MAPPING TWO DECADES OF EVOLUTION OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN DIGITAL MARKETING AND DIGITAL PROMOTION TO DETERMINE THE CURRENT DIRECTION: A SYSTEMATIC REVIEW USING BIBLIOMETRICS

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ABSTRACT

The past two decades have seen a significant rise in research exploring the applications of artificial intelligence (AI) and machine learning (ML) in digital marketing. This study conducts a comprehensive bibliometric analysis to map the intellectual evolution of this field, offering a longitudinal perspective across two periods: 2000–2021 and 2022–2024. Using SciMAT, the research identifies motor, transversal, emerging, and specialized themes, highlighting key topics such as recommender systems, anthropomorphism, natural language processing (NLP), and social media marketing. The findings reveal how foundational themes, like technology acceptance and user-generated content, have evolved into advanced applications focused on real-time personalization, consumer interaction, and automated decision-making. This work not only outlines the conceptual structure of AI in digital marketing but also identifies critical gaps and future research opportunities. Practical implications are provided for industry professionals, emphasizing strategies for leveraging AI-driven tools to enhance customer engagement, optimize campaigns, and foster trust. By mapping the progression of research themes, this study offers a roadmap for academics and practitioners aiming to navigate the dynamic landscape of AI in digital marketing.

Keywords: Artificial intelligence; Machine learning; Digital marketing; Bibliometrics; Science mapping

1. Introduction

In 2022, generative AI models like ChatGPT marked a key point in AI adoption across industries. This shift is driven by the development of commercial AI applications and machine learning capabilities (Grawal et al., 2017; Dhar,

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Cite:Sánchez-Camacho, C., Miguel San-Emeterio, B., Carranza, R., & Feijoo, B. (2025, Feb.). Mapping two decades of evolution of artificial intelligence and machine learning in digital marketing and digital promotion to determine the current direction: A systematic review using bibliometrics. *Journal of Electronic Commerce Research*, 26(1).

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2016). Additionally, the incorporation of machine learning (ML) has enabled AI to establish connections between data autonomously, enhancing decision-making and business process automation (Aljabri et al., 2023). Consequently, AI is becoming popular in areas such as commercial management and marketing.

Marketing has evolved significantly with the rise of digital technologies like mobile connectivity and virtual reality (Kim and Lee, 2021). These technologies have transformed traditional marketing into digital marketing. In this field, AI has experienced notable evolution over the past two decades, significantly impacting professional processes. AI improves consumer behavior analysis, enhances engagement, and automates processes like content creation and lead generation, reducing acquisition costs (Campbell et al., 2020; Thakur and Kushwaha, 2024). Despite its advancements, the full capabilities and limitations of AI in digital marketing remain unknown (van Esch and Stewart, 2023).

Digital marketing leverages digital media and channels to engage consumers and promote products effectively (American Marketing Association, 2024). It integrates online and offline interactions between businesses and customers, utilizing technologies such as the Internet, social media, email, and mobile devices to connect with specific audiences and deliver value efficiently (Kotler et al., 2017). Key strategies include search engine optimization (SEO), search engine marketing (SEM), content marketing, social media marketing, and e-commerce, among others (Bala and Verma, 2018).

With billions of connected consumers worldwide, digital communication technologies have become integral to everyday life (Dwivedi et al., 2021). As of October 2024, 5.52 billion people, representing 67.5 percent of the global population, were internet users, and 5.22 billion were active on social media platforms (Statista, 2024). This dynamic digital ecosystem fosters opportunities driven by technological advancements, particularly artificial intelligence (AI) and machine learning (ML), which are transforming digital marketing practices. These advancements, coupled with the growing number of connected consumers, underline the need for a focused analysis of AI's role in shaping the future of digital marketing.

Futhermore, the academic study of AI in digital marketing mirrors its professional adoption. While publications linking AI and digital marketing have been recorded since 2000, a significant increase in studies occurred in 2022. Evaluating research on AI in digital marketing is crucial to measure its present and future impact, which has significant implications for processes and professional profiles, generating new research lines.

Understanding this evolution is essential for identifying future trends and leveraging AI opportunities in digital marketing. AI and ML offer numerous applications in digital marketing (Davenport et al., 2020). Previous works such as Han et al. (2021), Haleem et al. (2022), and Thakur and Kushwaha (2024) have focused on the bibliometric analysis of AI in marketing research generally, while Kim et al. (2021) and Krisheen et al. (2021) have analyzed digital marketing. This research adds value by specifically focusing on marketing affected by AI and ML-based tools.

Despite the great growth experienced by this academic field in recent years, it has been found that the whole of the scientific production has never been analyzed to understand the historical evolution, key changes, and potential research gaps. Thus, a systematic analysis is needed to identify the key characteristics of the social structure (such as countries, affiliations, authors, journals, and years), the predominant topics in each period, topics approaching a maturity point, emerging topics, and future lines of research.

This research contributes to the field by adopting a longitudinal perspective that captures the historical and conceptual evolution of Artificial Intelligence (AI) and Machine Learning (ML) in digital marketing. By dividing the analysis into two distinct periods (2000–2021 and 2022–2024), this research identifies significant shifts in publishing dynamics, thematic focus, and technological advancements. The first period centers on foundational themes, such as technology acceptance and user-generated content (e.g., word-of-mouth communication), which laid the groundwork for the adoption of AI in marketing. In contrast, the second period highlights the emergence of advanced AI applications, including generative language models, real-time recommender systems, anthropomorphic technologies, and artificial neural networks (ANN), reflecting a shift towards more personalized and consumer-centric marketing practices.

Through a bibliometric approach, this study uncovers novel research trajectories that are shaping the future of the field. Four key areas of high research potential are identified: 1) Natural Language Processing (NLP) and Artificial Neural Networks (ANN): transforming brand-consumer interactions through advanced chatbots, sentiment analysis, and predictive models. 2) Human-robot interaction and anthropomorphism: highlighting the role of human-like traits in enhancing trust, satisfaction, and engagement. 3) Machine Learning and Recommender Systems: optimizing user experiences through real-time personalization and automation. 4) Social media marketing and engagement: leveraging AI to enhance interactivity, campaign effectiveness, and consumer relationships on digital platforms.

The study has two main objectives: (i) Mapping the evolution of the scientific production on AI and ML in digital marketing to identify driving and emerging lines of research, thus highlighting the areas of greatest impact and research gaps, and (ii) to provide practical recommendations for future research and professional applications, helping

to target studies in areas of high relevance and to apply knowledge in digital marketing strategies in an effective way. This involves posing the following research questions:
RQ1: What thematic areas structure the conceptualization of AI in digital marketing, and what are their key characteristics?
RQ2: What motor and transversal topics are driving the evolution of AI applied to digital marketing, and how are they impacting emerging research lines?
RQ3: What new emerging topics are gaining relevance in AI applied to digital marketing, and how are they interacting with established topics?
RQ4: How can future research and practical applications guide the development of AI-based marketing strategies?

To address these questions, this study employs a bibliometric approach supported by SciMAT, focusing on scientific mapping to analyze the conceptual structure of the field. Using strategic diagrams and evolution maps, the study visualizes longitudinal trends, thematic relationships, and the evolution of key topics over time. This approach identifies motor, transversal, emerging, and specialized themes, providing a comprehensive understanding of the intellectual framework of AI and ML in digital marketing. These insights uncover opportunities for future research and practice, offering actionable recommendations for this evolving field.

The paper is organized as follows. The next section provides a literature review of AI and ML applications in the digital marketing field and discusses the utility of bibliometric studies. The method section details the methodological approach used to analyze the evolution of AI and ML research in digital marketing. In the analysis and results section, we present the findings and identify emerging research topics. Finally, the discussion section offers an interpretation of the results and outlines future research directions and managerial recommendations.

2. Literature Review

2.1. Integrating Artificial Intelligence, Machine Learning, and digital marketing

The academic study of digital marketing has continuously examined various topics related to the theory and practice of integrating Artificial Intelligence (AI) and Machine Learning (ML). Artificial intelligence significantly enhances customer relationship management (CRM) performance in e-commerce by enabling personalized, data-driven strategies and improving automation capabilities (Li et al., 2023). This enhancement aligns with broader efforts to leverage AI in understanding consumer behavior and optimizing engagement, which are crucial in digital marketing (Chaffey and Ellis-Chadwick, 2019). This theoretical framework examines the roles and applications of AI and ML within digital marketing. Huang and Rust (2021) further emphasize the transformative impact of AI in marketing by proposing a strategic framework that aligns AI capabilities with consumer trust, personalization, and long-term engagement strategies. Their work highlights the necessity of aligning AI personalization efforts with trust-building mechanisms, ensuring that consumer data privacy is prioritized to foster long-term loyalty.

AI refers to the development of computer systems capable of performing tasks that normally require human intelligence, such as visual perception, speech recognition, decision-making, and language translation (Russell and Norvig, 2021). To further understand the adoption of AI in marketing, theoretical frameworks such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) are particularly relevant. These models guide the design of consumer-centric AI technologies, increasing adoption and reducing resistance to innovations. As proposed by Venkatesh et al. (2003), these models provide critical insights into how trust, perceived usefulness, and ease of use shape consumer acceptance of AI technologies. By guiding the design of consumer-centric AI strategies, they promote higher adoption rates and mitigate resistance to innovations. AI powers personalization and chatbots, transforming customer interactions in digital marketing. Lin et al. (2024) build on AI's capabilities in personalization by examining multilingual eWOM frameworks. Their findings demonstrate how AI-driven sentiment analysis can effectively tailor engagement strategies to linguistically diverse consumer bases, enhancing satisfaction and loyalty. AI algorithms analyze large datasets to identify distinct customer segments, allowing for more targeted marketing efforts (Ngai et al., 2009; Moradi and Dass, 37022). AI can create personalized marketing content by predicting individual customer preferences and behaviors. It processes unstructured data and natural language, delivering accurate and personalized outcomes to users (Dwivedi et al, 2023; Thakur and Kushwaha, 2024). Additionally, AI-driven chatbots and voice assistants, which use Natural Language Processing (NLP) and Deep Learning (DL) methods, offer round-the-clock assistance to customers, enhancing the shopping experience and reducing employee workload (Kamoonpuri and Sengar, 2023). These AI models also predict future consumer trends based on historical data, helping marketers optimize their campaigns (Davenport et al., 2020). AI tools can analyze competitors' campaign performance and reveal customer expectations (Haleem et al., 2022).

ML, a subset of AI, involves algorithms and statistical models that allow computers to improve their performance on tasks through experience (Jordan and Mitchell, 2015). In digital marketing, ML is applied in content generation, ad targeting, customer journey mapping, and sentiment analysis. Asante et al. (2023) highlight how predictive analytics and real-time personalization, core components of AI strategies, enhance consumer loyalty and reinforce the transformative potential of AI in digital marketing. ML algorithms can generate marketing content, such as social media posts and email campaigns, by analyzing past content performance (Mandal and Maiti, 2021; Taufique & Mahiuddin-Sabbir, 2023). ML optimizes ad targeting by analyzing user behavior and predicting engagement likelihood (Bucklin and Sismeiro, 2009). Furthermore, Dwivedi et al. (2021) discuss how ML algorithms can address dynamic consumer preferences by integrating real-time behavioral data, thereby improving engagement rates and conversion outcomes. It tracks and predicts customer journeys, enabling marketers to deliver timely and relevant messages (Javornik and Mandelli, 2012). Furthermore, ML tools analyze social media interactions and customer feedback to gauge public sentiment, informing marketing strategies (Aljabri et al., 2023). However, as Dwivedi et al. (2021) point out, implementing AI tools requires mechanisms to ensure transparency and mitigate biases, crucial for maintaining consumer trust in AI-driven decisions. Deep learning analyzes customer data to recommend products based on individual needs and could potentially assist in creating products and suggesting purchases (Ullal et al., 2021). Huang and Rust (2021) argue that personalized recommendations not only enhance satisfaction but also build trust, a key factor for long-term loyalty in AI-driven marketing.

Integrating AI and ML into digital marketing enhances strategies through advanced data analysis and automation (Verma et al., 2021). AI algorithms analyze large datasets to identify relevant audience segments for campaigns (Chaffey and Ellis-Chadwick, 2019) and manage real-time promotional optimization (Kumar et al., 2024). ML analyzes historical pricing data to optimize strategies, while dynamic pricing allows businesses to adjust based on market dynamics, competitor pricing, and customer preferences (Bharadiya, 2023). AI customizes messages in real-time to align with customer profiles and preferences (Huang and Rust, 2020). Emotional AI fosters stronger brand connections by enhancing personalization depth (Rust and Huang, 2021). AI tools track customer preferences and optimize content effectiveness using emotive algorithms (Verma et al., 2021). Additionally, AI offers deep campaign insights, enabling continuous improvement and helping marketers anticipate consumer needs (Wedel and Kannan, 2016).

In addition to consumer challenges, AI implementation in digital marketing faces organizational barriers (Bérubé et al., 2021). Resource allocation and accountability are key issues, as integrating AI demands investments in infrastructure, skilled talent, and training. Transparency concerns and unclear responsibilities also hinder AI-driven decision-making. Addressing these challenges requires developing internal capabilities, clear governance frameworks, and effective change management strategies (Benjelloun and Kabak, 2024). These measures enable the ethical and strategic integration of AI, maximizing its transformative potential in digital marketing.

2.2. Bibliometrics

Bibliometrics is a scientific discipline that employs various methods to explore the evolution and impact of different topics over time, facilitating a deeper understanding of an academic field (Moral-Muñoz et al, 2019; Sánchez-Camacho et al, 2021). It involves mathematical and statistical processes within the broader field of scientometrics (Pritchard, 1969).

Bibliometrics provides objective criteria to evaluate existing research, quantifying academic productivity and quality (Cobo et al., 2011a; Koseoglu et al., 2015). It aids scientific growth by identifying reliable sources of scientific publication, evaluating progress, establishing academic foundations for new developments, and developing indexes to assess academic production (Martínez-López et al., 2020; Diaz et al., 2022). According to Merigó et al. (2019), bibliometric studies offer an alternative approach to conducting literature reviews in an academic field. Authors such as Ferreira et al. (2014) and Kim et al. (2021) state that bibliometric analyses, including those of citations and co-citations, are useful for understanding the patterns and characteristics of published work, facilitating the exploration, organization, and articulation of research in a specific discipline.

Specifically, in the context of this study, AI and digital marketing professionals can use bibliometrics to identify the most covered topics and those yielding the most significant results (Anayat and Rasool, 2024). This allows them to follow the latest professional trends and make informed decisions about future projects (Alcaide-Muñoz et al., 2017). Recent bibliometric studies, such as those by Han et al. (2021), Verma et al. (2021), Haleem et al. (2022), Anayat and Rasool (2024), and Thakur and Kushwaha (2024), have significantly contributed to understanding AI's applications in marketing. However, these studies primarily examine marketing as a broad discipline, focusing on general themes such as CRM, data mining, and AI adoption, without narrowing their scope to digital marketing. While digital marketing is occasionally mentioned as an area of potential, it is not explored in depth. For instance, Verma et al. (2021) provide a systematic review of AI's importance in marketing, and Haleem et al. (2022) focus on AI's specific applications in traditional marketing activities, but neither delves into the unique challenges and opportunities of digital marketing. Similarly, Anayat and Rasool (2024) and Haleem et al. (2022) explore topics such as AI's use in market research but do not target digital marketing as their primary focus.

Marketing as a discipline has rapidly adopted AI-based technological innovations, but digital marketing, as a specialization, integrates these technologies more organically due to its inherently technological nature. AI applications in digital marketing directly address objectives such as facilitating product offerings, attracting customers, and ensuring customer retention, yet the field remains underexplored in academic literature. Existing works like Kim et al. (2021) and Krisheen et al. (2021) apply bibliometric methods to digital marketing but do not incorporate AI in their analyses, further highlighting this gap.

This research directly addresses this gap by focusing exclusively on digital marketing and examining AI's transformative role within this subdiscipline. Unlike previous works, it adopts a longitudinal perspective, segmenting the analysis into two key periods (2000–2021 and 2022–2024), to capture structural changes such as the widespread adoption of generative AI in 2022. Furthermore, it identifies emerging topics uniquely relevant to digital marketing, including recommender systems for personalized content delivery, real-time sentiment analysis for optimizing consumer engagement, and human-robot interaction to enhance user experience. These findings provide a deeper understanding of AI's integration in digital marketing and offer actionable strategies to improve personalization, engagement, and campaign effectiveness.

3. Method

3.1. Data Collection and Data Set

In bibliometric research, the representativeness of the database significantly affects the validity of the analysis and, consequently, the results (Mongeon and Pauls-Hus, 2016). Scopus and Web of Science (WoS) are the two most used bibliographic sources in bibliometric studies due to their reputation as the most comprehensive and exhaustive options (Abdekhoda et al., 2023; Caputo and Kargina, 2022; Liu et al., 2021). Although both sources can be complementary, several authors emphasize WoS as the most frequently used (Zupic and Čater 2015; Zhang et al. 2016; Birkle et al. 2020). They offer various key arguments. For example, Martínez et al. (2014) indicate that WoS is used more often in bibliometric research due to its superior reliability in terms of quality and impact. Additionally, Álvarez-Mergalejo and Torres-Barreto (2018) assert that journals indexed by WoS outperform those in Scopus in productivity and impact. Singh et al. (2021) also note the advantage of WoS as a highly selective source without adversely affecting quality. Moreover, authors such as Piñeiro-Chousa et al. (2020) argue that using a single source like WoS allows researchers to manage all publications in a standardized and consistent manner for systematic reviews. Another added argument is that WoS provides highly comprehensive bibliographic information about publications, enabling the collection of detailed data (Zupic and Čater 2015). Other authors, such as Yadav and Banerji (2023), focus on highlighting WoS for its strict quality control and reliability in conducting bibliometric research. As can be seen, many authors agree that WoS is a source of excellent quality. This quality is reflected in the high impact and relevance of the journals it contains, making it a more selective source (Centobelli et al., 2021). Given the length limitations of this manuscript, additional arguments regarding the use of Web of Science can be found in **Appendix A** of the web appendix. As a result of all the arguments presented, many high-impact studies have relied on WoS as a single bibliographic source for conducting systematic reviews. Notable examples include recent research from a broad range of academic fields. (e.g., Bhatt et al., 2020; Biju et al., 2024; Campos-García et al., 2024; Casali et al., 2022; Diaz et al., 2022; Djeki et al, 2022; Grabowska and Saniuk, 2022; Lin et al., 2023; Liu et al., 2023; Piñeiro-Chousa et al., 2024; Qiao et al., 2024; Qiu et al., 2024; Sánchez-Camacho et al., 2021; Sánchez-García et al., 2023; Urbán et al., 2024; Wang et al., 2024; Wider et al., 2023; Xu et al., 2022; Xue et al., 2023; Yang et al., 2024).

Due to space constraints, detailed technical information about the search process and parameters can be found in **Appendix B** of the web appendix. As a result, 422 articles in English were collected from high-impact specialized journals, forming an exhaustive and selective database. The documents collected cover a range from 2000 (first publication found) to 2024 (the search was carried out in May). They were downloaded for analysis in specialized bibliometric software.

3.2. Preprocessing and analysis

The dataset was analyzed using SciMAT (Science Mapping Analysis Software Tool), which enables a comprehensive bibliometric method to map the conceptual structure of the study area. The procedure follows the methodology proposed by Cobo et al. (2011a) and involves several key phases. First, the preprocessing phase addresses and corrects conceptual biases and errors inherent in the raw database (Cobo et al., 2011b; Cobo et al., 2013), involving the analysis of 2365 unique keywords that form 1458 word groups.

Bibliometric software like SciMAT currently lacks the capability to automatically create time periods for conducting longitudinal studies. This responsibility lies entirely with the researcher. Therefore, the design of the time periods must be well-reasoned, consistent, and realistic. To achieve this, researchers must identify a key indicator: is there a noticeable pattern change in the database, such as a significant increase or decrease in the annual number of publications during a specific year?

In this study, such a change was observed between 2021 and 2022. The number of published studies rose from 45 in 2021 to 85 in 2022, representing an 88.9% increase in just one year. This figure stands out, as other fluctuations in the dataset are more gradual, and some years even show a decline in publications. For example, there was a drop from 8 to 7 publications between 2016 and 2017, and from 52 to 45 publications between 2020 and 2021. To provide further context, there was a 24.7% increase in publications between 2022 and 2023, rising from 85 to 106. This reflects a more gradual and consistent growth pattern. Therefore, when the growth observed between 2021 and 2022 is fully contextualized, it becomes even more striking. The sharp rise between 2021 and 2022 clearly indicates a significant shift. This was a crucial clue for the authors, suggesting a notable change in trends. Such a marked inflection point in the longitudinal arrangement of the database is likely driven by one or more underlying reasons that warrant further exploration. The authors of this research found answers in the arguments provided by various organizations, institutions, and credible expert authors in the field of AI.

Due to the length of this manuscript, additional arguments from organizations and companies such as the World Economic Forum, IBM, and McKinsey & Company supporting this turning point can be found in **Appendix C**. Therefore, it can be concluded that several expert professionals and renowned global tech companies agree in placing an inflection point in 2022. All with different arguments that converge on the same idea. For this reason, the pattern detected in the database of this research is justified. As a result, the longitudinal study was designed through two periods: 2000-2021 (from the publication of the first document in the database to the cutoff point) and 2022-2024 (from the cutoff point to the present).

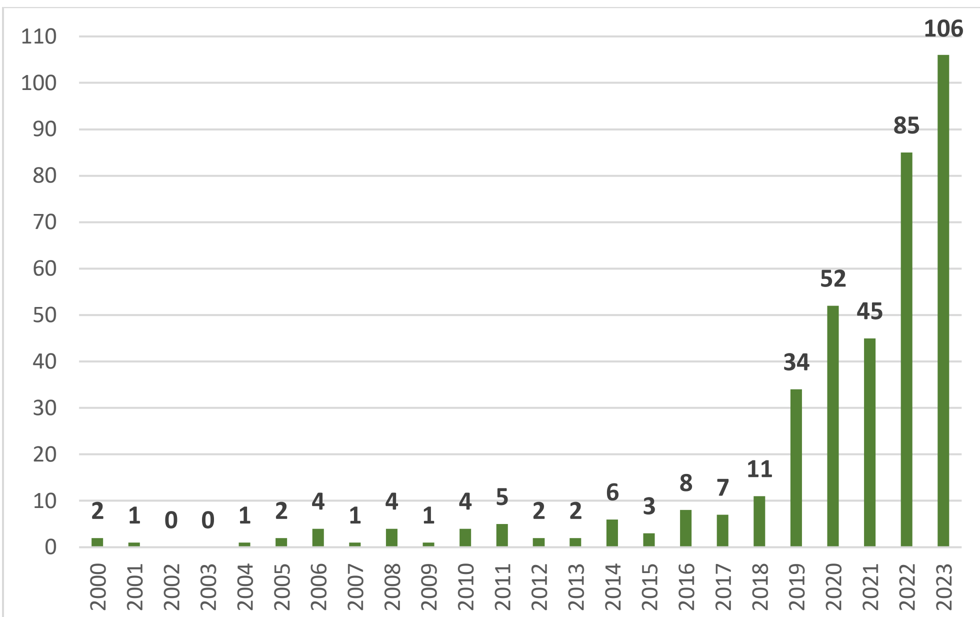

Figure 1: Distribution and evolution of articles on AI and Digital Marketing.

To conclude this section, it is essential to explain the main technical aspects of the analysis conducted with SciMAT. This tool is based on the approach to scientific mapping introduced by Cobo et al. (2011a), which supports longitudinal studies of scientific maps (Garfield, 1994; Price and Gürsey, 1975). Due to space limitations, all detailed technical information about the bibliometric analysis process using SciMAT can be found in **Appendix D**.

SciMAT generates a strategic diagram for each period, visually showing the conceptual structure based on two parameters: centrality and density (He, 1999; Sánchez-Camacho et al., 2021). These two factors are crucial for understanding the positioning and significance of different themes within the conceptual structure. The strategic diagram categorizes themes into four types:

- Motor themes: Located in the upper right quadrant, these themes occupy a central position in scientific production and are well-formed internally. They are the leading and driving topics of scientific production during their respective periods.
- Developed but isolated themes: Located in the upper left quadrant, these themes have high internal consistency but are not strongly related to other themes in the field (specialized but peripheral).

- Transversal themes: Located in the lower right quadrant, these themes occupy central positions in scientific production but are generalist and not very dense internally.
- Emerging themes: Located in the lower left quadrant, these interesting themes do not yet stand out for their external relationship (centrality) or internal consistency (density).

4. Results

Although not the primary purpose of this research, **Appendix E** provides a brief descriptive analysis of the social structure. Readers can find information about the journals with the most publications in this field, the most contributing authors, and the most cited contributions. These details offer brief contextual information of interest. Subsequently, the focus shifts to the main subject of this research: the analysis and mapping of the conceptual structure.

4.1. Conceptual structure analysis and mapping

This chapter examines the scientific mapping of the conceptual structure underlying the discipline under study: AI integrated into digital marketing. With a longitudinal focus, it compares and connects the thematic networks from two study periods: 2000–2021 (P1) and 2022–2024 (P2). To provide a deep, comprehensive, and interconnected analysis, it combines three visual tools: the strategic diagram of each period, the evolution map, and the keyword networks defining thematic clusters.

Phase 1: Visualization of the scientific map by contrasting diagrams and evolution map.

As the methodology explains, strategic diagrams illustrate how each period's conceptual framework is organized. Clusters are positioned based on their levels of centrality and density (ranging from 0 to 1) and are classified into motor themes, transversal themes, specialized yet isolated themes, or emerging/declining themes. However, strategic diagrams alone have a limitation: they provide only a snapshot of a single period, making them insufficient for comprehensive longitudinal analysis. Figure 2 simultaneously presents the strategic diagrams for the two study periods. The diagram on the left illustrates the conceptual structure of the first period (2000–2021), while the diagram on the right depicts the organization of the scientific production in the second period (2022–2024).

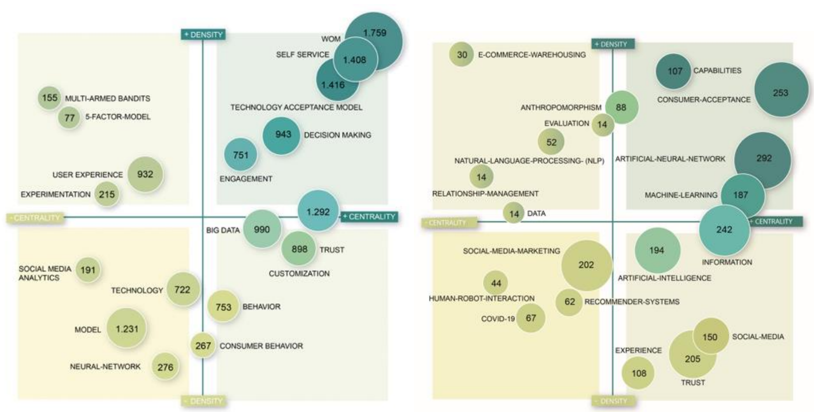

Figure 2: Strategic diagrams for period 1 (left) and period 2 (right).

The evolution map addresses some of the limitations of strategic diagrams by offering a longitudinal perspective. Unlike strategic diagrams, it reveals relationships between clusters from different periods and the intensity of those connections. Figure 3 presents the evolution map for this study. The left column displays the 18 thematic clusters from Period 1 (P1), while the right column shows the 19 clusters from Period 2 (P2). Lines connect clusters. A solid line indicates that both clusters share the same primary keyword. A dashed line means those clusters share one or more keywords, but none is primary. The thickness of the line represents the number of shared keywords, reflecting the strength of the relationship between the themes (with a level or grade ranging from 0 to 1). Considering all this, analyzing the evolution map (Figure 3) reveals several clear relationships. For example, some notable cases include:

- Technology-Acceptance-Model (P1) and Consumer-Acceptance (P2), which exhibit the strongest possible connection (1) and share the main keyword.
- WOM (P1) and Information (P2) demonstrate a robust relationship (0.75) and share the main keyword.
- Decision-Making (P1) and Customization (P1) show a significant connection (0.50) with Recommender-Systems (P2). Moreover, this P2 cluster incorporates the main keyword from both P1 clusters.

The longitudinal relationships highlighted in these three examples cannot be observed in the static strategic diagrams of each period (Figure 2). Therefore, the evolution map provides critical longitudinal insights. At this stage, researchers must question how to interpret the detected longitudinal relationships. For instance, how do Technology-Acceptance-Model (P1) and Consumer-Acceptance (P2) precisely interact? The following outlines what information is currently known and unknown to the researcher:

- Technology-Acceptance-Model is one of the primary motor themes of P1, with high levels of centrality and density (0.89, 0.89). This indicates it is both specialized and well-developed,
- Consumer-Acceptance emerges as a leading motor theme in P2, characterized by maximum centrality (1) and very high density (0.89).
- The evolution map reveals a strong connection between these clusters, showing a maximum relationship and shared main keyword.
- However, the exact nature of this connection remains unresolved: Has Technology-Acceptance-Model from P1 become integrated into Consumer-Acceptance in P2? Did Consumer-Acceptance branch off independently from Technology-Acceptance-Model? Or is their relationship more complex?

To address these questions, the third figure in this results analysis is utilized: the internal keyword network of each cluster. This network reveals two critical insights: first, the specific keywords within a cluster, indicating those shared with related clusters; second, the detailed meaning and interpretation of the thematic cluster. Together, these three figures (diagram, evolution map, and keyword network) provide a comprehensive longitudinal perspective, enabling a full analysis of the conceptual structure of AI in digital marketing and its evolution. Strategic diagrams position clusters within each period and assign their roles. The evolution map identifies inter-period cluster relationships. Cluster composition (keyword network) unveils details about these relationships and defines the thematic significance of each cluster.

By aligning these three figures in perspective, it is possible to identify and analyze a series of major thematic areas, each composed of interrelated clusters (Table 1). These thematic areas represent the longitudinal arrangement of the conceptual structure of AI integrated into digital marketing. Table 1 presents the eight major thematic areas, detailing the clusters from both periods (P1 and P2) that form each area. Subsequently, each area is thoroughly analyzed in terms of its theme, how new clusters in P2 build upon P1 clusters, its evolution, and its current role. The figures showing the keyword network of the clusters are included in this analysis.

Table 1 provides a visual synthesis of the eight major longitudinal thematic areas identified in this research. These areas represent the conceptual framework of all scientific production on AI integrated or applied in digital marketing since the first publication recorded in 2000. As shown, each area (each row in the table) comprises a group of interrelated thematic clusters that span both periods of the study. Furthermore, within each period, every cluster is classified by its role: driving, transversal, developed but isolated, or emerging/declining. Therefore, data from the strategic diagrams and the evolution map inform Table 1. The following sections analyze each area individually, incorporating some of the internal word networks from the most significant clusters. This approach offers an in-depth understanding of how clusters within each area interact.

Thus, the results are organized as follows. It has been verified that the entire body of scientific production on AI applied in digital marketing revolves around eight major thematic areas. Each thematic area consists of a series of more interconnected topics, interacting with each other and fulfilling different roles (motor, transversal, specialized, or emerging). Furthermore, each topic (cluster) comprises a network of keywords that define its meaning. This study, therefore, includes 37 keyword networks, represented by 37 distinct figures (18 corresponding to P1 clusters and 19 to P2 clusters). Due to space limitations in this manuscript, it is not possible to incorporate all 37 figures illustrating the keyword networks for each topic. For this reason, in the analysis of each area (from A1 to A8), only the internal composition of one or more clusters is presented. Priority is given to significant clusters and those from P2, as they reveal the current state of research. This approach ensures that the reader gains a clear understanding of how these results are visualized and presented.

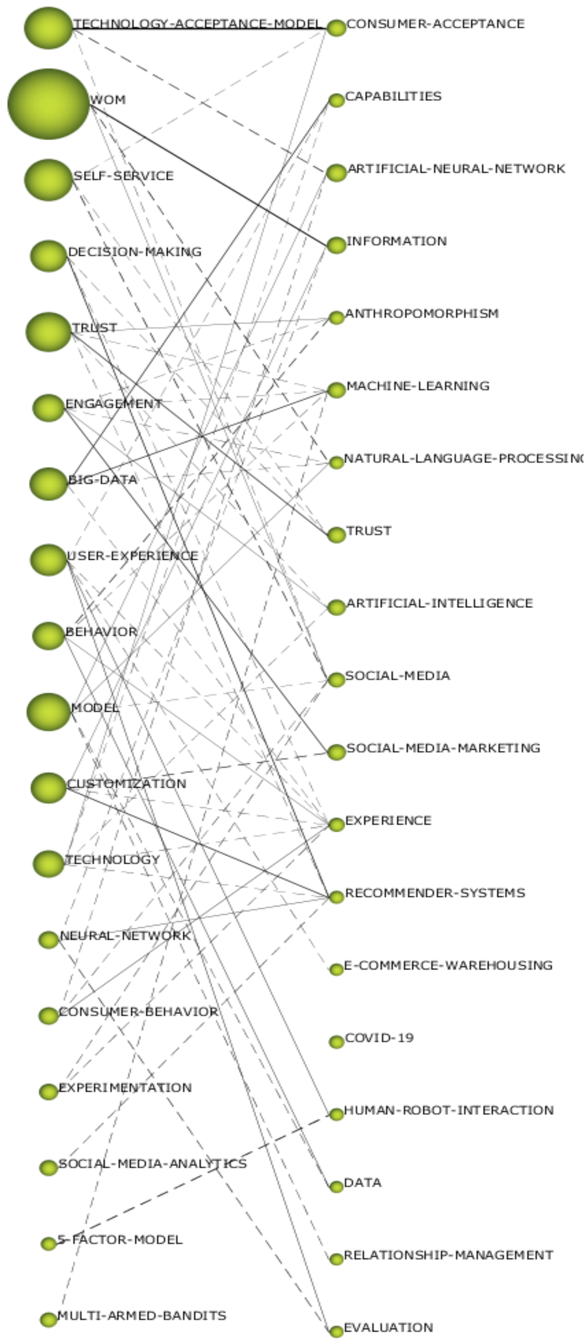

Figure 3: Evolution map

Phase 2: Analysis of the scientific map and thematic areas from a longitudinal perspective.

Table 1. List and composition of the thematic areas

	P1				P2			
	Motor	**Transversal**	**Specialized and isolated**	**Emerging or decline**	**Motor**	**Transversal**	**Specialized and isolated**	**Emerging or decline**
A1	Self-Service, Technology-Acceptance-Model	Trust		Technology	Consumer-Acceptance, Anthropomorphism	Trust		
A2		Big-Data	Multi-Armed-Bandits		Capabilities, Machine-Learning			
A3				Model	Artificial-Neural-Network		Natural-Language-Processing	
A4	Decision-Making	Customization		Social-Media-Analytics, Neural-Network				Recommender-Systems
A5	WOM					Social-Media, Information		
A6		Consumer-Behavior, Behavior	Experimentation			Experience	Data	
A7	Engagement					Artificial-Intelligence		Social-Media-Marketing
A8			5-Factor-Model, User-Experience				Evaluation	Human-Robot-Interaction

At this stage, a detailed analysis of each of the 8 longitudinal thematic areas is conducted. The analysis is extensive because the 8 thematic areas yield relevant results. For this reason, the results of the first two areas (A1 and A2) are presented below. This allows readers to understand how the results are obtained and presented. The results of the other areas (from A3 to A8) can be found in **Appendix F** of the web appendix.

A1. Consumer technology acceptance: from self-service to new anthropomorphic assistants.

Focus and evolution. This is the most significant longitudinal thematic area in terms of scope and impact. Consequently, its analysis is particularly dense and comprehensive. Area A1 demonstrates a clear evolution regarding the adoption of digital technologies and consumer perception. In P1 (2000–2021), the focus was on topics such as self-service and the Technology Acceptance Model (TAM), exploring customer satisfaction, intention to use, and the quality of mobile services. Within this framework, concepts like consumer acceptance and anthropomorphism were secondary components within broader clusters (TAM and Trust, respectively). In P2 (2022–2024), a significant transformation is evident: consumer acceptance emerges as a standalone driving theme, solidifying its importance through models such as UTAUT and PLS-SEM. Simultaneously, anthropomorphism detaches from Trust to become a central driver, reflecting a shift toward concerns about human-machine interaction, emphasizing chatbots, robots, and customer experience in online services. Conversely, the theme of self-service, which was pivotal in P1, disappears in P2, giving way to new trends in technology adoption.

Current status. In P2, A1 solidifies as an area focused on technology adoption and user experience in digital environments. The driving themes, Consumer Acceptance and Anthropomorphism, lead the research. Consumer Acceptance maintains a thematic consistency with P1, emphasizing the adoption of mobile technologies with applications in sectors such as banking and education. Meanwhile, Anthropomorphism emerges as a distinct cluster, addressing human-machine interaction, social perception, and its presence in digital customer service contexts. The theme of Trust, while transversal, remains relevant in P2, adapting to new concerns such as purchase intention, privacy, and perceived risk. However, its separation from Anthropomorphism reflects a specialization in more traditional lines of digital trust. In summary, A1 represents an evolution toward a more specific focus on human-technology interaction, with an internal structure characterized by the independence and strengthening of key clusters.

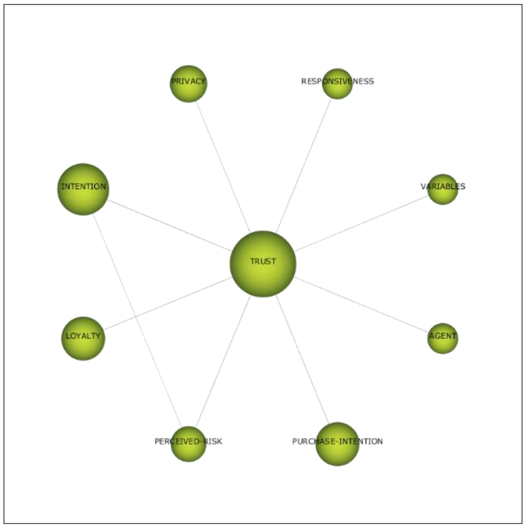

Figure 4: Keyword network of the Trust cluster (P2) from A1

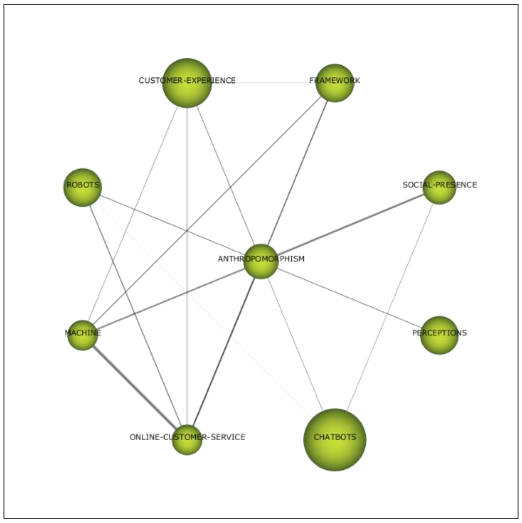

Figure 5: Keyword network of the Anthropomorphism cluster (P2) from A1

A2. Big data and machine learning for decision making.

Focus and evolution. Area A2 has evolved from focusing on Big Data in P1 (2000–2021), where Machine Learning was integrated to process and analyze large volumes of data, to a more specialized focus on Machine Learning in P2 (2022–2024). In P1, Multi-Armed Bandits was a specialized topic that concentrated on efficient resource allocation through field experiments, a crucial approach in online learning. This technique, which optimizes decisions under uncertainty, formed the foundation for many more advanced Machine Learning algorithms. The advances in Machine Learning in P2 build upon this experimental approach by integrating exploration-exploitation concepts—central features of Multi-Armed Bandits—to improve prediction models and decision-making in more complex scenarios. As the field progresses into P2, Big Data is incorporated into the new driving cluster Capabilities, which encompasses topics such as resource management and dynamic capabilities within the context of Industry 4.0. This shift reflects how data analysis technologies have evolved towards a more strategic approach, focusing on decision-making.

Current status. A2 focuses on two driving clusters: Machine Learning and Capabilities. Machine Learning has emerged as a key theme in decision optimization, predictive analytics, and personalization, with applications in e-commerce. This cluster has strengthened, partly due to its connection with techniques like Multi-Armed Bandits, which provide optimization strategies that enhance the ability of Machine Learning models to make efficient decisions in dynamic contexts. Meanwhile, Capabilities integrates Big Data into a broader approach that encompasses dynamic capabilities management, innovation, and business agility. This cluster emphasizes the importance of applying advanced technologies not only to analyze data but also to optimize business processes and make strategic decisions at the organizational level. Together, area A2 highlights how data analytics and machine learning technologies have been strategically integrated to optimize decision-making in digital marketing.

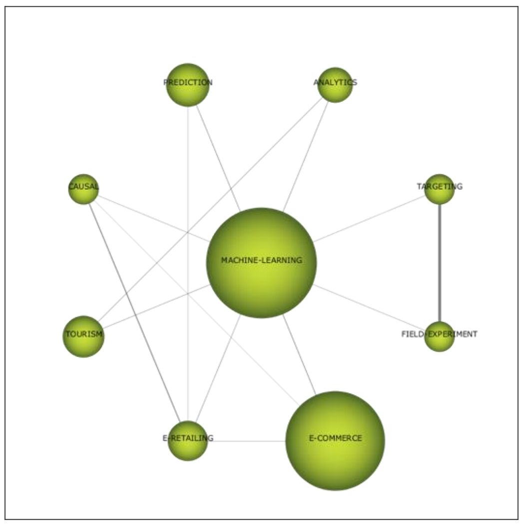

Figure 6: Keyword network of the Machine Learning cluster (P2) from A2

Phase 3: Analysis of the status of P2 clusters to determine their position and potential

The longitudinal analysis offers a comprehensive view of the evolution of artificial intelligence in digital marketing, revealing how current topics have emerged and developed within their historical context. Unlike static strategic diagrams, this approach uncovers the dynamics and connections between clusters over time, providing a holistic perspective. It assesses the status and potential of topics based on their roles—driving, transversal, emerging, or specialized—while highlighting their unique development patterns and impact. From the scientific map, the analysis identifies 5 core topics, 2 transversal topics, 3 emerging topics, and 1 specialized yet isolated topic.

Motor themes form the foundation for interdisciplinary research and practical applications, driving ongoing exploration and the emergence of subtopics. Their high centrality and density establish them as theoretical cornerstones supported by robust conceptual models. The key motor topics in P2 are:

Consumer-Acceptance. A motor topic with maximum centrality and high density in P2, reflecting its importance in the study of technological adoption. Its centrality connects various research areas, while its applicability in consumer acceptance analysis ensures its relevance, particularly in dynamic fields like AI in digital marketing. Its connection to other motor topics, such as anthropomorphism, highlights potential interactions between emerging technologies and consumer perception.

Anthropomorphism. This evolving topic, with high density (0.84), stems from Trust in P1 and has significant implications for human-machine interaction. It influences areas like chatbots, customer experience, and automated services, offering avenues to explore the humanization of technology and its impact on trust and acceptance.

Machine-Learning. A core topic with high centrality (0.89), Machine Learning drives personalization, automation, and decision-making optimization in digital marketing. Emerging from Big Data in P1, it bridges areas like consumer behavior, recommender systems, and predictive analytics, solidifying its role as a fundamental driver of AI innovation.

Capabilities. With strong internal development (density 0.95), Capabilities integrates management, big data, agility, and innovation. It explores how dynamic capabilities enhance personalization, analytics, and customer experience management, positioning itself as a key axis for optimizing digital marketing strategies.

Artificial-Neural-Network (ANN). ANN is a core topic with high centrality (0.95), pivotal in decision optimization and personalization through techniques like regression and structural modeling. It bridges areas such as consumer behavior, e-commerce, and machine learning, enhancing automation and commercial strategies while driving the evolution of AI in digital marketing.

Secondly, transversal topics have the potential to evolve into motor themes if their density increases. However, they lack specialization, a limitation they offset by interacting with numerous other topics and acting as a bridge between them. Their broad scope makes them ideal for integrative studies that summarize the state of the art. Their density can be enhanced through research that delves deeper into their specific characteristics or applications. There are two transversal topics that will be highlighted due to their past and current roles. They are chosen for their ability to connect key research areas across different periods, reflecting both their historical importance and current relevance in the development of AI-based digital marketing:

Trust. A consistent transversal theme in digital marketing, Trust plays a crucial role in models of technology acceptance and purchase intention. In P2, its scope includes loyalty, perceived risk, and trust in virtual agents, adapting to technologies like personalization and automation. While its density has declined (from 0.5 to 0.11) due to widespread use, its centrality remains strong (0.74), highlighting its continued importance in AI acceptance and trust measurement in digital marketing.

Information. Consolidated as a key transversal theme in P2, Information integrates concepts like WOM, product recommendation, and user-generated content. With WOM (formerly a core theme in P1) as a central element, Information connects areas like social media marketing and consumer behavior. Its high centrality (0.84) enables it to act as a bridge for developing AI themes such as recommender systems, optimizing recommendations through user data.

Emerging topics hold significant potential to shape future trends, offering opportunities for researchers to explore novel or underdeveloped areas, often involving technological or theoretical innovations. Although their centrality may be low, they connect to established topics and provide a foundation for practical applications. This research identifies three key emerging topics:

Recommender-Systems. Emerging in P2 as a standalone topic, it integrates themes from P1 such as decision-making, customization, and neural networks. By consolidating personalization, decision optimization, and automation, it has become essential for digital marketing, enhancing personalized experiences and strategies.

Human-Robot-Interaction. Derived from the user-experience cluster in P1, HRI focuses on personality, cues, and automation, integrating concepts like the 5-factor model to create personalized and natural interactions. Although its centrality is low (0.16), its higher density (0.32) underscores its specialization and growing importance in automating and personalizing human-robot interactions in digital marketing.

Social-Media-Marketing. Focused on communication, influencer marketing, brand value, and engagement, this topic reflects the integration of Engagement (a motor theme in P1). With a centrality of 0.42, it is increasingly relevant for fostering authentic interactions between brands and consumers, potentially evolving into a transversal topic. It has significant potential for AI applications, such as sentiment analysis and campaign automation, to enhance personalization and consumer interaction.

Specialized but isolated topics offer opportunities for innovation in niche areas that remain underexplored. While their limited interaction with other fields may keep them as research niches, they can evolve into transversal or driving topics if they establish connections with broader themes or if the discipline integrates their concepts. One standout specialized topic is Natural Language Processing (NLP), given its current impact, reflected in 52 publications and its association with a key thematic area (A3).

Natural-Language-Processing (NLP). As a specialized topic in P2, NLP has moderate centrality (0.32) and high density (0.74), indicating robust internal development. Its keyword network focuses on text-analysis, sentiment-analysis, and consumer-reviews, positioning it as essential for understanding consumer opinions and emotions in digital marketing. Applications such as automated text analysis and text mining underscore its relevance, while its connection to Artificial Neural Networks (ANN), a motor topic in P2, highlights its potential to integrate with emerging technologies. NLP is poised to enhance personalization, optimize consumer interaction, and drive advancements in digital marketing strategies.

5. Implications, recommendations and limitations

This study identifies key research areas and practical applications of AI in digital marketing. Human-robot interaction can improve user trust and satisfaction through anthropomorphic features, recommender systems can balance personalization and privacy with federated learning, and NLP tools can enhance customer engagement by refining campaigns through sentiment analysis. These applications bridge theory and practice for industry professionals. The results presented in the previous section address the proposed research questions, translating into valuable academic implications for researchers in this field and proposing new research directions. Additionally, these findings serve to offer management recommendations for companies interested in the latest advances in AI applied to digital marketing.

5.1. Academic conclusions and implications: Future research lines.

First, this study addresses RQ1, exploring the thematic areas that structure the conceptualization of AI in digital marketing and their key characteristics. The analysis identifies eight thematic areas: (1) consumer technology acceptance, (2) big data and machine learning for decision-making, (3) advances in neural networks and natural language processing, (4) evolution of decision-making and customization through recommender systems, (5) WOM and online reviews-based information, (6) the evolution of consumer behavior and experience, (7) The role of artificial intelligence in enhancing engagement in social media marketing, (8) and human-robot interaction. These areas reveal the field's progression from foundational themes such as technology acceptance and WOM (2000–2021) to advanced applications like recommender systems and anthropomorphic technologies (2022–2024), offering a comprehensive framework for understanding the intellectual evolution of AI in digital marketing. Identifying this structure provides a clear framework for understanding the intellectual evolution of AI in digital marketing and offers a roadmap for future research by highlighting the interconnectedness and potential of these thematic areas.

This analysis directly addresses RQ2, identifying the motor and transversal topics driving the evolution of AI applied to digital marketing and their impact on emerging research lines. The motor topics identified in this study, such as Machine Learning, Consumer Acceptance, Anthropomorphism, Capabilities, and Artificial Neural Networks (ANN), are pivotal in shaping the field. These topics demonstrate high centrality and density, indicating their well-developed and influential roles. Motor themes like Machine Learning and Capabilities serve as foundational pillars for advancing technologies, enabling predictive analytics, decision optimization, and strategic agility in digital marketing strategies. Meanwhile, transversal topics like Trust and Information act as bridges, connecting established areas with emerging trends and fostering interdisciplinary approaches. These topics appear to influence the emergence of new research lines by creating opportunities for integration and specialization. For instance, the evolution of Anthropomorphism from the Trust cluster suggests a growing focus on understanding how human-like traits in AI systems might enhance user trust and satisfaction, potentially contributing to the development of themes like Human-Robot Interaction. Similarly, Artificial Neural Networks are closely aligned with advancements in unstructured data analysis, such as sentiment analysis and real-time decision-making, which are central to the growing importance of Recommender Systems. Additionally, the transversal role of Information aligns with the evolution of Social Media Marketing, likely facilitating the adoption of AI-driven tools for campaign optimization, influencer marketing, and consumer engagement. These motor and transversal themes thus provide a foundational framework that supports existing areas while opening pathways for the emergence and refinement of specialized topics, reflecting the dynamic landscape of AI in digital marketing.

On the other hand, the findings directly address RQ3, exploring how emerging topics in AI applied to digital marketing are gaining relevance and interacting with established themes. The study highlights three key emerging topics (Recommender Systems, Human-Robot Interaction, and Social Media Marketing) as well as a specialized but isolated theme, Natural Language Processing (NLP), which demonstrates strong internal development and significant potential for future academic exploration.

- Recommender Systems presents a valuable opportunity for advancing research on real-time personalization and adaptive decision-making models. Their integration with predictive analytics and machine learning frameworks opens new avenues for exploring how data-driven recommendations influence consumer behavior across various contexts. Researchers could investigate interdisciplinary approaches that combine recommender systems with behavioral sciences to optimize consumer decision-making.
- Human-Robot Interaction represents a fertile area for studying the psychological and behavioral dimensions of human-machine interaction. Future research could examine how anthropomorphic traits in AI systems influence trust and satisfaction, particularly in scenarios involving emotional engagement and complex decision-making. This theme also encourages investigations into the ethical implications of designing human-like AI, focusing on user acceptance and social dynamics in human-robot relationships.

- Social Media Marketing, as an emerging topic, invites academic inquiry into the intersection of AI and digital communication strategies. Potential research areas include the role of AI-driven sentiment analysis in measuring consumer engagement and the development of frameworks for understanding how AI algorithms influence the visibility and effectiveness of social media campaigns. This topic also highlights the need for longitudinal studies to track how AI tools reshape brand-consumer relationships over time.
- Finally, NLP, while specialized and isolated, offers a promising domain for advancing the study of unstructured data analysis in marketing. Research could focus on refining sentiment analysis methods to better understand consumer perceptions or exploring how NLP algorithms can improve text generation for personalized messaging. As NLP matures, its integration with neural networks could drive innovation in areas like conversational AI, further enriching its academic relevance.

Together, these topics represent a dynamic landscape of emerging and specialized themes that build on the foundational strength of motor and transversal clusters. They provide a roadmap for future investigations, highlighting the potential for interdisciplinary collaboration and the continued evolution of AI research in digital marketing. This point in the conclusions directly connects to the next research question, which delves further into future research recommendations.

To address RQ4, this study proposes several research lines that arise from the interaction between key and emerging topics in AI applied to digital marketing. Specifically, the identified emerging topics—Recommender Systems, Human-Robot Interaction, and Social Media Marketing—along with the specialized but isolated theme, Natural Language Processing (NLP), provide fertile ground for advancing knowledge in the field. These research lines are designed to inspire future academic investigations and address critical gaps by leveraging the interplay between established and emerging areas. To present these proposals to the readers, each one is explained individually. For each proposal, the topic, the main research question, and the suggested method are outlined. Five highly specific proposals are summarized:

- Balancing personalization and privacy in Recommender Systems: Recommender systems are crucial for enhancing personalization and optimizing decision-making in digital marketing. How can federated learning techniques be used to enable these systems to process data locally, balancing personalization with user privacy in industries handling sensitive information, such as healthcare or financial services?

  Suggested method: Explore the implementation of federated learning-based recommender systems that analyze user behavior locally to deliver personalized suggestions without compromising data security. Experimental studies could assess their impact on user satisfaction, trust, and conversion rates, offering actionable insights for applying these systems in diverse marketing contexts, such as e-commerce platforms or personalized healthcare solutions.
- Enhancing Human-Robot Interaction (HRI) in customer service: HRI can address user resistance and build trust in AI-based customer service by integrating anthropomorphic features, such as empathetic communication, natural language patterns, and context-aware responses. How can these traits improve user trust and satisfaction while reducing perceptions of impersonality in industries where customer confidence is critical, such as financial services or healthcare?

  Suggested method: Conduct experimental studies comparing interactions with chatbots or virtual assistants that feature anthropomorphic traits to those with traditional AI interfaces. These studies could measure trust, satisfaction, and usability, providing evidence for the effectiveness of these features in enhancing user experience and guiding their broader adoption in digital marketing strategies.
- Leveraging social media marketing for predictive insights: Social media platforms provide valuable data for predicting long-term consumer engagement and optimizing retention strategies. How can AI-driven tools utilize this data to develop accurate predictive models?

  Suggested method: Perform a longitudinal big data analysis of social media interactions, including sentiment analysis and behavioral trends. By applying machine learning and NLP, researchers can identify patterns that predict engagement and retention, validating these models through metrics like loyalty and long-term activity.
- Natural Language Processing (NLP) can significantly enhance sentiment analysis by adapting to linguistic and cultural nuances. How can NLP models refine their ability to analyze consumer emotions and generate personalized marketing messages in multilingual campaigns?

  Suggested method: Conduct comparative studies on the performance of NLP models across diverse linguistic datasets. These studies could evaluate their effectiveness in identifying sentiment variations and tailoring messages that resonate with different cultural audiences. This research has the potential to improve customer engagement and optimize the effectiveness of global marketing strategies.

- Bridging NLP and Artificial Neural Networks for conversational AI: What synergies between NLP and Artificial Neural Networks (ANN) can improve the sophistication and adaptability of conversational AI systems in digital marketing?
  Suggested method: Design conversational AI prototypes that integrate NLP for language understanding and ANN for decision-making and response generation. Conduct experiments in real-time consumer interaction scenarios, such as e-commerce chatbots or virtual assistants, focusing on metrics like response accuracy, coherence, and user satisfaction. Comparative studies could also evaluate the adaptability of these systems to dynamic inputs, such as varying customer intents or emotional tones, providing insights into their potential for improving personalization and engagement in digital marketing contexts.

5.2. Managerial recommendations

The findings from this research offer valuable practical recommendations (RQ4) for companies aiming to enhance critical aspects such as customer experience, satisfaction, recommendation accuracy, loyalty, conversion optimization, and the adoption of advanced technological tools. These insights provide actionable strategies to integrate AI into marketing practices effectively.

One key recommendation is for companies to focus on collecting, organizing, and analyzing user-generated content (UGC), including online reviews, comments, and social media interactions. This foundation is essential for leveraging advanced tools like Natural Language Processing (NLP) for sentiment analysis and opinion mining. By extracting insights from UGC, businesses can better understand consumer perceptions, refine their marketing strategies, and deliver more personalized experiences. For example, sentiment analysis can help identify trends in customer satisfaction and dissatisfaction, enabling targeted improvements in products or services.

Simultaneously, businesses should prioritize the adoption of advanced recommender systems powered by deep learning algorithms and neural networks. These systems enable real-time personalization by integrating diverse data sources, such as user behavior, purchase history, and social media engagement metrics. This integration can significantly enhance the accuracy and relevance of recommendations, improving customer loyalty and optimizing conversion rates. Such approaches offer a distinct competitive advantage by providing highly adaptive and user-centric experiences.

Trust and perceived security remain critical elements in driving online purchase intent. Companies should ensure that their platforms emphasize transparency in data handling and privacy policies. Clear communication regarding how consumer data is used, coupled with swift responses to privacy concerns, can foster trust and improve consumer confidence. AI-driven tools that monitor and address potential security threats can further reinforce these efforts, ensuring a seamless and secure shopping experience.

Another important recommendation concerns the use of advanced chatbots and other automated customer service systems. The integration of anthropomorphic traits, such as empathetic communication and contextual awareness, can significantly enhance user interactions. Businesses should design these systems to not only resolve customer queries efficiently but also to simulate human-like behavior that fosters trust and engagement. Tailoring these traits based on demographic and cultural preferences can further improve their effectiveness.

Finally, companies should leverage AI tools to optimize their social media marketing strategies. Sentiment analysis and trend prediction algorithms can provide real-time insights into consumer preferences, allowing businesses to adapt campaigns dynamically. By identifying patterns in engagement and adjusting strategies accordingly, brands can improve their relevance, foster stronger connections with their audience, and drive long-term retention.

These recommendations underscore the transformative potential of AI in reshaping marketing strategies. By integrating tools and practices aligned with key and emerging themes such as recommender systems, human-robot interaction, social media marketing, and NLP, businesses can remain competitive and effectively meet the evolving needs of their customers.

A critical aspect of implementing the proposed recommendations lies in understanding how research in artificial intelligence (AI) and machine learning (ML) aligns with their adoption timing in the industry. This analysis can influence the decision to prioritize dominant or emerging themes as strategic areas for future research and managerial practices. On one hand, if industry practices often precede research developments, emerging themes may hold greater strategic interest. Innovations and technologies currently less prominent in research could represent future industry directions. Focusing on these themes would allow companies to anticipate trends and position themselves as leaders in innovation. For instance, Ghobakhloo et al. (2024) discuss how generative AI can enhance responsible manufacturing within the context of Industry 5.0, highlighting the importance of aligning technological advancements with industry practices. On the other hand, if research advances typically precede industry adoption, dominant themes—such as technology acceptance or the use of machine learning in e-commerce—could still provide significant benefits. These themes may be in early stages of transitioning into widespread industry application, making them a priority for both researchers and practitioners aiming to maintain competitiveness. Yu et al. (2022) emphasize the importance of understanding the antecedents and outcomes of AI adoption in the workplace, suggesting that research can guide effective implementation in industry settings.

In this context, organizations must carefully evaluate their position within the technological adoption cycle. Companies with the capacity to innovate and lead could benefit from exploring emerging themes, while those focused on consolidating current practices might prioritize dominant themes, ensuring the effective implementation of research-validated technologies.

5.3. Social Implications of AI and ML in Digital Marketing

This research not only offers an updated perspective on the evolution of AI and ML in digital marketing but also underscores the societal challenges and opportunities arising from their development. The longitudinal analysis of two time periods (2000–2021 and 2022–2024) highlights how AI technologies—such as Natural Language Processing (NLP), human-robot interaction, and recommender systems—are reshaping customer experiences by providing personalized and efficient interactions. However, these advancements also introduce significant ethical and societal concerns. NLP, for instance, raises pressing issues regarding privacy, emotional data manipulation, and the transparency of algorithmic processes. Similarly, human-robot interaction, while enhancing accessibility through anthropomorphic interface design, redefines the relationship between technology and humanity, potentially contributing to the dehumanization of experiences and job displacement in certain sectors. Recommender systems, despite optimizing personalization, necessitate ethical safeguards to avoid adverse effects such as filter bubbles and algorithmic bias.

To mitigate these risks, it is imperative to implement regulatory frameworks that prioritize transparency, accountability, and fairness in the deployment of AI-driven marketing technologies. For instance, businesses can employ transparency tools such as algorithmic dashboards or explainable AI (XAI) systems, which visually represent how decisions are made, thus allowing users to better understand and trust the process. These tools can be complemented by mandatory documentation of algorithm updates and decision logic to ensure traceability.

Additionally, the concept of a moral collapse zone, where responsibilities become ambiguous in AI-driven decision-making processes, highlights the need for clear accountability structures. Organizations should develop incident-response protocols that include predefined roles and escalation paths to ensure prompt and ethical decision-making during unexpected events. For example, assigning designated AI ethics officers or implementing accountability matrices can clarify the division of responsibilities among human operators, developers, and automated systems. These measures can prevent the diffusion of responsibility and enhance trust in AI systems.

Furthermore, ethical training for marketing and development teams is essential to ensure the responsible use of AI tools. Such training should include case-based learning focused on real-world scenarios, emphasizing the long-term implications of biases, privacy violations, and unintended consequences. By addressing these challenges through actionable strategies, businesses can harness the potential of AI and ML while safeguarding societal values and fostering trust among consumers.

5.4. Limitations

As with any research, this study is not without its limitations. Firstly, despite the justification provided in the methodology chapter, it must be noted that the study relied solely on data extracted from the Web of Science. Other valuable contributions might have been omitted if they were found in non-indexed journals or other databases.

Furthermore, despite the rigorous process of monitoring and refining the search command, it is possible that the search criteria were not entirely perfect. Additional search considerations could have been included, such as publications in computer science or engineering journals, which might be relevant to this study.

The study prioritized quality over quantity to ensure rigorous analysis, which resulted in a smaller dataset. However, the number of articles analyzed was deemed sufficient. Additionally, the bibliometric process with SciMAT involves manual pre-processing of the database, which may introduce small biases when grouping terms.

Lastly, the creation of periods for the longitudinal study was determined by the researchers based on significant changes and turning points, rather than being proposed by the software itself. Researchers had to consider these important changes to define the periods accurately.

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APPENDIXES

Appendix A. Additional arguments on the use of Web of Science.

A noteworthy article was published in Quantitative Science Studies by Birkle et al. (2020), entitled "Web of Science as a data source for research on scientific and scholarly activity". This article has had a significant impact in the last few years: it has been cited 457 times in the WoS Core Collection and 792 times in Google Scholar. The purpose of this study was to analyze and justify the suitability of WoS for bibliometric and other scientific research. Among the main arguments outlined in Birkle et al. (2020) are the following: coverage, citation data richness, data stability, quality control, comprehensiveness, citation accuracy, and usability for bibliometric studies. Another key study is the one conducted by Gusenbauer and Haddaway (2020). Their objective was to evaluate the suitability of major information retrieval systems for systematic reviews and meta-analyses, considering aspects such as precision, scope, reproducibility, and efficiency. Regarding WoS, they concluded that it meets the essential criteria to be effective in systematic reviews. Among its main advantages, they highlighted its simultaneous access to multiple databases and indexes, the use of strictly controlled vocabulary, extensive refinement options, and its ability to ensure reproducible results (Gusenbauer and Haddaway, 2020). This is another high-impact study, widely used by researchers as a methodological justification. To date, it has been cited 1,670 times in Google Scholar and 829 times in WoS.

Appendix B. Detailed information on the method and search parameters in the Web of Science.

This bibliometric study uses WoS as the data source for data collection. A comprehensive and precise search command was designed through a thorough process, including:

- Preliminary keyword search and review. The process began with an initial, broad selection of keywords using several approaches. First, a review of the highest-impact literature in AI, ML, and digital marketing was conducted to identify essential keywords, providing a foundational basis for the study. This was done under the guidance of four experts: an Assistant Professor, two Associate Professors specializing in marketing, and a Full Professor with expertise in digital marketing. Additionally, AI tools (Google Gemini, OpenAI ChatGPT, and Microsoft Copilot) were utilized to review and refine the keyword list.
- Iterative search. When conducting searches in bibliographic systems such as WoS, initial searches serve as a tool to observe, learn, and identify how best to refine the search command. Subsequent searches are always necessary to determine which keywords should be omitted, which should be included, and what other criteria should be improved (for example, journal selection or thematic category selection). For this study, a total of 32 successive searches were carried out, based on continuous feedback. As this is one of the most technical and complex steps of the bibliometric method, the process was extensive. All searches were carried out between April and May 2024. The last search where the final command was used took place on 17 May 2024.
- Field-specific limitation. The search was limited to Web of Science categories related to management and business (Business, Management, Economics, Business-Finance, Communication, and Hospitality, Leisure, Sport and Tourism). Initially, additional categories were included and evaluated in preliminary test searches. This included thematic categories within the computing field (e.g., Computer Science Information Systems, Computer Science Artificial Intelligence) and psychology-related categories (e.g., Psychology Multidisciplinary, Psychology Applied) due to their relevance to consumer behavior within marketing. However, the findings revealed that the results indexed under these categories were not appropriate for a study focused on digital marketing from a pure managerial perspective. It is important to note that the thematic categories in WoS are generic. Specific categories such as e-commerce, social media, or marketing analytics do not exist. However, research on AI and digital marketing is expected to be published in journals such as the Journal of Electronic Commerce Research (indexed in Business), Electronic Commerce Research (indexed in both Business and Management), Journal of Business Research (indexed in Business), Journal of Retailing and Consumer Services (indexed in Business), among other specialized journals. Additionally, there are other factors to consider. For example, research on AI and digital marketing focused on the tourism sector may be published in specialized journals indexed in Hospitality, Leisure, Sport & Tourism. In fact, this is the case for the seventh most cited article in the database of this research. It is the article by Tung et al. (2018). Similarly, studies focused on digital marketing in the banking sector may be found in specialized journals indexed under the Business-Finance category. Therefore, the selection of WoS thematic categories does not represent an inconsistency with the focus of this research (AI applied to digital marketing). The selection of WoS categories will always be generic and serve as a first step in the search process. It is the use of specialized keywords that enables rigorous and comprehensive refinement, allowing for an accurate collection of documents.
- Selective search criteria: Keywords were searched in document titles (TI) and author's keywords (AK), prioritizing quality over quantity by discarding documents that do not genuinely address the researched topic despite mentioning a keyword. When conducting bibliometric research, keyword searches in sections like the abstract often yield less rigorous results. Abstracts may include contextual terms that do not necessarily align with the core theme of the research. This can lead to the retrieval of a larger number of documents but at the risk of compromising rigor. Bibliometric searches that target author keywords and titles, however, offer greater precision and are more likely to capture the true thematic content of articles. This approach ensures a more rigorous and accurate representation of the research landscape (Jesson et al., 2011; Passas, 2024; Pottier et al., 2024). To conduct effective searches in WoS, the correct use of Boolean operators is essential. In this study, the Boolean operators used were AND and OR. In parallel, the indicated nomenclature was used to search within the title (TI) and author keywords (AK) fields. The command differentiates between a block of terms related to AI and another related to digital marketing. This ensures that only documents containing at least one keyword from each area (AI and digital marketing) in either the title or author keywords are selected.

Appendix C. Additional arguments from organizations and companies supporting the turning point 2021-2022.

In the IBM Global AI Adoption Index 2022, the renowned IBM (2022) highlighted the significant popularization that took place that year in the use of AI. The company clearly pointed out the main reason: the significant increase in accessibility, coinciding with the launch and mass adoption of new generative models such as ChatGPT. That same year, the World Economic Forum (2022) emphasized the recent rapid advancements in AI and, above all, the widespread diffusion and adoption of AI tools across various industrial sectors. All of this occurred in the last year (between 2021 and 2022).

Another key analysis was conducted by Nirmal (2022), Vice President of IBM. This professional stated, 'We're at an exciting inflection point for AI. Adoption of AI among businesses is increasing, and research and AI development on foundation models is enabling use cases like generative AI to become even more sophisticated and powerful.' Nirmal (2022) highlighted several important reasons to justify this inflection point in 2022. Among these reasons is a transition to more accessible, less costly, and more sustainable models, which fostered democratization in access to and use of AI. Furthermore, this period was influenced by the growing need to address the environmental and economic impact of large models, prompting companies and researchers to prioritize more compact and practical solutions.

McKinsey & Company (2023) analyzed the use of generative AI and how it has evolved since the emergence of ChatGPT. In their article (published in the context of a broader study), the consultancy pointed out a key aspect, stating, 'The percentage of organizations adopting any AI tool has remained stable since 2022.' At the same time, Kalser (2023) published an interesting analysis in HR Dive, the popular U.S. platform specializing in managerial issues related to human resources. Kalser's (2023) article discusses the impact of AI on the demand for skilled professionals in the business sector. The article has a striking title, asserting that demand for generative AI skills has exploded by 1,848% since 2022.

Appendix D. Detailed technical information on the bibliometric analysis process using SciMAT.

SciMAT is a powerful and comprehensive bibliometric software, as it includes all necessary modules to execute the full scientific mapping workflow, from data loading and preprocessing to final visualization (Cobo et al., 2012). Furthermore, it offers a wide range of preprocessing tools, such as duplicate and misspelling detection, temporal segmentation, and data and network reduction. The analysis here followed the methodology defined by Cobo et al. (2012), which has become a key reference due to its significant impact in major bibliographic sources. This method involves four main stages:

- Data set construction. Since this study focuses on analyzing conceptual structure, the chosen unit of analysis was the word group. Next, data reduction was designed. This sets the minimum number of documents in which an analysis unit (keyword) must appear to be included. Cobo (2012) suggests always starting with a standard value of 2. If the final number of clusters on the map for each period falls within or near the 20-25 range, the threshold is retained. However, if each period has more than 25 clusters, raising the minimum threshold is advisable, as themes that mainly add noise may be included, so it is better to be more selective. Conversely, if a period has far fewer clusters (e.g., around 10), lowering the threshold to 1 may be necessary. In this study, an initial threshold of 2 resulted in 29 clusters in each period. Given this, the threshold was adjusted to 3 in both periods, yielding networks of 18 and 19 clusters, respectively.
- Network creation and normalization. The network can be constructed using various methods. This research employs the term co-occurrence method, assessing keyword similarity based on how often they co-occur in documents (Santana and Cobo, 2020). Another essential step is network reduction, which assigns a value to each edge in the word network. This value represents the strength of the relationship between two words based on the number of times they appear together in documents. SciMAT enables filtering the network by setting a minimum edge threshold. For each selected period, a threshold value must be set. Here, a minimum threshold was used to streamline and optimize the network. In other words, for the software to consider a word pair (co-occurrence), they must appear together in at least n documents. Cobo (2012) suggests starting with a standard minimum threshold of 2. As the resulting network in this case did not show issues with the number of clusters per period, it was unnecessary to adjust this parameter. The next step was selecting the similarity measure to normalize the network, for which the Equivalence Index (Callon et al., 1991) was used.
- Clustering algorithm. This phase involves selecting a clustering method to build the map, which serves as the foundation for visualizing results in each period. This research utilized the Simple Centers Algorithm (Cobo et al., 2011a; Coulter et al., 1998), a popular choice in bibliometrics due to its suitability and effectiveness in consistently grouping related terms, which enhances visualization.

- Analysis set. SciMAT incorporates by default Callon's centrality and density measures (Callon et al., 1991; Cobo et al., 2011a) as network metrics for each cluster detected in every period. Consequently, these analyses were applied in this study. Callon's centrality measure evaluates the level of interaction between a network and others, essentially representing the external cohesion of the network. In contrast, Callon's density measure quantifies the internal strength of the network, reflecting its internal cohesion. These measures are particularly useful for categorizing the clusters identified in each period within a strategic diagram (Cobo et al., 2011a). Finally, this phase also includes a performance analysis. In this process, each cluster is assigned a set of documents using a document mapping function, followed by an evaluation of the performance based on both quantitative and qualitative measures (e.g., citation-based metrics). SciMAT is capable of aggregating multiple documents sets within the same analysis, calculated using different document mappers. For this research, the core-mapper (Cobo et al., 2011a) was employed because it optimizes the relevance of the documents assigned to each cluster, ensuring that the representation of central topics is both robust and reliable.

Appendix E. Brief descriptive analysis of social structure.

This research primarily aims to analyze the conceptual framework of AI and ML in the context of digital marketing. Additionally, it seeks to provide researchers with key insights into performance-related aspects, such as identifying the most prominent journals and authors in AI and digital marketing publications and highlighting the most cited articles in the field. This simple initial description is a valuable resource for authors seeking reliable sources. It highlights key publications, authors, and high-performing journals in the field of AI integration within digital marketing processes.

Table 2 lists the journals with the highest number of published documents in this academic discipline. Notably, journals specializing in e-commerce are prominent, with three journals among the top six. This finding aligns with key points identified in the conceptual framework. The rest of the ranking includes journals specializing in retailing, general marketing, digitalization, and general management.

Table 2: Journals with the most publications.

JOURNAL	PUBLICATIONS
Electronic Commerce Research and Applications	21
Electronic Commerce Research	21
Journal Of Retailing and Consumer Services	18
Journal Of Business Research	14
Technological Forecasting and Social Change	13
Journal Of Theoretical and Applied Electronic Commerce Research	12
IEEE Transactions on Engineering Management	11
Management Science	10
Marketing Science	10
Information Systems Research	10
Journal Of Organizational and End User Computing	9
Information Systems And E-Business Management	8
Journal Of Electronic Commerce Research	7
Journal Of Research in Interactive Marketing	7
Industrial Marketing Management	7
International Journal of Electronic Commerce	6
Electronic Markets	6
Transportation Research Part E-Logistics and Transportation Review	6
Journal Of Hospitality and Tourism Insights	5
International Journal of Mobile Communications	5
International Journal of Research In Marketing	5
Journal Of Marketing Research	5

Table 3 shows the authors with the highest number of publications within the discipline under study. Only authors with three or more published works are included. These authors are divided into five groups, labeled A, B, C, D, and E, using a simple nomenclature. Each group represents a team based on co-authorship among its researchers. For example, Group B consists of co-authors Sivathanu, B., and Pillai, R., whose publications focus on the use of AI in the context of automated e-retailing, chatbots, and digital advertising. This information allows readers to identify prominent authors in the field of AI applied to digital marketing, as well as to understand their main research lines. This brief analysis is particularly interesting, as the research topics of these authors align with some of the key findings discussed in Chapter 4.2 of this manuscript (the analysis of the conceptual framework, which is the primary objective of this research). Topics such as technology acceptance, human-robot interaction, shopping experience, and predictive analytics emerge as prominent research areas in the subsequent results.

Table 3: Authors with the most contributions.

AUTHOR	GROUP	MAIN TOPICS	CONTRIBUTIONS
Tan, Garry Wei-Han	A	• Voice assistants • Customer experience • Technology Acceptance Model 2 (TAM2) • Predictive analytics	5
Ooi, Keng-Boon			5
Dwivedi, Yogesh Kumar			5
Sivathanu, Brijesh	B	• Automated e-retailing • Digital advertising • Chatbots	4
Pillai, Rajasshrie			4
Rahman, Muhammad Sabbir	C	• Shopping experience • Engagement • Marketing analytics	4
Hossain, Md Afnan			3
Willems, Kim	D	• Shopping experience • Service robots • Human-robot interaction	3
Vanderborght, Bram			3
De Gauquier, Laurens			3
Brengman, Malaika			3
Al-Sharafi, Mohammed A.	E	• Chatbots • Unified Theory of Acceptance and Use of Technology (UTAUT) • Mobile payments	3
Al-Emran, Mostafa			3

Table 4 presents the top 10 most cited articles, with almost all surpassing 200 citations according to Web of Science data. These highly cited articles were published between 2018 and 2020, coinciding with a high contribution and allowing enough time to accumulate significant impact.

Table 4: Most cited contributions

TITLE	AUTHORS	PUBLICATION YEAR	CITATIONS
Chatbot e-service and customer satisfaction regarding luxury brands	Chung, M., Ko. E, Joung, H. & Kim, S.J.	2020	330
Is a Picture Worth a Thousand Words? An Empirical Study of Image Content and Social Media Engagement	Li, Y.Y. & Xie, Y.	2020	281
Understanding the role of individual innovativeness in the acceptance of IT-based innovations: Comparative analyses of models and measures	Yi, M.Y., Fiedler, K.D. & Park, J.S.	2006	252
Algorithmic Bias? An Empirical Study of Apparent Gender-Based Discrimination in the Display of STEM Career Ads	Lambretch, A. & Tucker, C.	2019	241
Adoption of AI-based chatbots for hospitality and tourism	Pillai, R. & Sivatanhu, B.	2020	240
Predicting the determinants of mobile payment acceptance: A hybrid SEM-neural network approach	Liébana-Cabanillas, F., Marinkovic, V., de Luna, I.R. & Kalinic, Z.	2018	232
Exploring customer experiences with robotics in hospitality	Tung, V.W.S. & Au, N.M.	2018	226
Identifying Customer Needs from User-Generated Content	Timoshenko, A. & Hauser, J.R.	2019	207
Analytics for an Online Retailer: Demand Forecasting and Price Optimization	Ferreira, K.J., Lee, B.H.A. & Simchi-Levi, D.	2016	198
Examining the impact of luxury brand's social media marketing on customer engagement: Using big data analytics and natural language processing	Liu, X., Shin, H. & Burns, A.C.	2021	191

Appendix F. Results of the longitudinal analysis for thematic areas A3 to A8.

A3. Advances in neural networks and Natural Language Processing in digital marketing.

- Focus and evolution. A3 has undergone a significant shift in focus from P1 (2000-2021), where Model was an emerging or declining topic, to a more specialized approach in Artificial Neural Networks (ANN) and Natural Language Processing (NLP) in P2 (2022-2024). In P1, the Model cluster included terms related to text and data analysis, such as natural language processing and data mining, but it was not fully developed. Despite being an emerging topic, it had not yet solidified as a core theme due to its lack of specialization and definition. However, in P2, NLP emerges as a central topic, showing clear specialization and development, particularly in sentiment analysis, text analysis, and online consumer reviews. This advancement reflects the growing demand for technologies that enable the understanding and processing of natural language in digital marketing. The independence of NLP from Model in P2 highlights the maturity of this theme, which now plays a central role in consumer interaction and analysis. On the other hand, Artificial Neural Networks establishes itself as another central theme in P2, contributing to the enhancement of predictive models in areas such as mobile commerce and mobile payment. The fact that both clusters (ANN and NLP) are now core topics reflects the evolution toward increasingly complex and specialized technologies that are integrated into marketing decision-making.
- Current status. A3 is structured around two clearly defined core topics: Artificial Neural Networks (ANN) and Natural Language Processing (NLP). NLP, with its focus on text analysis, sentiment analysis, and consumer reviews, has solidified as a key theme in digital marketing strategy, enhancing brands' ability to interact effectively with consumers on digital platforms, especially through Twitter (now called X) and other social media. Its independence in P2 marks a shift towards specialization in the analysis of unstructured data and its interpretation within a commercial context. On the other hand, Artificial Neural Networks is now crucial for developing predictive models and optimizing decisions in mobile commerce and other areas related to mobile payments. The integration of deep neural networks enables the creation of more accurate models to predict consumer behaviors and dynamically adjust marketing strategies. Although both NLP and ANN have become core topics, each still maintains a clear distinction in its internal composition: NLP continues to focus on text analysis and online opinions, while ANN is more oriented towards predictive modeling and decision optimization based on both structured and unstructured data. Together, both clusters reinforce the growing specialization and sophistication of AI tools applied to digital marketing, offering new ways to interact with consumers and optimize strategic decisions.

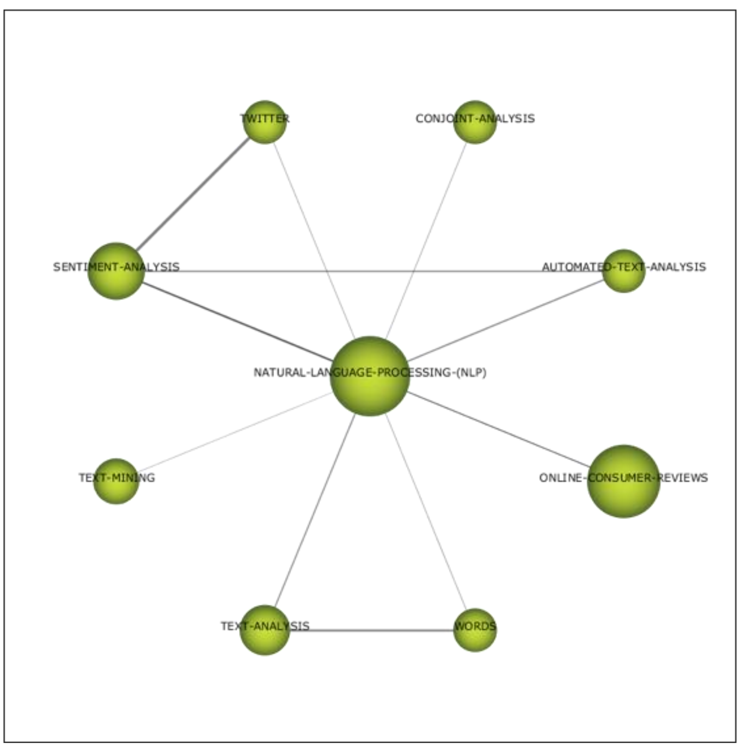

Figure 7: Keyword network of the Natural-Language-Processing (NLP) cluster (P2) from A3

A4. Evolution of decision-making and customization through recommender systems.

- Focus and evolution. A4 shows a clear transition from a focus on decision-making in P1 (2000-2021) to the consolidation of recommender systems in P2 (2022-2024). In P1, decision-making was a motor theme that integrated key subthemes such as recommender systems, reinforcement learning, and choice, all aimed at optimizing consumer decisions. The customization cluster, on the other hand, focused on online advertising, product recommendations, and interactivity, providing an important foundation for personalization in digital marketing. Additionally, in P1, both social-media-analytics and neural-network were considered emerging or declining topics, although the relationship between neural-network and decision-making was already evident, especially in areas like sales prediction and product classification. In P2, the A4 area takes a significant turn as recommender systems consolidate as an emerging theme. While it does not become a motor theme in this period, recommender systems gather and unify several previous approaches of decision-making, customization, and neural-network, creating an integrated system that optimizes consumer experience through advanced personalization and recommendation algorithms.
- Current Status. In P2, A4 is dominated by recommender systems, which, although still not a motor theme, have enormous potential by integrating key concepts from decision-making, customization, and neural networks. Recommender systems now act as a synthesis of these three clusters, combining decision algorithms (such as reinforcement learning and choice), product personalization (such as product recommendation and online advertising), and the use of neural networks to improve the accuracy of recommendations, based on techniques like deep learning. Recommender systems are at the heart of personalizing the shopping experience and digital marketing, being able to adjust marketing strategies based on individual preferences and consumer differences. This unified approach makes recommender systems a fundamental tool for improving the effectiveness of decisions in digital marketing, from personalized advertising to sales optimization through product recommendations.

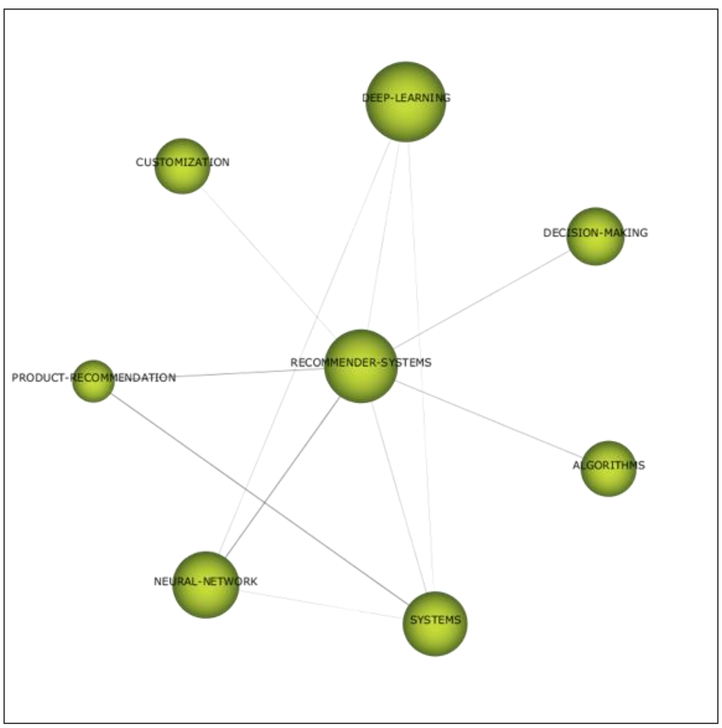

Figure 8: Keyword network of the Recommender-Systems cluster (P2) from A4

A5. WOM and online reviews-based information: the value of user-generated content.

- Focus and evolution. A5 has undergone a notable evolution in its focus from P1 (2000-2021), where Word of Mouth (WOM) was the dominant motor theme, to P2 (2022-2024), where Information and Social Media emerge as transversal themes. In P1, WOM covered a broad spectrum of terms related to online reviews, user-generated content, impact, and sales dynamics, consolidating itself as the most central and dense theme within digital marketing. WOM was crucial for how consumers influenced purchase decisions and how brands responded to these changes, particularly through social platforms. As we move into P2, Social Media, which was part of WOM in P1, becomes an independent transversal theme. This shift reflects how social media has gained relevance on its own, now being a key component for studying topics such as service quality, customer satisfaction, and purchasing behavior on digital platforms. At the same time, the Information theme emerges as transversal in P2, absorbing part of the essence of WOM but with a broader focus on product recommendations, certainty, and the impact of information, expanding its influence beyond direct consumer-to-consumer interactions.

- Current status. In P2, the A5 area has diversified with the consolidation of Information and Social Media as essential transversal themes. Information has transformed into a key theme for understanding product recommendations and the impact of user-generated content on purchase decisions, absorbing the essence of WOM. Its focus on certainty, involvement, and price highlights how information has become a powerful tool to guide consumers and enhance the effectiveness of digital marketing strategies. On the other hand, Social Media has evolved into an independent transversal theme, focusing on service quality, customer satisfaction, and consumer behavior on digital platforms. This cluster reflects the growing importance of social media not only as a communication channel but also as a fundamental space for brand-consumer interaction. Together, Information and Social Media are interconnected through their focus on how consumers generate and consume content, and how brands use this information to improve their marketing strategies. The impact of WOM in P1 remains relevant in P2, but now it manifests through greater specialization and expansion into the themes of Information and Social Media, which play key roles in shaping purchase decisions and brand perception in the digital age.

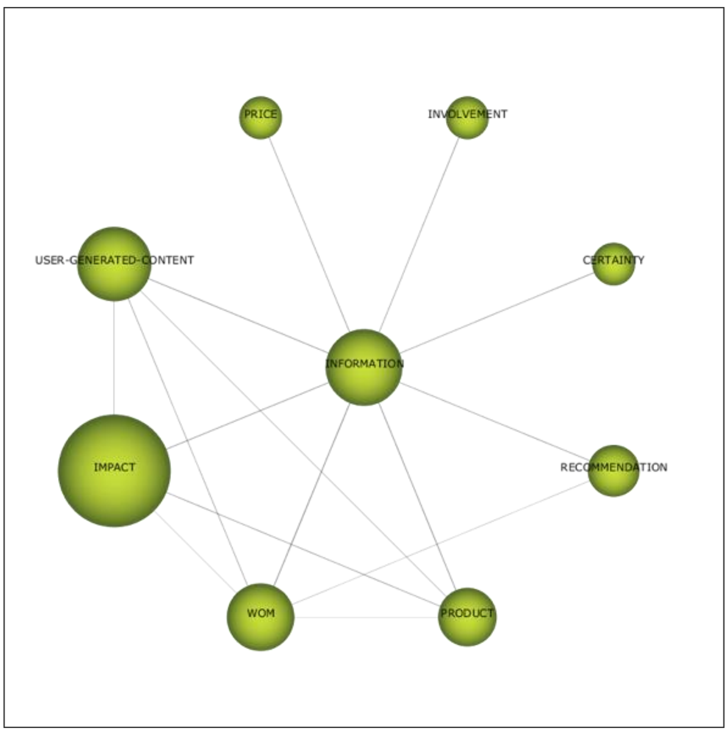

Figure 9: Keyword network of the Information cluster (P2) from A5

A6. Evolution of consumer behavior and experience in digital marketing.

- Focus and evolution. The A6 area shows an evolution centered around the transformation of the study of consumer behavior over time. In P1 (2000-2021), the key themes were consumer-behavior and behavior, with an emphasis on analyzing behavior within the context of digital marketing. Tools like structural equation modeling and empirical analysis were used to unravel the dynamics influencing purchase decisions. Additionally, behavior incorporated experience, indicating that consumer behavior was closely linked to the user experience on digital platforms. In P2 (2022-2024), there is a clear transition. Consumer-behavior shifts within experience, reflecting how the consumer experience has become a central focus, covering topics such as motivation, satisfaction, and interactivity in the digital environment. On the other hand, behavior moves towards a more data-driven approach, under the data cluster, emphasizing the analysis of behavior patterns and learning through large volumes of information. This transformation shows how consumer behavior studies are increasingly relying on data analysis to gain more accurate and predictive insights.

- Current status. A6 reflects a shift in focus and approach to studying consumer behavior. Cluster experience, now a transversal theme, has consolidated as the central axis of research, encompassing the study of consumer behavior through preferences, motivation, and satisfaction. This cluster highlights the importance of consumer experience as a key factor in decision-making within digital marketing, particularly in sectors such as hospitality and online experiences. On the other hand, cluster data emerges as a new specialized theme focused on analyzing behavioral patterns and how data can be used to predict and learn from consumer behavior. This data-driven marketing approach involves the use of data mining and machine learning to optimize personalization and real-time segmentation. The relationship between experience and data is clear in P2, as consumer experience is now analyzed more deeply using data to understand and predict behavioral patterns. The integration of these two approaches indicates that the study of consumer behavior in digital marketing has matured into a combination of subjective experience and objective data, where both dimensions complement each other to provide more effective and personalized strategies.

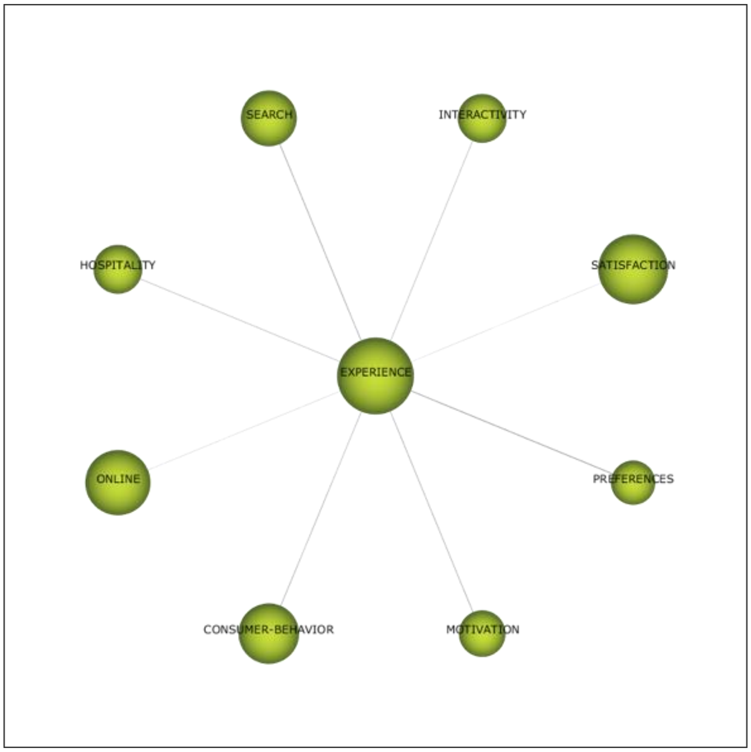

Figure 10: Keyword network of the Experience cluster (P2) from A6

A7. The role of Artificial Intelligence in enhancing engagement in social media marketing.

- Focus and evolution. A7 has undergone an interesting evolution, reflecting the growing role of artificial intelligence (AI) in optimizing engagement and its integration into social media marketing. In P1 (2000-2021), Engagement was the central theme, focusing on brand impact, customer experience, and online purchasing. As brands began experimenting with AI on digital platforms, Engagement incorporated technologies like AI, suggesting that AI was beginning to play a role in generating and measuring engagement through platforms like Twitter and other e-retailing environments. In P2 (2022-2024), the focus evolves as Social Media Marketing emerges as a key theme, "absorbed" in part by Engagement but extending its boundaries to include broader elements like influencer marketing, digital communication, and online advertising strategies. Here, AI becomes independent as a fundamental transversal theme, with applications extending not only to marketing analytics and automation but also as a central component in creating competitive advantages in digital marketing

- Current status. In P2, A7 is characterized by a clear distinction between key themes: Artificial Intelligence and Social Media Marketing. Artificial Intelligence has solidified itself as a significant transversal cluster, with applications ranging from voice assistants and virtual assistants to marketing analytics and marketing automation. Its role as a transversal axis in digital marketing highlights its ability to enhance both efficiency and personalization in marketing strategies. On the other hand, Social Media Marketing has emerged as a key theme, integrating the concept of engagement that previously dominated in P1. This cluster focuses on the use of social media to build connections with consumers through online advertising, influencer marketing, and digital communication. Interactivity and engagement remain central concepts, but they are now expanded with tools and approaches that maximize brand impact and customer experience on social media platforms. In summary, the A7 area reflects how AI has transformed the way brands interact with consumers on social media, from creating automated content to personalizing marketing, while Social Media Marketing has broadened its scope, integrating engagement strategies and adding new layers of complexity through advanced digital tools.

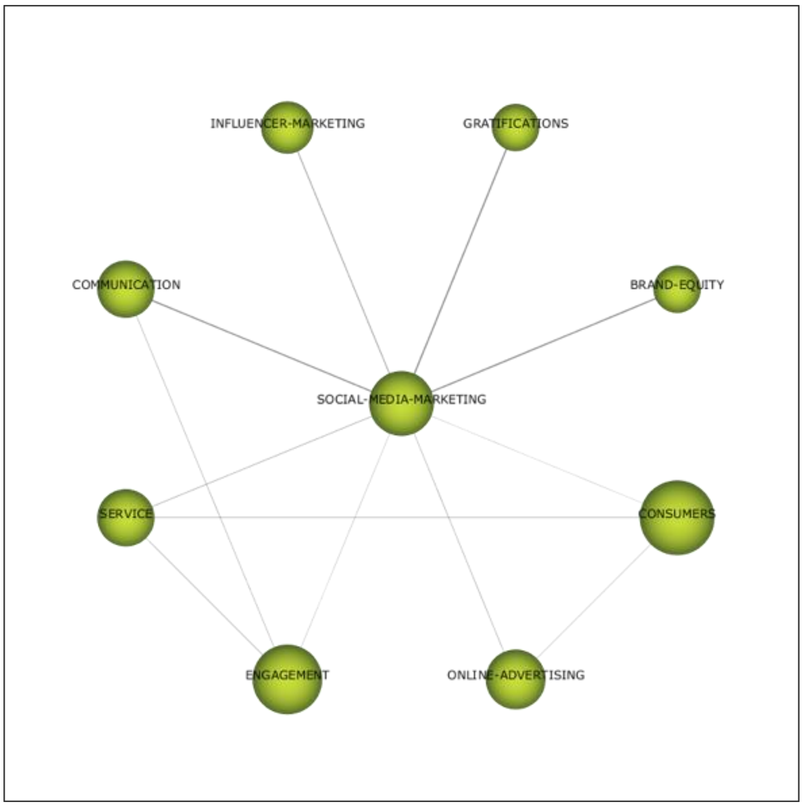

Figure 11: Keyword network of the Social-Media-Marketing cluster (P2) from A7

A8. Human-Robot Interaction: integrating user experience and personality models.

- Focus and evolution. A8 has undergone a significant transition, particularly with the emergence of the human-robot interaction theme in P2. In P1, two specialized but isolated themes stood out: the 5-factor model and user experience. The 5-factor model focused on personality psychology, analyzing elements like gender and personality traits, while user experience explored usability, web design, and the nascent field of human-robot interaction. The inclusion of human-robot interaction within the user experience cluster in P1 suggests that research on AI interactions was still in its early stages, embedded within the broader context of digital user experience. With the transition to P2, human-robot interaction has solidified as an independent cluster, gaining prominence through topics like personality, automation, and the cues machines use to interact with users. This evolution highlights the growing importance of human-robot interaction in designing interactive AIs, particularly for digital platforms. The connection with the 5-factor model, a cornerstone of personality psychology, underscores how studies on human personality are increasingly incorporated into the development of personalized AI systems, aiming to enhance user interactions and improve engagement through tailored responses.

- Current status. A8 is primarily defined by human-robot interaction, which has gained prominence due to the rise of automation and AI interfaces in digital environments. This cluster not only continues to explore interactions between humans and robots but also draws on psychological models, such as the 5-factor model, to enhance the personalization of these interactions. The inclusion of personality in this context highlights the focus on how AIs can adapt to human traits to deliver more natural and effective interactions. The evaluation cluster in P2 complements this approach by emphasizing models and promotions that assess the impact of human-robot interactions and their effectiveness in enhancing user experiences. Despite this, human-robot interaction remains the most relevant emerging theme, with a clear emphasis on how machines can simulate human characteristics to create more engaging and intuitive user experiences. In summary, A8 reflects a shift towards deeper integration of personality psychology in the development of interactive AI, especially in the context of digital marketing. Here, the personalization of human-robot interaction is becoming a key element for improving user experience and optimizing engagement strategies.

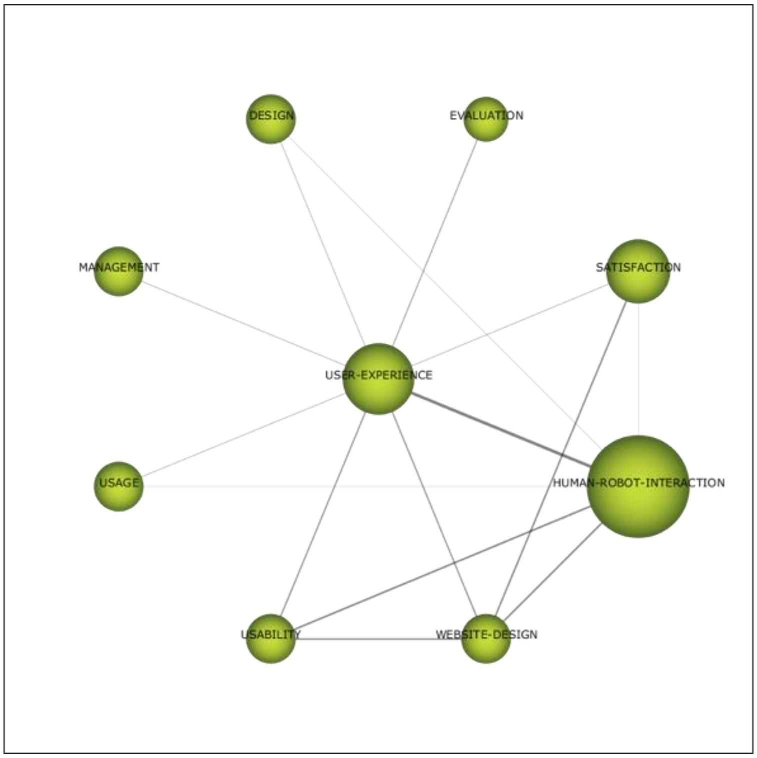

Figure 12: Keyword network of the User-Experience cluster (P1) from A8