-Chousa, López-Cabarcos, & Ribeiro-Soriano, 2021).

Nevertheless, AI, despite its potential and benefits for companies, is complex in technical and implementation terms. Authors such as Martínez-López and Casillas (2013) indicate that the use of artificial intelligence-based CRMs in B2B can contribute to (i) business intelligence decisions, (ii) competitive intelligence, and (iii) knowledge discovery and management.

As noted, although the use of CRM in B2B marketing has been studied and discussed previously (Jabbar, Akhtar, & Dani, 2019; Pathak, Ashok, & Tan, 2020), there is a gap in the literature (Lilien, 2016) regarding the identification of the uses that artificial intelligence-based CRMs can specifically bring to the B2B digital marketing ecosystem (Herhausen, Miočević, Morgan, & Kleijnen, 2020; Kannan & Hongshuang, 2017). For example, Martínez-López and Casillas (2013) approach the use in B2B systems using AI in traditional B2B marketing. However, the identification of specific uses and techniques in the B2B digital marketing environment with the use of AI focused on CRMs is missing in the scientific literature.

In this research, therefore, we rely on the theoretical framework that identifies the use of the typology of three types of CRMs that can work with AI: analytical CRM (Xu & Walton, 2005), collaborative CRM (Alavi, Ahuja, & Medury, 2012), and operational CRM (Iriana & Buttle, 2007). These CRMs in B2B digital marketing can apply AI to improve data processing and the identification of new patterns by analyzing user data in digital environments (Saura, Palos-Sanchez, & Blanco-González, 2019). The novelty of the present study lies that, despite the exponential development of AI and its emerging application to various production environments, none of the previous studies has addressed the issues in B2B digital marketing.

Therefore, to cover the problems raised above, we intend to answer the following research question (RQ):

RQ1. *What are the main applications and uses of AI-based CRMs in B2B Digital Marketing strategies?*

Focusing on this perspective of analysis, this research aims to answer the following objectives:

- Identify the main uses and techniques of AI-based CRMs in B2B digital marketing using Multiple Correspondence Analysis (MCA) developed in R.
- To provide future guidelines to develop strategies based on AI-based CRMs in B2B digital marketing

To meet the objectives set, this research develops a systematic review of the literature to identify the main contributions to date in the subject of study. The results are analyzed by applying the statistical analysis known as MCA in the programming language R, to represent the results visually and identify correlations between them and thus define unique results for this study. A discussion and future research directions in this area are then presented.

The remainder of this manuscript is structured as follows: Firstly, the theoretical framework is presented, followed by the research methodology. Secondly, the analysis of results is presented, followed by a discussion. Finally, the conclusions of the research are presented, taking into account the practical and theoretical implications of the research.

2. Theoretical framework

2.1. AI-based CRMs functionalities and characteristics

The development of the B2B business ecosystem has been identified through AI and automation opportunities towards connected business models (Ferasso, Beliaeva, Kraus, Clauss, & Ribeiro-Soriano, 2020). We are in a digital era where data provides competitive advantages and added value. Therefore, one of the ways to identify these opportunities is through the use of CRM that works with any form of AI (Castelo-Branco, Cruz-Jesus, & Oliveira, 2019). If these CRMs in B2B are applied to digital marketing strategies, the functions and utilities are multiplied (Deb, Jain, & Deb, 2018).

AI-based CRMs are systems that include customer relationship management tasks, usually focused on commercial management, marketing, and after-sale service or the traditional customer service. However, in the last decade, with the addition of elements that work with AI to automate processes, digital ecosystem analysis, prediction and forecasting, and the client behavior's study using data analysis and customer experience algorithms, these systems have evolved and become more sophisticated (Chatterjee, Nguyen, Ghosh, Bhattacharjee, & Chaudhuri, 2020; Chatterjee, Tamilmani, Rana, & Dwivedi, 2020).

CRM should be understood as a strategic concept, not a technological one (Wright, Stone, & Abbott, 2002). Although it is true, CRMs are applications in which the final objective is to optimize the satisfaction of clients, partners, or suppliers, with the aim of increasing solid and loyal relationships through the use of intelligent management systems (Choudhury & Harrigan, 2014).

Authors such as Faase, Helms, and Spruit (2011), identify that three fundamental pillars characterize CRMs, which are (i) technology, (ii) processes, and (iii) human resources. The processes must be implemented as structural changes oriented to satisfy more quickly the needs of the clients, and the human resources strategies must be centered on involving the workers so that they understand which are the tasks of the human resources. However, in this research, it is focused on the technology pillar as a fundamental theoretical basis (Fournier & Avery, 2011).

In recent years, the use of CRMs in companies has considerably evolved (Nitu, Tileaga, & Ionescu, 2014). At first, these systems were used only to organize customer information (Bohling et al., 2006). Due to the development of new technologies and the database storage capacity, as well as the increase of the amount of data from customers (Wahab, 2010), CRMs acquired new functionalities focused on the management of the interaction processes between the company and its customers. In addition, in the B2B ecosystem, when the interaction with the customers increases, so do the data that can be analyzed with different tools. Therefore, at this point, the technology and use of new innovations allow CRMs to evolve in order to acquire different types of management and functionalities (Nitu et al., 2014).

A CRM is capable of collecting all types of information regardless of the channel used to do so (Wright et al., 2002). Technology in CRMs provides competitive advantages and authors such as Bahari and Elayidom (2015) argue that, with the use of AI, optimization processes are more effective, and therefore, the identification of trends and patterns is considerably intensified.

There are examples such as Deb et al. (2018) in which the use of data automation with CRMs is studied, also studies in which AI in CRM is presented in the B2B sector (Paschen, Kietzmann, & Kietzmann, 2019). However, it is still unknown how companies in the B2B sector should develop their digital marketing strategies using the different forms of AI in these intelligent management systems.

Therefore, within the main characteristics of CRMs, we must emphasize that they are intelligent systems that allow the establishment of business intelligence strategies for the exploitation and analysis of customer information, as well as the activity concerning a product or service (Ferasso et al., 2020). Each one of the processes is generated through digital or traditional channels, in which information is extracted and the actions that the business strategy defines are developed.

The main research works analyzed in this field and focused on CRM analysis identify three main typologies of these applications and all of them can be implemented in digital marketing ecosystems. These are analytical CRM, operational CRM, and collaborative CRM (See Table 1).

Table 1
AI-based CRMs functionalities.

Type	Functions	Authors
Analytical CRM	■ Construction of purchase affinity models ■ Identification of potential clients and leads ■ Capturing customer interactions (customer journey) ■ Identification of the most profitable customer segments ■ Analysis of customer affinities ■ Adequacy of the product portfolio ■ Automation of communication actions ■ Improved relevance and timelines ■ Collecting user-generated content (UGC) or data (UGD)	Nemati, Barko, and Moosa (2003) Xu and Walton (2005) Gončarovs (2017) Liu (2019) Harrigan, Miles, Fang, and Roy (2020) Saura et al. (2021a)
Operational CRM	■ Information integration and automation ■ Interaction with the rest of the organization's systems ■ Support to the main business processes ■ Sales automation ■ Collection of customer information. ■ Management of incidents, complaints and claims, shipment status, collections, etc. ■ Planning marketing, sales, or customer service campaigns. ■ Return of Investment (ROI) measurement	Teo, Devadoss, and Pan (2006) Alavi et al. (2012) Liu (2015) Cao and Tian (2020)
Collaborative CRM	■ Integration of communication customization resources ■ Knowledge of customer behavior patterns ■ It is the strategic basis for development in CRM ■ Aligns information sources for all departments ■ Establishes two-way communication addresses	Iriana and Buttle (2007) Alavi et al. (2012) Geib, Kolbe, and Brenner (2006) Dubey, Sharma, and Sangle (2020)

Source: the authors.

2.2. CRMs uses by type of CRM

In addition, of the main types of CRM that exist, these can be complemented according to the way they are implemented in companies (Wright et al., 2002). In this way, On Premise CRMs are those CRMs that are created, personalized, and structured for large companies that have the capacity and need to develop management platforms for their information (Harrigan et al., 2020). This type of CRM also tends to have a great cost for companies. Therefore, the configuration is personalized, and the data can be extracted in different ways and adapted to any type of server that databases that the company wants to implement within this system (Harrigan, Soutar, Choudhury, & Lowe, 2015).

On the other hand, there also exist CRM On Demand systems that offer standard functionality and data management and work in a cloud-connected ecosystem (Gurău, Ranchhod, & Hackney, 2003). The customization and implementation as well as the maintenance of the data can have specific peculiarities and characteristics. In this type of system, the operation is by subscription and each subscription can add new blocks of analysis, intelligence, or sales, among others.

So far, it has been possible to identify the main functions performed by intelligent systems such as CRMs in B2B marketing (see Table 2), although the relevance of the study environment of B2B strategies in digital marketing has yet to be defined if it is referred about activities linked to artificial intelligence (Ransbotham, Khodabandeh, Fehling, LaFountain, & Kiron, 2019).

The digital marketing ecosystem has consolidated itself as a market

Table 2
AI uses of CRMs by type of CRM.

Type	Main AI uses	Type of B2B CRM
Chan and Ip (2011)	■ Predict customer purchasing behavior ■ Estimate the net customer lifetime value ■ Decision models that optimally solve the production lot-size/scheduling problem	On Demand
Chen and Chen (2008)	■ Maximizing the profit and other quantifiable measures such as minimizing inventory investment and storage capacity ■ Encompasses the main relevant business processes.	On Premise
Laínez et al. (2010)	■ Applies s data mining techniques ■ Enables descriptive data-driven models to obtain for the marketing activities ■ Develops an intelligent system that supports the marketing strategy process. ■ Logical process for strategic analysis	On Premise
Li (2000)	■ Support Group assessment of strategic marketing factors ■ Helps managers to deal with uncertainty and fuzziness. ■ Produces intelligent advice on setting marketing strategy	On Premise
Li and Li (2009)	■ Supports the process of marketing strategy and decision making	On Demand On Premise
Li and Li (2010)	■ Develops a multi agent-based hybrid system for international marketing decision-making.	On Premise
Metaxiotis et al. (2002)	■ Develops an expert system that helps to schedule the production ■ Develops a model that simulates the decision-making process	On Premise
Cruz (2009)	■ Measures how companies perceive, analyze and consider the market's ■ How they learn from their experiences and modify their beliefs.	On Demand

Source: the authors.

in which business models focus on B2C as well as B2B, companies are finding opportunities to increase the profitability of their actions by analyzing large amounts of data (Järvinen, Tollinen, Karjaluoto, & Jayawardhena, 2012). Overall, digital marketing has become a data-centric ecosystem where understanding the customer journey and customers are critical to understanding sales or new lead acquisition opportunities (Hossain, Akter, Kattiyapornpong, & Dwivedi, 2019; Saura, 2021).

Thus, Table 2 shows the main AI uses of CRMS, which will serve to understand which of these applications can be improved (Syam & Sharma, 2018), with the implementation in digital marketing ecosystems.

The strategies that companies can develop in B2B using digital marketing are diverse (Harrigan et al. (2020). For example, the use of digital platforms and websites allows to understand how users behave in these channels; understand the audience and provide personalized results with their interactions (Kumar, Mangla, Luthra, Rana, & Dwivedi, 2018); perform audience retargeting on different platforms (Saura, Palacios-Marqués, & Iturricha-Fernández, 2021); develop search engine optimization (SEO) (Saura, 2021); integrate traditional communication actions and digital ecosystems in the intelligent system to extract insights (Crittenden, Crittenden, & Crittenden, 2019); increase the visibility in social networks to capture new audiences (Smith, 2011); click advertising campaigns (PPC) in social networks or search engines or social ads and social selling in social media (Herhausen et al., 2020).

Finally, it should be noted that the main objective of these strategies in B2B is to create a funnel in the AI-based CRMs to understand how future customers interact step by step with the customization strategies and content published by the company (Busca & Bertrandias, 2020). But, what are the main digital marketing techniques used in B2B when working with AI-based CRMs?

3. Methodology

3.1. Systematic literature review

This study proposes the development of a systematic review of the literature. Systematic reviews are characterized by finding the answers to questions posed by researchers (Wang, Shen, Wang, Yang, & Liu, 2019). In this way, authors such as Webster and Watson (2002) and Stieglitz, Mirbabaie, Ross, and Neuberger (2018) or Saura (2021) indicate that first a theoretical framework that highlights the theory and previous studies in the industry studied is needed. Later, the research problem is formulated, and proposals are presented to cover a gap in the literature, understanding that the main academic contributions to date in the chosen field of study are identified. With this objective, it is presented the theoretical framework of the research that is linked to the proposed objectives, is explained which is the gap that is intended to be covered and it is identified which is the emerging theme that drives the use of this methodology (Bem, 1995).

As argued by Stieglitz et al. (2018), the emerging issue that a systematic review must justify is the need to understand such topic and its contributions to the industry, which makes the systematic literature review an ideal methodology to understand emerging research objectives. In the present study, the application and use of AI-based CRMs in the B2B digital marketing ecosystem were studied as an emerging topic. In this way, our literature review, as a methodology that studies emerging issues, may offer benefits to future research (Bem, 1995). The study of new applications in different industries through the use of a literature review defines and identifies new contributions to the literature.

In order to structure the review process, the structure proposed in Stieglitz et al. (2018) and have been followed. The methodological approach is therefore structured in three parts. In the first of these, the main theoretical contributions that support the proposed problems are analyzed and defined. In this way, using the process of a systematic review the study will identify the existence of techniques and uses related to AI-based CRMs in B2B digital marketing.

Supporting the findings in the research question and the established objectives, the review is used to classify the identified contributions in three typologies of CRMs: (i) Analytical CRM, (ii) Operational CRM and (iii) Collaborative CRM. In addition, the results are classified into uses of B2B traditional Marketing or B2B digital marketing, to understand what the uses of AI in B2B digital marketing may be when companies use CRMs that work with such technology.

Secondly, the systematic review identifies relevant studies linked to the subject matter of the study. In this step, it is appropriate the use of the relevant academic databases that bring together the main contributions in the field of study. In this research, the databases used were ACM Digital Library, AIS Electronic Library, IEEE Explore, ScienceDirect, and Web of Sciences. These databases were selected following the contributions of Stieglitz et al. (2018) and Saura (2021) when developing research within the area of business, marketing, information sciences, and computer sciences.

The searches carried out in the databases were as follows using boolean operators, as it is a standard approach in literature reviews appraches (Bem, 1995): "CRM AND B2B" OR "Customer relationship management AND B2B" OR "CRM AND B2B AND artificial intelligence" OR "CRM AND B2B AND AI". The queries were done between November 4 and December 15, 2020. The Title, Abstract and Keywords sections were used to filter the content of the articles that are included in the results. (Section 4.1).

Finally, in the third step of the research development, the main contributions that can be analyzed with different qualitative, quantitative, exploratory, or descriptive approaches are presented (Bem, 1995). In this way, the main contributions are identified, and the findings and purposes proposed by each study are analyzed in depth and linked to the proposed objectives.

3.2. Multiple correspondence analysis developed in R

In order to statistically represent the results of the systematic literature review, a Multiple Correspondence Analysis (MCA) has been developed using the programming language R. R is an open source statistical programming language that has aroused the curiosity of researchers for its flexibility and adaptability to research (Morandat, Hill, Osvald, & Vitek, 2012; Ramlall, 2016).

Authors such as Ihaka and Gentleman (1996) indicate that R is a language used for data analysis and graphics with the aim of consistently representing statistical computing and graphics generation. In addition, Ferraro and Giordani (2015) indicate that it is a powerful tool for both large and small samples because of its ability to identify patterns and adapt the results statistically to the objectives of the research (Wagner, Miller, & Garibaldi, 2011).

Therefore, using R as the vehicular language, the results of the systematic literature review applying MCA have been analyzed. MCA is a statistical approach that visually summarizes more than two categorical variables in a database. It can also identify which are the main components of analysis in different categorical variables that are not quantitative, as is the case in this research (Kiessling, Vlačić, & Dabić, 2019).

MCA is used in academic research mainly to group individual variables together and find associations between different variables (Wagner et al., 2011). Following this premise, we apply these considerations to the present research and compute the relationships between the variables that compose the sample in the MCA process (see Gonzalez-Loureiro, Dabić, & Kiessling, 2015). Overall, the MCA analysis offers a graphic visualization of the relationships between the results of the review in groups of words and their relevance measured in the proximity between them (Abdi & Valentin, 2007). Therefore, the categorical variables in the present study were selected based on the review and taking into account the number of times that they are repeated, relevance attributed to them, and a direct link to the purposes of the present study.

According to Abdi and Valentin (2007), MCA can be used to generalize the main components of the current topic when categorical variables (rather than quantitative ones) are used. Morover, Kaciak and Louviere (1990) highlighted that MCA can be used to explore the relationships between one or more variables, which could be of empirical interest to other researchers in the future.

In this way, following the indications for the development of MCA using R, categorical variables are established that are codified as each of the contributions identified in the systematic review of the literature. Then, variables are recognized as keywords that appear in the identified research. MCA under the framework of homogeneity analysis of variance by means of alternating least squares known as HOMALS analysis (Gonzalez-Loureiro et al., 2015; Kaciak & Louviere, 1990; Kiessling et al., 2019) allows a value of "1" to be entered when the keyword is found in relation to a subject, in this case, the study found in the literature, and the value "0" otherwise. It should be understood that the two dimensions together provide an interpretation in terms of distances (Kaciak & Louviere, 1990).

When computing the study with R the MCA analysis, it is obtained relative variables to chi-square, *p*-value, variance, % of the variance and cumulative percentage of variance (Ihaka & Gentleman, 1996). Chi-square is a statistical test used to determine whether there is a significant difference between an expected distribution and an actual distribution. Variance is the squared deviation of a variable from its mean. It measures the spread of random data in a set from its mean or median value (Soetaert, Petzoldt, & Setzer, 2010). The percentage of variance and cumulative percentage of variance measure the accumulative percentage of the cumulative input parameters that exist in the database.

Lastly, *p*-value is the probability that when the null hypothesis is true, the statistical summary is equal to or greater than the actual observed results and in HOMALS analysis is used to test the accuracy of the display of the variables that are part of the study (Gonzalez-Loureiro et al., 2015; Kiessling et al., 2019; Soetaert et al., 2010).

4. Analysis of results

4.1. Systematic literature review results

This research develops a database-oriented approach considering all articles published and indexed in the ACM Digital Library, AIS Electronic Library, IEEE Explore, ScienceDirect, and Web of Science databases. After performing the searches indicated in section 3.1., the results were as follows: ACM Digital Library 6 results, included in study 1; AIS Electronic Library 38 results in total, included in study 6; IEEE Explore 88 results in total, included in study 2; ScienceDirect 59 results in total, included in study 9 and finally Web of Sciences 30 results in total, 12 included in the study. Therefore, from a total of 221 studies, 34 studies that meet the selection criteria are included in the final sample.

Concerning the selection criteria, after the first search, inappropriate or non-inclusive terms were identified and a total of 91 articles were eliminated, so the potentially suitable articles were in this step of the filtering process of 131 articles. Of these 131 articles, after the analysis of the full articles, non-inclusive objectives, non-direct relationships with the field of study, quality assessment, and description and specification of terms, the number of articles eliminated was 101.

The final sample of articles included in the systematic review was 30 articles (see Table 3) in which the authors, the title of the article, the journal and its category are shown. It is interesting to note that the categories that include the journals that publish the selected articles are mainly business, marketing and management, information sciences and computer sciences. Both categories of research highlight the use of technology in business and marketing, as well as the discipline of information sciences. This explains the need to manage the information of the companies in a digital way, as well as the improvement in the marketing decision making using computer sciences tools.

In the following step of the systematic review of literature, the 30 articles are in depth examined according to its purpose and the main concepts which are analysed (See Table 4).

Furthermore, Table 4 presents a classification of the contents that appear in the selected articles. Firstly, the classification is presented based on the type of CRM that is used (Analytical, Collaborative or Operational). Likewise, it is categorized if the strategies and actions studied are made from a traditional or digital marketing perspective. In this sense, the actions developed in each CRM according to the type of approach of traditional or digital B2B marketing are considered.

Additionally, in Table 4, there is a column in which is presented the main concepts analyzed in the selected articles. This classification is intended to give an idea of the main factors that act as variables in the performance of traditional/digital B2B marketing using CRMs.

Then, from these functions are selected those that use AI as a channel for the development or enhancement of strategies. This step allows us to understand the possibilities of action that the AI based CRMs have in the selected articles.

4.2. Multiple correspondence analysis (MCA) and homogeneity analysis of variance by means of alternating least squares (HOMALS)

For the development and analysis of MAC under the HOMALS framework developed in R, this study relies on the research of Kaciak and Louviere (1990), Gonzalez-Loureiro et al. (2015) and Kiessling et al. (2019).

HOMALS is a procedure used in order to build a matrix from data (Furrer, Thomas, & Goussevskaia, 2008; Hoffman & De Leeuw, 1992; Hoffman & Franke, 1986). This analysis was initially computed with SPSS software, but has later evolved into different programming and statistical software languages. HOMALS proposes that the results can be represented as a dimensional map where the keywords are depicted in two axes and where the positions represent an actual distance between the pairs of keywords in terms of their association (Furrer et al., 2008).

While known as MCA in research, HOMALS theoretically justifies conducting an exploratory statistical analysis to analyse the descriptors that appear closer in a graphical map; this approach has been emploted in several previous studies (Gonzalez-Loureiro et al., 2015; Kiessling et al., 2019) mining that such pairs will have been associated jointly in a relevant portion of articles. Likewise, if such descriptors appear separate, there is no linkage between them (Hoffman & De Leeuw, 1992). In this way, Hoffman and Franke (1986) proposed that possible gaps and cluster indicators in the literature can be identified by measuring the distance between the classified variables (D'Esposito, De Stefano, & Ragozini, 2014).

For the correct performance of MCA, categorical variables which are codified as the contributions identified in the the systematic literature review are established. These categorical variables are structured as groups of keywords that form multivariate groupings of categories. In total this study is composed of 6 multivariate groupings and 21 individual variables. In turn, each of the 30 investigations identified as a result of the systematic review of literature are individual variables that are represented visually as a result of the application of MCA and HOMALS using R. These groupings of variables are also known as the dimensions of the graphic representation model (Kiessling et al., 2019).

In this way, the first category is formed by CRM Analytical, CRM Operational or CRM Collaborative, as different authors highlighted the relevance of the different types of CRMs (Saura et al., 2019). The grouping is formed by B2B traditional marketing or B2B digital marketing, since large differences can be found in the uses of AI-based CRMs in both ecosystems (Lipiäinen, 2015). The next category is formed by the grouping of words related with any form of AI and is titled as AI, Machine Learning, Big Data, Data Sciences, among others (see also Saura, 2021).

Another variable is the one that corresponds to actions developed with the CRM as keywords such as the following: sales-based CRM, Sales forecasting, Social CRM, Post-sale service, Loyalty-Inbound and Behavioral Response (see Zhang et al., 2020). The following one is formed by the grouping of variables as Information Communication, Relationship Marketing, e-Business model, Innovation and Digital Communication, as these variables have been identified as relevant variables in previous research (see Wongsansukcharoen et al., 2015; Teo et al., 2006; Petrović, 2020). Finally, the variable formed by Metrics Indicators, Decision-making and Knowledge Management have been identified as important for the present research purpuses following Nguyen, Sherif, and Newby (2007a, 2007b) and Paschen et al. (2019).

As mentioned above, the variables that form the keyword groups have been identified in the selected research as relevant to the study (Kiessling et al., 2019). In this way, when computing the study, the variables related to chi-square, *p*-value, variance, % of variance and cumulative percentage of variance are measured. In this research, the chi-square of independence between the two variables is equal to 378,8669 and the result for ρ-value is 1, meaning that if the results of chi-square is greater than the critical value calculated from df $=$ (row$-$1) (colum$-$1) degrees and $p = 1$, then the row and the column variables are not independent from each other. This implies that the variables are associated (see Figs. 1 and 2). The Eigenvalues indicators (Gonzalez-Loureiro et al., 2015) corresponding to variance, percentage of variance and, cumulative percentage of variance, can be seen in Table 5 and 6. In Annex 1, all variables and dimension performance can be consulted.

In the visual representation of the results, the keywords are close to each other because they belong to the same category (See Fig. 1 and 2). Thus, if they are in the same relative space within the X and Y axis, it means that they are grouped in the results and therefore are related between them. The categories are closer to each other if their linkage is higher. The distance from a keyword to the origin reflects variance from

Table 3
Identification of the studies for the research.

Authors	Title	Journal	Category
Agnihotri, Trainor, Itani, and Rodríguez (2017)	Examining the role of sales-based CRM technology and social media use on post-sale service behaviors in India	*Journal of Business Research*	Business
Nedbal, Auinger, and Hochmeier (2013)	An Enterprise 2.0 project management approach to facilitate participation, transparency, and communication	*Inter. Journal of Information Systems and Project Management*	Computer Sciences & Information Sciences
Barac, Ratkovic-Živanovic, Labus, Milinovic, and Labus (2017)	Fostering partner relationship management in B2B ecosystems of electronic media	*Journal of Business & Industrial Marketing*	Business
Brown and Vessey (2008)	Managing the Next Wave of Enterprise Systems: Leveraging Lessons from ERP	*MIS Quarterly Executive*	Information Sciences & Management
Duffy, Bruce, Moroko, and Groeger (2020)	Customer orientation: Its surprising origins, tumultuous development and place in the future of marketing thought and practice	*Australasian Marketing Journal*	Marketing
Fotiadis and Vassiliadis (2017)	Being customer-centric through CRM metrics in the B2B market: the case of maritime shipping	*Journal of Business & Industrial Marketing*	Business
Fraccastoro, Gabrielsson, and Pullins (2020)	The integrated use of social media, digital, and traditional communication tools in the B2B sales process of international SMEs	*International Business Review*	Business
Gneiser (2010)	Value-Based CRM	*Business & Information Systems Engineering*	Computer Sciences & Information Sciences
Gurău (2007)	Digital B2B interactions in Romania	*Inter. Journal of Emerging Markets*	Business and Management
Haddara and Constantini (2020)	Fused or Unfused? The Parable of ERP II	*Inter. Journal of Information Systems and Project Management*	Computer Sciences & Information Sciences
Hallikainen, Savimäki, and Laukkanen (2019)	Fostering B2B sales with customer big data analytics	*Industrial Marketing Management*	Business & Management
Hasani, Bojei, and Dehghantanha (2017)	Investigating the antecedents to the adoption of SCRM technologies by start-up companies	*Telematics and Informatics*	Information Sciences
Huemer, Liegl, Schuster, and Zapletal (2009)	B2B Services: Worksheet-Driven Development of Modeling Artifacts and Code	*The Computer Journal*	Computer Sciences
Karakostas, Kardaras, and Papathanassiou (2005)	The state of CRM adoption by the financial services in the UK: an empirical investigation	*Information & Management*	Computer Sciences & Information Sciences & Management
Kim, Suh, and Hwang (2003)	A model for evaluating the effectiveness of CRM using the balanced scorecard	*Journal of Interactive Marketing*	Business
Kumar and Reinartz (2018a)	Applications of CRM in B2B and B2C Scenarios Part II. In: Customer Relationship Management	*Springer Texts in Business and Economics*	Business
Kumar and Reinartz (2018b)	Applications of CRM in B2B and B2C Scenarios Part I	*Springer Texts in Business and Economics*	Business
Latusek (2010)	B2B relationship marketing analytical support with GBC modeling	*Journal of Business & Industrial Marketing*	Business
Medjahed, Benatallah, Bouguettaya, Ngu, and Elmagarmid (2003)	Business-to-business interactions: issues and enabling technologies	*The VLDB Journal*	Computer Sciences
Qurtubi and Kusrini (2019)	Research in Industrial Marketing: Issues and Opportunities Classification	*International Journal of Integrated Engineering*	Engineering
Rotovei (2020)	Opportunity activity sequence investigations in B2B CRM systems	*Acta Universitatis Sapientiae, Informatica*	Computer Sciences
Saura et al. (2019)	The importance of information service offerings of collaborative CRMs on decision-making in B2B marketing	*Journal of Business & Industrial Marketing*	Business
Schubert and Glitsch (2016)	Use Cases and Collaboration Scenarios: how employees use socially enabled Enterprise Collaboration Systems	*International Journal of Information Systems and Project Management*	Computer Sciences & Information Sciences
Shah and Murthi (2020)	Marketing in a data-driven digital world: Implications for the role and scope of marketing	*Journal of Business Research*	Business
Sheikh, Ghanbarpour, and Gholamiangonabadi (2019)	A Preliminary Study of Fintech Industry: A Two-Stage Clustering Analysis for Customer Segmentation in the B2B Setting	*Journal of Business-to-Business Marketing*	Business
Trainor, Andzulis, Rapp, and Agnihotri (2014)	Social media technology usage and customer relationship performance: A capabilities-based examination of social CRM	*Journal of Business Research*	Business
Vlachos, Vassiliadis, Heckel, and Labbi (2016)	Toward interpretable predictive models in B2B recommender systems	*IBM Journal of Research and Development*	Computer Sciences & Information Sciences
Wali, Uduma, and Wright (2016)	Customer relationship management (CRM) experiences of Business-to-Business (B2B) marketing firms: A qualitative study	*Cogent Business & Management*	Business
Wongsansukcharoen, Trimetsoontorn, and Fongsuwan (2015)	Social CRM, RMO and business strategies affecting banking performance effectiveness in B2B context	*Journal of Business & Industrial Marketing*	Business
Zaby and Wilde (2018)	Intelligent Business Processes in CRM - Exemplified by Complaint Management	*Business & Information Systems Engineering*	Computer Sciences & Information Sciences

the "average" response pattern. This variance from the average corresponds to the most frequent categories of the analyzed variables. Therefore, keywords that appear in the graphs with many characteristics corresponding to the most frequent categories lie near the origin. In contrast, keywords with unique characteristics are located far from the origin.

Fig. 1 shows the Eigenvalues / Variances results in which there are two dimensions. Dimension 1 obtains 17.83% and dimension 2, 14.08% of the representation of the variables that make up the sample. The cos2 measures the percentage of distance to the central mean of the graphical representation between 0 and 0.8 points. The axes of the graph represent the center of the mean of correlations that exist between the terms that are part of the study.

Fig. 2 is used to draw the biplot of individuals and variable categories that are used to emphasize variations and bring out strong patterns in a dataset. Dimension 1 is represented by 23.19% of the sample and

Table 4
Main literature review results.

Autores	Purpose	Main concepts analyzed	Analytical CRM	Operational CRM	Collaborative CRM	Traditional Marketing	Digital Marketing
Agnihotri et al. (2017)	To explore the impact that sales-based CRM technology and social media have in salesperson service behavior (SSB) after closing a deal.	CRM, sales-based CRM technology, Salesperson Service Behavior (SSB), Social CRM, post-sale service behavior, social media, information communication			•	•	
Nedbal et al. (2013)	To find evidence that exist methodologies and support tools for the improvement of communication, interaction, transparency, cooperation and trust of users in Enterprise 2.0.	Enterprise 2.0, Critical Success Factors (CSF), Change Management Principles (CMP), Enterprise 2.0 Roadmap Strategies (ERS), communication, participation, transparency.	•		•	•	
Barac et al. (2017)	To study the impact of Customer Relationship Management (CRM) adoption technology on B2B relationship surrounding e-business ecosystem.	Relationship quality, relationship capability, relationship fulfilment, relationship marketing, analytical, operational and social Partner Relationship Management (PRM) and readiness for new e-business models.	•	•			•
Brown and Vessey (2008)	To study how the five-success-factor model for ERP projects proposed by the authors is changed when other enterprise systems are implemented.	Enterprise Systems Planning (ERP), maturity curve, enterprise systems and five-success-factor model.	•	•		•	
Duffy et al. (2020)	To demonstrate where the concept of Customer Orientation (CO) comes from, its evolution and to explain its advantages in both disciplines, management and marketing.	Customer orientation, scientific management, marketing, customer orientation strategy, customer orientation innovation.	•				•
Fotiadis and Vassiliadis (2017)	To specify and evaluate what CRM metrics are most significant to the formation and development of CRMs and also how it can be used to make customer-centered decisions in B2B business.	CRM metrics, B2B, customer-centered metrics, decision-making, satisfaction, loyalty, company's performance and company's growth	•	•		•	•
Fraccastoro et al. (2020)	To study the integration of social media and digital and traditional sales communication tools in SMEs to enhance the B2B sales process phases.	Social media, digital communication tools, sales process, Relationship Management, B2B.		•	•	•	
Gneiser (2010)	To analyze value-based CRM in marketing interaction, financial management and IT when it is adopted.	CRM, financial management, value-based management, management decision making, marketing metrics, long-term customer relationship, IT, innovative technologies.	•	•			•
Gurău (2007)	To explore B2B interactions and level of satisfaction of service providers and client firms in different interactive channels.	Information Technology and Telecommunication (ITT), CRM function, satisfaction level, visibility, reliability, accessibility and mobility, efficiency, usefulness and customisation.		•		•	
Haddara and Constantini (2020)	To know why companies are investing on separate CRM systems when they have already included CRM modules in their ERP systems.	ERP systems, CRM systems, ERP II	•	•		•	
Hallikainen et al. (2019)	To study how Big Data analysis improves B2B customer relationship performance, sales growth, and its significance in marketing analytics in the decision-making strategies.	Customer big data analytics, customer relationship performance, sales growth, analytics culture, firm size	•			•	
Hasani et al. (2017)	To explain what factors are affecting the adoption of social CRM in start-up companies.	Technological characteristics (TC), Organizational Characteristics (OC), Environmental Characteristics (EC), Managerial Characteristics (MC)			•		•
Huemer et al. (2009)	To propose the implementation of the worksheet-driven approach for the improvement of software engineering and the	Service-oriented architecture, work-sheet driven requirement engineering, business process modeling, UN/CEFACT modelling	•	•		•	

(continued on next page)

Table 4 (*continued*)

Autores	Purpose	Main concepts analyzed	Analytical CRM	Operational CRM	Collaborative CRM	Traditional Marketing	Digital Marketing
	assessment of its advantages in the B2B business models.	methodology (UMM), business collaboration					
Karakostas et al. (2005)	To investigate to what extent CRM systems are implementing tin Financial Services organizations.	Motivation for CRM implementation, CRM as a strategic tool, CRM as a tool to support communication channels, CRM as a tool for supporting the B2C interaction, CRM tools selection priorities, Performance evaluation	•	•	•		•
Kim et al. (2003)	To propose an evaluation model to observe the effectiveness of CRM by using the balanced scorecard (BSC).	CRM, BSC, Customer Knowledge, Customer interaction, Customer value, Customer satisfaction.	•	•			•
Kumar and Reinartz (2018a)	To study the adoption of CRM in B2B to make smarter decisions related to customer acquisition, retention, profitability and optimal resource allocation.	CRM, customer acquisition, customer retention, customer profitability, customer brand value, customer referral value.	•	•		•	
Kumar and Reinartz (2018b)	By using CRM, understand the importance of the Customer Lifetime Value (CLV) for driving marketing decisions and the existing connection between customer lifetime with companies' profitability. It is also proposed an approach to measure CLV.	Customer Lifetime Value (CLV), CRM, firm's profitability, lost customers.		•		•	
Latusek (2010)	To analyze the B2B marketing analytical approach through the application of predictive modeling of consumer behavior.	Customer relationship management analytical techniques, predictive analytics, customer behavior modeling, financial impact, marketing profitability	•				•
Medjahed et al. (2003)	Finding main techniques, issues and solutions to B2B e-business interactions.	B2B architecture, layers, Electronic Data Interchange (EDI), XML, workflow, Web services, Collaboration Management Infrastructure (CMI), major software, B2B interaction technologies	•	•		•	
Qurtubi and Kusrini (2019)	To review different areas wherein Industrial Marketing is connected.	B2B marketing, B2C marketing, CRM, Information technology, Purchasing and supply chain management, marketing-selling interface.	•	•		•	
Rotovei (2020)	Gathering CRM dataset information regarding salespeople activities to determine the influence in the final result of each B2B operation.	Sales forecasting, B2B selling, win and lost deals, Dynamic Time Warping (DTW), histogram analysis, Damerau-Levenshtein distance.	•			•	
Saura et al. (2019)	The identification of different the type of information collected in collaborative CRMs that B2B companies share to customers and its influence in the decision-making process and offerings strategies.	Collaborative CRM, B2B, external factors, cognitive beliefs, internal control factors, external control factors, intention and value offering, contextual factors, behavioral response			•		•
Schubert and Glitsch (2016)	To discover findings regarding the introduction and implementation of Enterprise Collaboration Systems (ECS) in companies.	Use Case, Collaboration scenarios, IREES Model	•		•	•	
Shah & Murthi, 2020	To review the historical evolution of data-driven marketing and the adoption of new digital technologies in marketing performance.	Data-driven marketing, new digital technologies, creativity, relevancy, analytics capability, accountability, technology,	•				•
Sheikh et al. (2019)	To propose a new methodology based on cluster analysis and behavior-based model for customer segmentation development and behavioral analysis in B2B models.	Recency, Frequency, Monetary value (RMF) model, cluster analysis, customer segmentation, customer behavior analysis	•	•			•
Trainor et al. (2014)	To study the contribution of social media technology and	CRM, Customer-Centric Management System, Social Media			•		•

(*continued on next page*)

Table 4 (*continued*)

Autores	Purpose	Main concepts analyzed	Analytical CRM	Operational CRM	Collaborative CRM	Traditional Marketing	Digital Marketing
	customer-centric management systems create direct value in CRM systems.	Technology Use, Social CRM Capabilities, Customer Relationship Performance, Training, Management Support, Size.					
Vlachos et al. (2016)	To build recommender systems for B2B by identifying groups of clients based on client-product historical data to encourage future sales.	Recommender systems, co-clustering, client-product matrix, the propensity to buy, value of a recommendation, textual interpretability	•	•		•	
Wali et al. (2016)	To explore what influence on customer relationship management (CRM) experiences of B2B.	Resource commitment behavior, product knowledge, customer relations orientation and B2B service personalization.		•			•
Wongsansukcharoen et al. (2015)	To understand success factors of social CRM and relationship marketing orientation in B2B industry.	Social customer relationship management, relationship marketing orientation, business strategies, performance effectiveness.		•	•		•
Zaby and Wilde (2018)	To review intelligent business processes in CRM in a theoretical and practical way.	Business processes, business intelligence, CRM, complaint management.	•			•	

dimension 2 by 15.7% of the total. The cos2 is represented in the same way as in Fig. 1. In this case, both graphs are analyzed based on the objectives of the research centered on AI-based CRMs in B2B digital marketing.

In Fig. 1, the variants show the relationship between two multivariate groups established around AI-based CRMs. In this way, the multivariate groups that have found a relationship between them with the development of MAC analysis are highlighted in two areas.

First, to the right of the upper-middle axis, it is observed how digital strategies are grouped using digital marketing techniques with which indicators are established, CRM related to digital purchasing, and relationship marketing strategies also linked to loyalty management and inbound marketing. Specifically, with these variables, there is a solid relationship to the AI strategies developed in this ecosystem. Besides, indicators to improve performance stand out in this set of variables.

On the upper left of the axis is another group of multivariables in which the actions of AI to establish parameters linked to knowledge management, behavioral response, sales forecasting and the establishment of metrics stand out. These two multivariable groups are directly linked to AI when using B2B digital marketing and AI-based CRMs. Analytical CRMs, innovation-focused strategies, ebusiness models, decision-making processing and information communication are closed to these multivariate groups and placed in the middle of the study's mean.

Fig. 2, the results show two linked multivariate groups in which the center is characterized by AI strategies. Again, in this individual analysis of the categorical variables, the digital marketing strategies used with CRM are analytical for knowledge management and sales performance. In addition, the metrics and indicators are directly linked to relationship marketing.

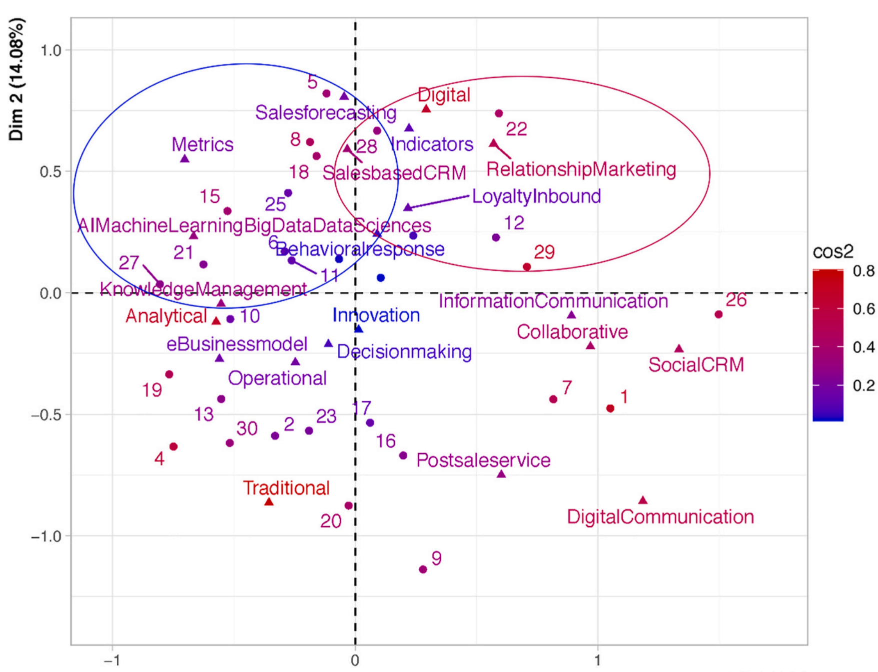

Fig. 1. Eigenvalues/Variances results using MAC and HOMALS analysis with R.

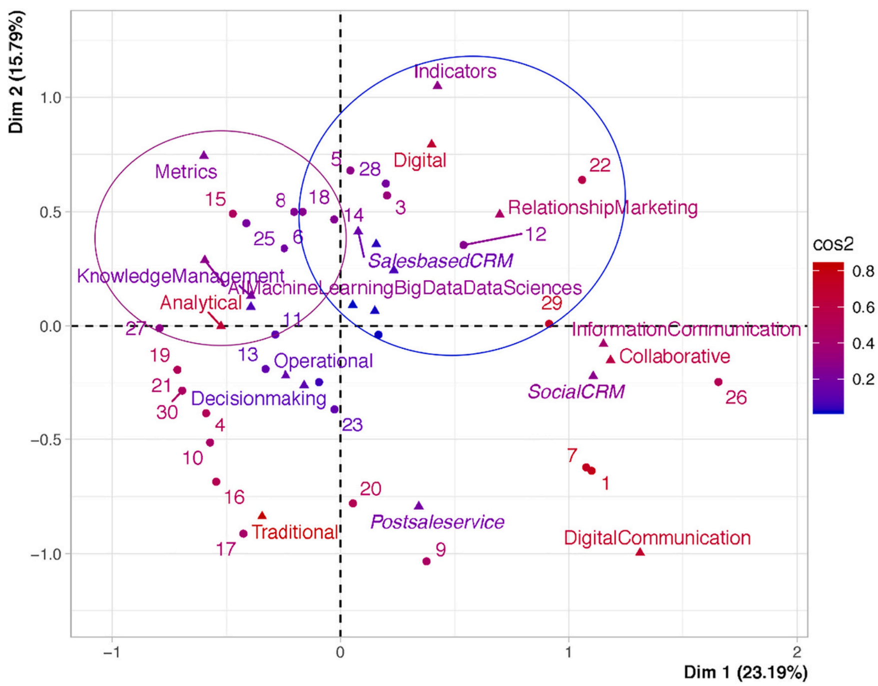

Fig. 2. Biplot of individuals and variable categories using MAC and HOMALS analysis with R.

Table 5
Eigenvalues dimensions 1 to 10.

R	Dim.1	Dim.2	Dim.3	Dim.4	Dim.5	Dim.6	Dim.7	Dim.8	Dim.9	Dim.10
1	0,285	0,225	0,174	0,15	0,126	0,111	0,099	0,082	0,075	0,069
2	17,827	14,078	10,908	9360	7863	6927	6223	5146	4714	4319
3	17,827	31,905	42,812	52,172	60,036	66,963	73,186	78,332	83,046	87,364

R1 = Variance, R2 = percentage of variance, R3 = cumulative percentage of variance.

Table 6
Eigenvalues dimensions 11 to 20.

R	Dim.11	Dim.12	Dim.13	Dim.14	Dim.15	Dim.16	Dim.17	Dim.18	Dim.19	Dim.20
1	0,05	0,038	0,03	0,028	0,016	0,013	0,011	0,008	0,006	0,002
2	3128	2352	1878	1763	0,990	0,812	0,672	0,526	0,359	0,154
3	90,492	92,84	94,723	96,486	97,477	98,288	98,961	99,486	99,846	100,000

R1 = Variance, R2 = percentage of variance, R3 = cumulative percentage of variance.

The main difference in Fig. 1 is that the variances are shown. This is because the categories are studied individually to be shown together so that the results vary slightly and the most relevant relationships are highlighted in terms of cos2. The main difference is that the AI actions are closer to the average of digital strategies. For example, it stands out that digital communication is not done through CRM and that decision making is outside the use of AI-based CRMS in B2B digital marketing. Furthermore, the results show that the analytical CRM is the one that works mainly with AI in the studies analyzed.

5. Discussion and directions for future research

The study by Herhausen et al. (2020) highlights the need for the study of new techniques and uses of B2B digital marketing in an industry that has been eminently focused on traditional business models. Following their considerations and to answer this need, this study has identified the existence of actions related to relationship management when companies use AI-based CRMs in B2B digital marketing.

According to Peppard (2000), relationship management involves strategies to build client support and increase brand loyalty. In B2B digital marketing, it creates an essential strategy because, with the study of customer loyalty and prediction models, it is possible to establish lasting relationships with customers in digital ecosystems that are managed with AI-based CRMs (Petrović, 2020).

Likewise, as indicated by Agnihotri et al. (2017), CRMs working on sales-based strategies can help perform sales forecasting, extract insights from business activities, or customer insights. When these strategies are used in ecosystems where data is generated daily, AI-based CRMs can add value to business development, as well as make digital B2B marketing a lasting strategy that can predict the steps a company must take to succeed in its marketing strategies. Therefore, we agree with Martínez-López and Casillas (2013) in the need for application and new uses of AI-based CRMs for companies in the B2B environment.

In addition, inbound marketing has been identified as an essential strategy in digital B2B marketing to establish metrics in relation to digital business models using CRM functionalities that work with AI. In this way, AI-based CRMs increase the profitability of marketing accounts and improve the performance of the business globally by collecting data and making predictions of sales, business and scalability. These assessments were also indicated by Nguyen et al. (2007a, 2007b) and Shim, Choi, and Suh (2012) in their research.

Moreover, in relation to AI within the functionalities of CRMs, it has been established that knowledge management, data sciences and automation techniques play an essential role (Wang, Xiong, & Olya, 2020), thus accepting the indications made by Duan et al. (2019) and Grover et al. (2020).

AI-based CRMs working in digital marketing environments use techniques focused on machine learning and big data (see Martínez-López & Casillas, 2013), as well as the support of data-driven marketing strategies to drive customer knowledge data collection and performance evaluation (Troisi, Maione, Grimaldi, & Loia, 2020). These activities are usually linked to the types of analytical CRMs, in which strategies have been developed that focus on (i)decision making, (ii)understanding user behavior and responses, (iii)innovation strategies, (iv)sales forecasting, (v) understanding social network strategies, as well as (vi)customer orientation in digital environments (Herterich, Uebernickel, & Brenner, 2016).

As can be seen, the different functionalities and research areas focused on digital marketing within the B2B ecosystem provide interesting insights into the techniques that can be used in these ecosystems to correctly develop strategies focused on the field of B2B digital marketing.

5.1. Main uses of AI-based CRMS in B2B digital marketing

As indicated by Cao and Tian (2020), both B2B digital marketing and AI and the use of CRM in B2B (Martínez-López & Casillas, 2013) have yet to be developed in depth, as both are advanced marketing strategies that must first be tested by companies, and subsequently improved and optimized for their businesses. Then, they will correctly extract the value they can bring to their businesses and over time the AI will improve the results in terms of profitability, effectiveness, efficiency and performance (Kim & Kim, 2009).

It is true that different studies have focused on these areas, but as it has been indicated at the beginning of the research, these areas and functions on the AI-based CRMs must answer to specific parameters for the foundation of the future of the applications and functionalities. Also, those questions related to technologies applied to the business environment of the B2B ecosystem on the Internet.

In this way, and in order to summarize the main activities and functionalities, as well as the characteristics that this study identifies in each of the three research areas chosen as relevant for the study of AI-based CRMS in B2B, Fig. 3 shows the elements that compose each of these areas. In line with our main research question and research objectives, these elements can be visually appreciated as key elements for future research is. In addition, although the MCA results are divided into two category usage clusters, we also found a third B2B Digital Marketing dimension (see Fig. 3) that encompasses relevant indicators that are not close to each other in terms of their categorical variables in MCA.

5.2. Future research agenda for AI-based CRMs in B2B Digital Marketing

Therefore, as presented in their research by Hughes et al. (2019) and Duan et al. (2019), in order to establish future parameters of our research findings, different (i)research areas are presented in Table 7, also (ii)research thrusts, with the aim of launching questions that other researchers can answer with their future studies, as well as (iii) research paths to establish questions that must be specifically answered within the established research areas.

These insights can be used to establish future research questions, hypotheses, or research objectives that help understand the proper functioning of AI-based CRMs in B2B digital marketing. In addition, with these contributions in the form of a research directions, other researchers can identify new gaps in the literature, as well as identify specific characteristics or strategies that should be investigated in depth in the future.

In order to set the future research agenda, and following Duan et al. (2019), the results of the present study were considered to both address the AI future in the B2B ecosystem when CRMs are used and to investigate how and which digital marketing strategies can enhance the use of these systems in companies. Moreover, uses and functions of analytical CRMs that work with data automation, correlations, and forecast of user behavior based on the collected data are proposed and linked to the main uses (see Fig. 3).

In doing so, we took into account the indications presented in the discussion; in these indications, different theories and definitions are explored and adapted so that the CRMs combine the technologies to improve the processes, data management, and the development of customer communications actions (Hughes et al., 2019). Therefore, the research paths proposed in Table 7 can be used in further research on solving and improving the use of AI-based CRMs in B2B Digital Marketing as research aims.

5.3. Research propositions for AI-based CRMs in B2B digital marketing

Following Kannan and Hongshuang (2017) and Dwivedi et al. (2021), in this section, we discuss in greater detail the research propositions regarding the AI-based CRMs in B2B Digital Marketing. As argued by Ambler and Kokkinaki (1997) and Bharadwaj, Clark, and Kulviwat (2005), two of the most important variables in business development are growth and success. Moreover, Hunt and Arnett (2006) and Hajli, Tajvidi, Gbadamosi, and Nadeem (2020) linked these variables to the use of appropriate tools when planning marketing, digital marketing, or sales strategies.

In this context, it is important to understand the use of AI-based CRM based on automatization and predictions and to correlate these variables with the development of strategies in this area (Harrigan et al., 2020). CRMs are classified as analytical when they can be set to perform these actions. Accordingly, in addition to the development of actions that can be measured with variables of success and growth, common measurement guidelines could be established in companies for their B2B marketing (Ipang, Suroso, & Novitasari, 2021). Based on these issues, the following research proposition is formulated:

Proposition 1. Well-defined B2B digital marketing strategies using AI-based CRMs would determine success and growth in marketing.

As highlighted by Järvinen and Taiminen (2016), modern B2B marketing may sometimes be ineffective, as new marketing strategies based on digital ecosystems have only recently appeared. These new strategies should be investigated in-depth to shed more light on long-term benefits for companies in terms of loyalty and compromise (Ipang et al., 2021). Modern strategies such as content marketing, branded content, influencer marketing, marketing automation, user behavior predictions, among others, should be analyzed in this business area (Saura, 2021).

However, as argued by Rodriguez and Peterson (2012), one of the most relevant strategies for modern B2B marketing is lead generation. This strategy aims to appeal to new clients interested in acquiring new products and services of the same brand—i.e., something that the three theoretical types of CRM can *a priori* carry out. Moreover, Paschen, Wilson, and Ferreira (2020) noted that CRMs and AI are two key elements for the development of these lead acquisition strategies in B2B ecosystems. Therefore, based on these insights, the following research proposition is formulated:

Proposition 2. Efficiency of AI-based CRMs in B2B digital marketing when corporates strategies are focused on lead generation should be explored.

In the last several decades, online brand building has been studied in depth in digital marketing (Makrides, Vrontis, & Christofi, 2020). For instance, Confos and Davis (2016) argued that brand building should be developed in short- and long-term growth. This is so because, when a

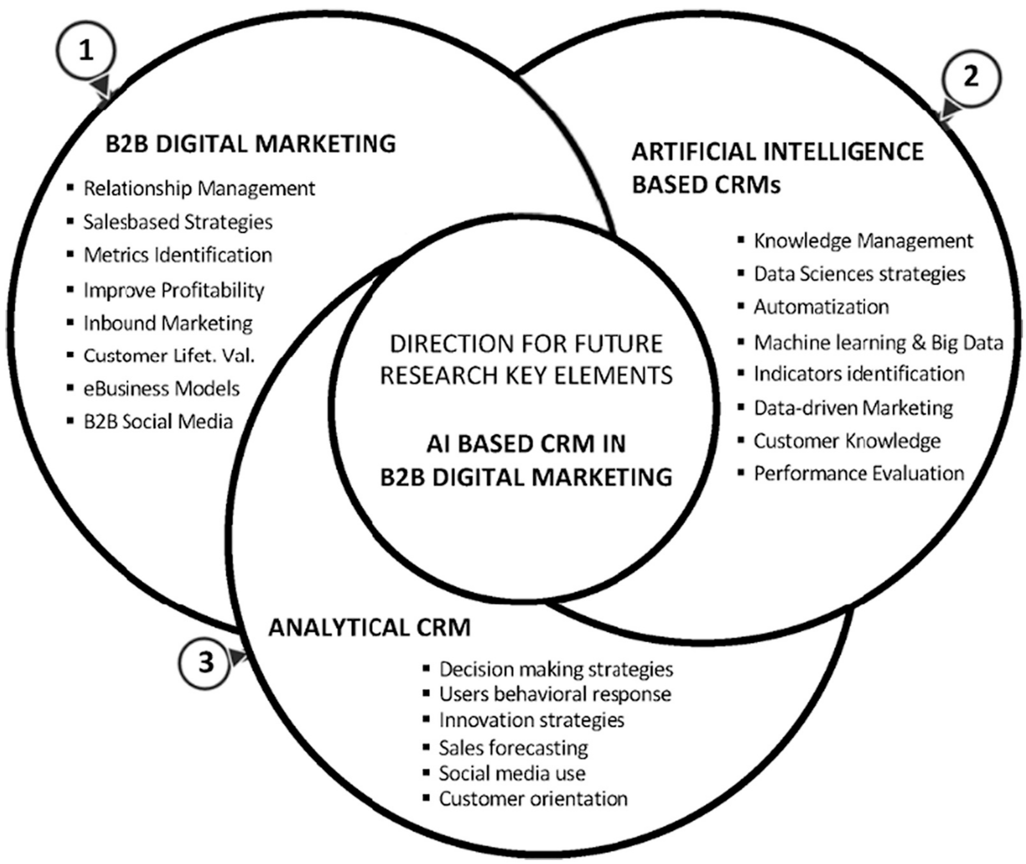

Fig. 3. Summary of characteristic per main uses in AI-based CRMs in B2B Digital Marketing.

brand creates demand, it also captures it. These strategies can be performed by CRMs (Saura et al., 2019). In addition, Nguyen et al. (2007a, 2007b) used different perspectives to analyze whether the best strategy to create online brand building is through customer data management and the use of CRMs.

However, in the B2B digital marketing ecosystem, brand building linked to the use of AI strategies or machine learning and CRMs has not been thoroughly investigated to date. Considering the need for brand building in companies in order to build customer loyalty and make advocates in digital platforms, the role of AI-based CRMS in B2B digital marketing should be explored and defined. Based on these insights, the following research proposition is formulated:

Proposition 3. Clearly defined uses of AI-based CRMs in B2B digital marketing would benefit online brand building.

Likewise, the customer experience quality in digital marketing is a key indicator for the online strategies' success (Parise, Guinan, & Kafka, 2016). However, as demonstrated by our findings, the customer experience is a mix of customer journey and customer orientation in B2B digital marketing; accordingly, AI-based CRMs is a strategy that should be better defined in the future. If the automatical systems that work with AI can predict user actions, it should also be considered that CRMs can automatically modify and adapt different funnels or buying cycles according to each user, as well as set funnel management actions (Kelly, 2000). Based on the above, the the following research proposition can be formulated:

Proposition 4. Well-defined key guidelines and actions to optimize the use of AI-based CRMs would determine success on the use of customer experience/journeys on B2B digital marketing.

In the last decade, new approaches focused on data-driven decision-making have remarkably increased in all areas of business ecosystems (e.g., strategy, communication, marketing, development, internationalization, etc.) (Janssen, van der Voort, & Wahyudi, 2017). Moreover, the field of innovation (Adamides & Karacapilidis, 2020; Gil-Alana, Škare, & Claudio-Quiroga, 2020), defined as the creation of new ways of obtaining insights, making decisions, adapting products and services, or improving strategic and product decisions, has experienced an increasing research interest (Van Riel, Lemmink, & Ouwersloot, 2004).

Acknowledging the exponential development of AI and the continuous growth of the use of CRMs in B2B digital marketing, innovation has to be understood as a new way to enhance the business characteristics in order to achieve success and optimize the results (Behrens, 2016). In view of these approaches, AI-based CRMs in B2B digital marketing can be used not only to innovate in the buying, selling, or strategy optimization processes, but also to create new products or services, or to generate knowledge that provides a competitive advantage. Based on these insights, the following research proposition is formulated:

Proposition 5. Innovation development protocols in B2B digital marketing when using AI-based CRMs should be developed, tested, and proposed as business innovation models.

6. Conclusions

This study has developed a review that has identified a total of 30 academic contributions that use CRMs, or AI-based CRMs in traditional or digital B2B marketing. These contributions have been analyzed in depth to explore the objectives of the research. In this way, the research question (*RQ1: What are the main applications of AI-based CRMs in B2B Digital Marketing strategies?*) has been answered, because the main techniques and uses of B2B digital marketing using AI-based CRMs have been classified and explained in Section 5 in which a summary of the characteristic per main uses in AI-based CRMs has been presented and

Table 7
Future research agenda for AI-based CRMs in B2B Digital Marketing.

Research area	Research thrust	Research path
AI-based CRMs	What are the future uses of AI-Based CRM in B2B?	▪ Establishing new uses and applications for B2B digital marketing ▪ Exploration of new strategies focused on the massive analysis of business data. ▪ Study of new tools for predicting sales and closing deals. ▪ A practical definition of knowledge management contributions to B2B digital marketing using AI-based CRMs. ▪ Improve understanding of AI-based CRMs in B2B when data samples are not large. ▪ Definition of the main AI techniques applied to business in B2B to be correctly implemented in B2B digital marketing when using AI-based CRMs. ▪ Establishment of experiments and tests using AI to improve processes.
B2B Digital Marketing	How can B2B digital marketing benefit from the development of comprehensive strategies in AI-based CRMs?	▪ Understanding the role of digital marketing strategies in B2B using AI-based CRM ▪ Definition of the functions of B2B digital marketing ▪ Exploring the role of user behavior and loyalty programs ▪ Development of new relationship marketing and inbound marketing strategies ▪ Understand what executives and managers think about the use of AI-based CRMs in B2B digital marketing. ▪ Definition of the correct implementation of performance indicators in B2B digital marketing to be integrated into AI-based CRMs. ▪ To measure the impact of traditional strategies of digital marketing (Search engine optimization, Search engine marketing, social media marketing, among others), when are integrated with AI-based CRMs.
Analytical CRMs	What are the new functionalities of Analytical CRMs?	▪ Definition of new combinations of CRMs and types of technologies that work with AI. ▪ Adaptation of AI advances applied to analytical CRMs. ▪ Exploration of marketing performance improvement processes using machine learning and data automation. ▪ Establish transition parameters to adapt and digitalize traditional business in B2B to the digital marketing sector using AI-based CRMs. ▪ Definition of parameters, metrics and rules for the correct adaptation of Collaborative CRMs to AI-based CRMs. ▪ Definition of new proposals for the integration of analytical software with CRMs that are trained with AI

divied in divided in to three sections (See Fig. 3): B2B Digital Marketing, Analytical CRM and, AI-based CRMs. In addition, with regard to the research objectives, the main uses and techniques have been identified, and future guidelines and propositions to develop strategies based on AI-based CRMs in B2B digital marketing have been raised and discussed.

Likewise, on the results of the systematic review, a MCA analysis has been developed under the characteristics of HOMALS using the programming language R, which adds originality and novelty to the study of these issues in the research field that we are coped with. With the development of the research, we have understood what are the main uses of B2B digital marketing strategies using AI-based CRMs. In this sense, three types of CRMs have been identified: (i)analytical, (ii)operational and (iii)collaborative. Of these three CRMs, the one that is directly linked to the development of strategies with the use of AI in B2B digital marketing is the analytical one. We agree with Rich and Latusek (2010) on this issue. Furthermore, characteristics have been obtained in relation to the functionalities that CRMs have in B2B, being classified according to whether they are developed “on demand” or “on premise” for companies in the B2B environment (Liang, Yang, Chen, & Ku, 2008).

6.1. Theoretical implications

This study has identified different uses and techniques of AI-based CRMs in B2B digital marketing covering a gap in research to date. In this way, the study contributes to the literature discoveries in the form of discussion and future direction for the study of the issues raised in the research question and objectives proposed. Future researchers can take the considerations presented in the study as starting points for their studies of both B2B digital marketing, AI-based CRM or Analytical CRMs when working with AI.

Furthermore, the study of B2B digital marketing in literature remains scarce, so this research also contributes to boosting the study of this area of research that still seems to be untapped (Cao & Tian, 2020). Furthermore, the consideration and conceptualization of AI-based CRMs presented in this study forms the basis for the development of research that focuses on expanding the contributions that AI can make not only to CRMs but to the entire B2B ecosystem, whether or not the products and services with which companies operate are traditional.

6.2. Practical implications

Digital marketing has become a key element in the development of B2B strategies (Saura et al., 2019). In this way, communication and marketing agencies, as well as companies that use CRMs, can use this research to understand, analyze and explore the possible uses and benefits that the application of AI-based CRMs can bring to their strategies.

Similarly, managers and executives of companies operating in the traditional B2B sector can understand the functioning of B2B digital marketing, as well as to measure the high influence that AI strategies can bring to their business ecosystems. In addition, the different uses, techniques and future directions proposed in the study can help companies to improve decision-making in this area of action. Using these exploratory findings, companies can glimpse and get ideas about the types of actions they can take in this area. Finally, the classification of the functionalities and typologies of CRMs based on the type of B2B marketing used can support companies to implement such strategies in their businesses.

6.3. Limitations

The limitations of the research are those related to the number of studies that are part of the sample, the databases used to carry out the systematic review of literature, as well as the in-depth study by the researchers of the selected studies. Besides, the interpretation of the results visually of the MAC process can also be considered a limitation. Finally, the technology corresponding to the development of AI-based CRMs in B2B digital marketing is constantly changing so future studies should continue the research directions proposed in the future to continue establishing solid pillars for the use of AI-based CRMs in B2B digital marketing.

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Appendix A. Annex 1

Table 8. Results of multiple correspondence analysis according to the coordinates established for the group of variables in graphic representations in Figs. 1 and 2, based on the coding of all studied variables.

Rows	Iner*1000	Dim.1	ctr	cos2	Dim.2	ctr	cos2	Dim.3	ctr	cos2
1	74,263	1051	14,730	0,565	−0,476	3816	0,116	0,231	1161	0,027
2	53,393	−0,331	0,971	0,052	−0,589	3902	0,164	0,842	10,287	0,336
3	69,827	0,239	0,846	0,035	0,235	1037	0,033	0,604	8838	0,221
4	41,117	−0,749	4987	0,346	−0,633	4505	0,247	0,328	1557	0,066
5	57,365	−0,118	0,145	0,007	0,820	8832	0,346	0,343	1996	0,061
6	48,103	−0,291	1378	0,082	0,170	0,597	0,028	−0,235	1472	0,053
7	64,539	0,816	8877	0,392	−0,438	3243	0,113	−0,423	3893	0,105
8	42,945	−0,187	0,568	0,038	0,621	7941	0,416	−0,263	1846	0,075
9	66,662	0,279	0,462	0,020	−1139	9722	0,328	−0,189	0,346	0,009
10	51,897	−0,515	2752	0,151	−0,108	0,153	0,007	0,478	3868	0,130
11	28,643	−0,262	1020	0,101	0,133	0,332	0,026	−0,220	1170	0,071
12	61,045	0,580	3980	0,186	0,228	0,780	0,029	0,774	11,582	0,331
13	54,718	−0,552	3163	0,165	−0,437	2508	0,103	0,417	2944	0,094
14	48,259	−0,067	0,086	0,005	0,139	0,469	0,022	0,176	0,979	0,035
15	43,905	−0,527	4110	0,267	0,336	2122	0,109	0,057	0,079	0,003
16	57,217	0,198	0,405	0,020	−0,670	5884	0,231	−0,407	2799	0,085
17	53,001	0,061	0,033	0,002	−0,535	3219	0,137	−0,985	14,088	0,463
18	33,587	−0,160	0,340	0,029	0,563	5341	0,358	−0,359	2811	0,146
19	41,897	−0,767	6092	0,414	−0,336	1478	0,079	−0,027	0,012	0,000
20	48,117	−0,027	0,007	0,000	−0,876	8626	0,403	−0,116	0,196	0,007
21	49,516	−0,626	4057	0,234	0,117	0,178	0,008	0,228	0,877	0,031
22	80,243	0,592	4670	0,166	0,738	9202	0,258	0,413	3707	0,081
23	44,678	−0,190	0,322	0,021	−0,568	3626	0,183	0,438	2780	0,109
24	45,599	0,105	0,130	0,008	0,062	0,057	0,003	−0,544	5725	0,219
25	43,314	−0,277	0,682	0,045	0,411	1902	0,099	−0,800	9301	0,374
26	92,700	1498	16,603	0,510	−0,089	0,074	0,002	−0,094	0,108	0,002
27	60,810	−0,805	5756	0,270	0,036	0,014	0,001	−0,129	0,242	0,007
28	43,298	0,090	0,084	0,006	0,667	5839	0,303	−0,519	4557	0,184
29	46,898	0,707	10,365	0,630	0,107	0,301	0,014	−0,019	0,012	0,000
30	51,037	−0,517	2378	0,133	−0,618	4300	0,190	−0,230	0,766	0,026

Table 9. Results of multiple correspondence analysis with categorial variables according to the coordinates obtained for the graphic representation by identified variables.

Columns	Iner*1000	Dim.1	ctr	cos2	Dim.2	ctr	cos2	Dim.3	ctr	cos2
Analytical	45,614	−0,573	10,221	0,639	−0,120	0,563	0,028	0,066	0,223	0,009
Operational	59,545	−0,247	1627	0,078	−0,287	2776	0,105	−0,273	3245	0,095
Collaborative	88,694	0,969	12,513	0,402	−0,222	0,830	0,021	0,622	8420	0,166
Traditional	77,922	−0,356	3185	0,116	−0,864	23,779	0,687	0,000	0,000	0,000
Digital	59,126	0,292	1770	0,085	0,754	14,931	0,568	−0,080	0,216	0,006
SalesbasedCRM	57,763	−0,033	0,023	0,001	0,590	9149	0,356	0,204	1404	0,042
Salesforecasting	91,687	−0,046	0,019	0,001	0,806	7314	0,180	0,471	3215	0,061
SocialCRM	99,750	1334	15,806	0,452	−0,233	0,611	0,014	0,435	2743	0,048
Postsaleservice	91,430	0,602	3754	0,117	−0,750	7384	0,182	−0,566	5433	0,104
LoyaltyInbound	64,654	0,217	0,907	0,040	0,348	2954	0,103	−0,779	19,082	0,515
Behavioralresponse	66,185	0,090	0,156	0,007	0,242	1429	0,049	−0,808	20,553	0,541
InformationCommunication	82,620	0,891	7049	0,243	−0,095	0,101	0,003	0,488	3460	0,073
RelationshipMarketing	64,268	0,570	5295	0,235	0,613	7748	0,271	0,122	0,398	0,011
eBusinessmodel	91,340	−0,560	4176	0,130	−0,273	1254	0,031	0,971	20,530	0,392
Innovation	74,541	0,014	0,004	0,000	−0,152	0,566	0,017	0,352	3899	0,091
DigitalCommunication	118,367	1185	14,558	0,351	−0,858	9652	0,184	−0,395	2640	0,039
Metrics	83,985	−0,703	3659	0,124	0,549	2822	0,076	−0,189	0,431	0,009
Indicators	77,858	0,222	0,291	0,011	0,676	3426	0,099	0,574	3185	0,071
Decisionmaking	57,916	−0,111	0,309	0,015	−0,212	1437	0,056	−0,042	0,071	0,002
KnowledgeManagement	62,001	−0,553	6794	0,312	−0,046	0,060	0,002	0,098	0,348	0,010
AIMachineLearningBigDataDataSciences	83,329	−0,666	7885	0,270	0,232	1213	0,033	−0,132	0,503	0,011

Table 10. Supplementary categorical variables results according to the number of reviewed articles and their coordinates.

Supplementary categorical variables	Dim.1	cos2	v.test	Dim.2	cos2	v.test	Dim.3	cos2	v.test
V1. Nedbal et al. (2013)	−0,331	0,052	−0,819	−0,589	0,164	−1458	0,842	0,336	2084
V1.Schubert and Glitsch (2016)	−0,190	0,021	−0,472	−0,568	0,183	−1406	0,438	0,109	1083
V1.Agnihotri et al. (2017)	1051	0,565	3209	−0,476	0,116	−1451	0,231	0,027	0,705
V1.Barac et al. (2017)	0,239	0,035	0,771	0,235	0,033	0,758	0,604	0,221	1949
V1.Brown et al. (2008)	−0,749	0,346	−1855	−0,633	0,247	−1567	0,328	0,066	0,811
V1.Duffy et al. (2020)	−0,118	0,007	−0,317	0,820	0,346	2198	0,343	0,061	0,920
V1.Fotiadis and Vassiliadis (2017)	−0,291	0,082	−0,986	0,170	0,028	0,577	−0,235	0,053	−0,797
V1.Fraccastoro et al. (2020)	0,816	0,392	2491	−0,438	0,113	−1338	−0,423	0,105	−1290
V1.Gneiser (2010)	−0,187	0,038	−0,633	0,621	0,416	2103	−0,263	0,075	−0,892
V1. Gurău (2007)	0,279	0,020	0,562	−1139	0,328	−2292	−0,189	0,009	−0,380
V1.Haddara and Constantini (2020)	−0,515	0,151	−1381	−0,108	0,007	−0,289	0,478	0,130	1281
V1.Hallikainen et al. (2019)	−0,262	0,101	−0,846	0,133	0,026	0,429	−0,220	0,071	−0,709
V1.Hasani et al. (2017)	0,580	0,186	1664	0,228	0,029	0,655	0,774	0,331	2221
V1.Huemer et al. (2009)	−0,552	0,165	−1481	−0,437	0,103	−1172	0,417	0,094	1117
V1.Karakostas et al. (2005)	−0,067	0,005	−0,248	0,139	0,022	0,513	0,176	0,035	0,653
V1.Kim et al. (2003)	−0,527	0,267	−1699	0,336	0,109	1085	0,057	0,003	0,184
V1.Kumar and Reinartz (2018a)	0,198	0,020	0,530	−0,670	0,231	−1794	−0,407	0,085	−1089
V1.Kumar and Reinartz (2018b)	0,061	0,002	0,151	−0,535	0,137	−1324	−0,985	0,463	−2439
V1.Latusek (2010)	−0,160	0,029	−0,487	0,563	0,358	1717	−0,359	0,146	−1097
V1.Medjahed et al. (2003)	−0,767	0,414	−2055	−0,336	0,079	−0,899	−0,027	0,000	−0,071
V1.Qurtubi and Kusrini (2019)	−0,027	0,000	−0,068	−0,876	0,403	−2168	−0,116	0,007	−0,288
V1.Rotovei (2020)	−0,626	0,234	−1677	0,117	0,008	0,312	0,228	0,031	0,610
V1.Saura et al. (2019)	0,592	0,166	1807	0,738	0,258	2254	0,413	0,081	1259
V1.Shah et al. (2020)	0,105	0,008	0,301	0,062	0,003	0,178	−0,544	0,219	−1562
V1.Sheikh et al. (2019)	−0,277	0,045	−0,686	0,411	0,099	1018	−0,800	0,374	−1982
V1.Trainor et al. (2014)	1498	0,510	3377	−0,089	0,002	−0,200	−0,094	0,002	−0,213
V1.Vlachos et al. (2016)	−0,805	0,270	−1993	0,036	0,001	0,088	−0,129	0,007	−0,320
V1.Wali et al. (2016)	0,090	0,006	0,241	0,667	0,303	1788	−0,519	0,184	−1390
V1.Wongsansukcharoen et al. (2015)	0,707	0,630	2722	0,107	0,014	0,412	−0,019	0,000	−0,072
V1.Zaby and Wilde (2018)	−0,517	0,133	−1281	−0,618	0,190	−1531	−0,230	0,026	−0,569

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