Impact of Emerging Technologies on Customer Loyalty: A Systematic Review

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***Abstract*—The rapid evolution of emerging technologies has generated growing interest in their potential to transform customer loyalty into digital environments. This study aims to conduct a systematic literature review (SLR) to analyze how emerging technologies influence customer loyalty. This review is focused on identifying how these technologies affect loyalty indicators in markets with developed digital environments. A total of 453 articles from the Scopus database were identified by applying the PRISMA methodology. After removing duplicates and applying filters by language and document type, 103 relevant articles were selected. Then, a detailed review based on inclusion and exclusion criteria was conducted. Hence, 51 documents were finally included for analysis. The main technologies investigated were Big Data, IoT, and Machine Learning. Big Data and Data Analytics were the most researched technologies, followed by IoT and Machine Learning. The systematic review demonstrated that emerging technologies significantly impact customer loyalty. Artificial intelligence and data analytics are key tools for improving customer experience and retention, which contributes to business growth. It is concluded that adopting these technologies enhances customer experience by offering personalization, behavior prediction, and inventory optimization, resulting in greater customer satisfaction and loyalty.**

Keywords*—*Emerging technologies; loyalty programs; customer loyalty; business growth

I. Introduction

In today's highly competitive business environment, customer loyalty has become crucial for sustainability and growth. Marketing strategies, particularly those based on customer relationship management (CRM), have proven effective in retaining and attracting more customers [1]. Companies adopt multiple approaches, such as personalization and promotions, to increase their customer base, including new reward program designs and small discounts for consumers [2]. Not only do companies benefit from loyalty programs, but customers also benefit, as they gain access to personalized products and services, great promotions, and a strengthened relationship with the company through more personalized treatment. The use of technologies like big data supports all of this. This technique collects transaction information to understand the customer, and this information becomes valuable for the company, as it can get to know the customer better to offer a discount or a product of interest [3]. Despite the progress, there are still gaps in knowledge about the global impact of emerging technologies on customer loyalty. Additionally, there are discrepancies in the literature regarding the comparative effectiveness of these new technologies versus traditional practices.

This study is justified by the need to provide a panoramic and updated view on using technologies such as IoT, Machine Learning, and blockchain in loyalty programs, addressing current trends and filling existing research gaps [4]. Another way to positively use technologies in loyalty programs is as investigated by Lu Wang, Xin Luo, and Frank Lee, where they explore the use of blockchain. They focus on using these new secure, immutable, low-cost networks used in Bitcoin transfers. However, their research uses blockchain to collect large amounts of information from customer transactions and exploit it with some data analysis techniques [5].

In addition to the growing prominence of big data, there is an increasing diversity in the adoption of emerging technologies applied to customer loyalty [6]. Tools such as Machine Learning, Artificial Intelligence (AI), the Internet of Things (IoT), social networks, augmented reality, blockchain, and other technological subcategories are being explored at various levels of depth and application. The findings indicate that, although Big Data and data analytics lead in frequency within the literature, technologies like Machine Learning and AI also carry significant weight due to their ability to automate processes, anticipate consumer behavior, and personalize the customer experience [7]. This technological heterogeneity reflects the fact that organizations are testing diverse approaches in an effort to optimize their loyalty strategies and highlights the need for evidence-based insights to guide informed decision-making regarding the most effective technological solutions across different business contexts.

This systematic review aims to evaluate the impact of emerging technologies on customer loyalty, providing a comprehensive and well-founded perspective for academics and professionals interested in understanding current trends and the effectiveness of various technological tools. By reviewing the existing literature on the use of Big Data, Artificial Intelligence, and blockchain in loyalty programs, this study aims to identify patterns, benefits, and limitations, offering a valuable resource for those who wish to base their decisions on previous research on loyalty strategies in a constantly evolving digital environment. The document is structured as follows: Section II details the methodology used in the literature review. Section III presents the results and addresses the research questions. In Section IV, an analysis and discussion of the results are conducted. Finally, Section V concludes the review by summarizing the key findings of the research.

II. METHODOLOGY

A. Search Strategy

This research was based on the systematic literature review (SLR) methodology. The PICO strategy was used for this review to structure and determine the components for searching relevant studies. The main PICO question formulated was: What is the impact of implementing emerging technologies on customer loyalty compared to traditional approaches in companies from various sectors, considering the implementation of personalized strategies and process automation in the current context of digital transformation? The sub-questions derived from the PICO question were: P (Problem): Who? (Companies from various sectors), I (Intervention): What? How? (Implementation of emerging technologies, personalized strategies, and process automation), C (Comparison): Compared to what? (Traditional approaches), and O (Outcomes): What to achieve? (Customer loyalty). Various keywords were chosen to suit the specific research case. The relevant keywords for each section of PICO are presented in Table I. Systematic research was conducted in the Scopus database due to its high relevance to the research field in question. The set of PICO keywords produced few results, probably because the search query was too restrictive, making it difficult to find results in the database. Therefore, it was decided to exclude the comparison keywords, which resulted in a better search. Table II presents the search equation performed in Scopus.

TABLE I. PICO KEYWORDS

	Problem	***Intervention***	***Comparison***	***Results***
	Who?	***What? How?***	***Compared to?***	***What to achieve?***
Keywords	Consumer behavior	Emerging technologies	Manual loyalty systems	Loyalty programs
	end users	Technology implementation	Traditional marketing techniques	Satisfaction
	customers experience	Blockchain for loyalty	Non-technological rewards	Successful loyalty cards
		Machine learning		Increased sales
		Data analysis		Business growth
		Technological innovation		Customer lifetime value
		Digital business		
		IoT in customer engagement		
		CRM systems		
		Data analytics in loyalty programs		
		Personalization technology		
		AI in customer relations		
		Augmented reality in retail		
		Big data analytics		

TABLE II. SCOPUS EQUATION

PIO	(TITLE-ABS-KEY ("Consumer behavior" OR "end users" OR "customers experience") AND TITLE-ABS-KEY ("Emerging technologies" OR "Technology implementation" OR "Blockchain for loyalty" OR "Machine learning" OR "Data analysis" OR "Technological innovation" OR "Digital business" OR "IoT in customer engagement" OR "CRM systems" OR "Data analytics in loyalty programs" OR "Personalization technology" OR "AI in customer relations" OR "Augmented reality in retail" OR "Big data analytics") AND TITLE-ABS-KEY ("Loyalty programs" OR "Satisfaction" OR "Successful loyalty cards" OR "Increased sales" OR "Business growth" OR "Customer lifetime value"))

B. Inclusion and Exclusion Criteria

In this systematic literature review, clear criteria were established for the selection of articles, ensuring that the selected studies were relevant to the research. Table III details the inclusion and exclusion criteria applied.

TABLE III. INCLUSION AND EXCLUSION CRITERIA

Inclusion criteria	Exclusion criteria
CI1: Studies evaluating the impact of specific emerging technologies (such as artificial intelligence, augmented reality, Internet of Things, etc.) on customer loyalty. CI2: The studies should include markets with highly developed digital environments or countries experiencing rapid growth in digital adoption, given the relevance of digital transformation in these areas. CI3: The studies should include quantitative data on loyalty indicators (such as customer retention, customer satisfaction, purchase frequency). CI4: Studies published in the last 6 years (considering the current date). CI5: The studies considered are articles and conference papers.	CE1: Companies that do not belong to the sectors of interest. CE2: Publications in languages other than Spanish or English. CE3: Studies that do not consider the current context of digital transformation. CE4: Studies that do not focus on the practical application of technologies for improving loyalty

These criteria were rigorously applied to ensure that only relevant studies that significantly contributed to the research objective were included.

C. Articles Selection Process

In the development of the systematic literature review conducted, 453 articles were found in the Scopus database. The selection process was based on the PRISMA methodology [8], designed to ensure transparency and organization in the review. Initially, a duplicate article was identified and removed, resulting in 452 unique articles for review. Automatic filters for languages (Spanish and English) and filters for articles and conference papers were then applied, leaving 292 articles. After reviewing the titles, abstracts, and keywords, 103 articles that met the review topic were selected. Subsequently, the full texts of 103 articles were retrieved and evaluated. During the detailed evaluation according to inclusion and exclusion criteria, some articles were progressively excluded: 4 for not belonging to the sectors of interest, 6 for not considering the context of digital transformation, and 8 for not focusing on the practical application of technologies for improving loyalty. Finally, 51 documents that met all the established criteria were included.

This process is visually structured in Fig. 1 which is PRISMA flow diagram, which clearly shows each phase of the study selection and evaluation process.

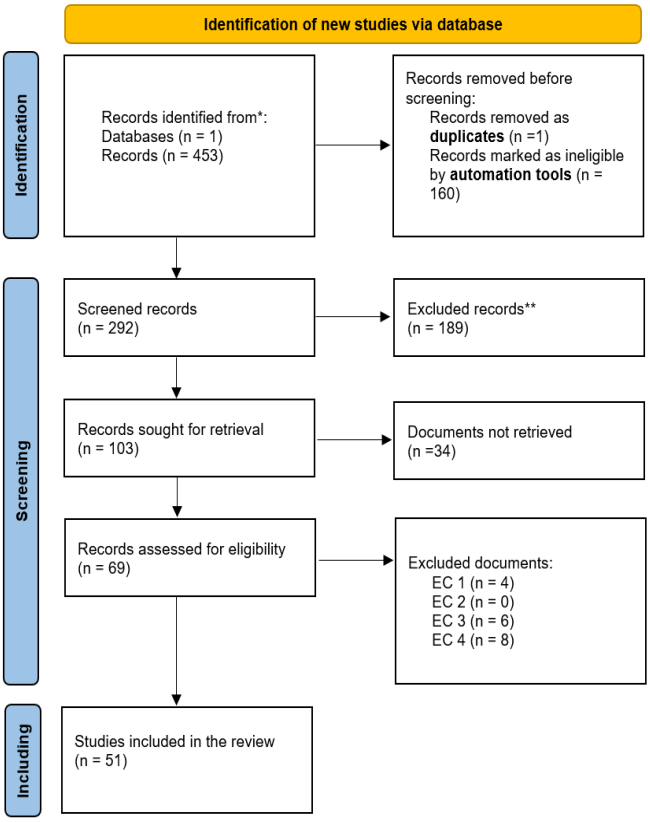

Fig. 1. PRISMA flow diagram, based on [8].

III. Results

Table IV presents the key results of the analysis, covering the period 2018-2024 and reviewing 51 documents. Each document had an average of 8.98 citations, totaling 1904 sources cited. Regarding the content of the documents, 354 general keywords and 206 author-specific keywords were identified. The research involved 178 authors, with only one single-authored document. Regarding collaboration, each document had an average of 3.53 co-authors, with 27.45\% of the collaborations being international. The types of documents analyzed included 35 articles and 16 conference papers.

TABLE IV. Key Findings of the Analysis

Description	Results
Period of time	2018 - 2024
Sources (Journals, Books, etc.)	47
Documents	51
Average Citations per Document	8.98
References	1904
DOCUMENT CONTENT	
Keywords Plus	354
Author Keywords	206
AUTHORS	
Authors	178
Single-authored documents	1
AUTHOR COLLABORATION	
Single Authorship Documents	1
Co-authors per Document	3.53
Percentage of International Co-authorships	27.45
DOCUMENTS TYPE	
Article	35
Conference Paper	16

A. Analysis of Frequent Keywords and Main Themes in Scientific Publications

Fig. 2 presents the analysis of the most frequent keywords, highlighting the main topics of the review. This figure was created using the VOSViewer program, a tool specialized in the visualization and analysis of bibliometric and keyword networks.

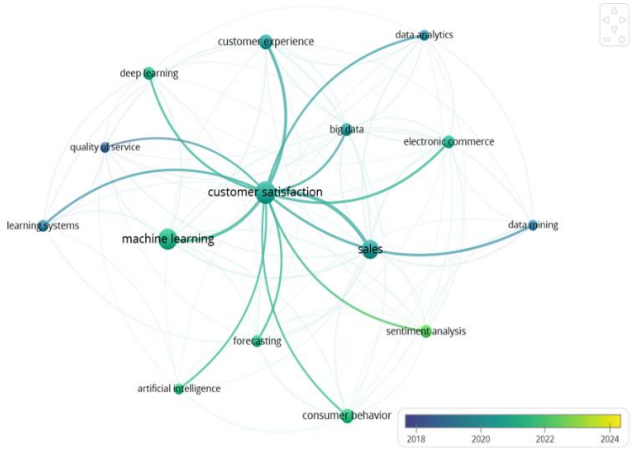

Fig. 2. Palabras clave.

TABLE V. Keyword and Occurrences

Keywords	Occurrences
customer satisfaction	24
machine-learning	21
sales	17
customer experience	10
consumer behavior	9
big data	7
electronic commerce	7
deep learning	7
sentiment analysis	7
forecasting	6
learning systems	6
artificial intelligence	5
data analytics	5
data mining	5
quality of service	5

Table V details the most mentioned keywords between the years 2018 and 2024, highlighting the importance of topics such as customer satisfaction, advanced data analysis techniques, and sales strategies in the commercial field.

B. Annual Trends in Scientific Production: Distribution of Publications

In Fig. 3, the Publication Distribution by Year Chart illustrates the number of articles published annually between 2018 and 2024, providing a clear view of trends in scientific production during this period. From this section onwards, the charts were generated using the R language in the RStudio IDE, a tool widely used for statistical analysis and data visualization in scientific research. In 2018 and 2021, seven publications were recorded each year, while in 2019, a slight increase was observed with eight publications. In 2020, the number of publications decreased to six, followed by a further drop in 2022 with only five publications. However, 2023 marked a notable increase with fourteen publications, representing the highest point of research activity in the analyzed period. Finally, in 2024, four publications have been recorded to date.

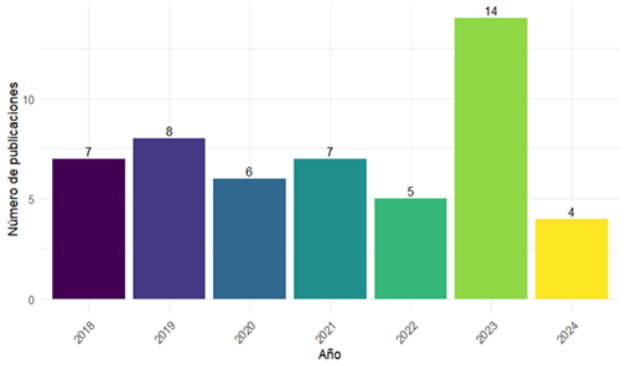

Fig. 3. Distribution of publication by year.

C. Author Productivity and Collaboration in the Field of Study

In Fig. 4, the analysis of the most productive authors in the reviewed publications is visualized, highlighting that Kumar S leads with two publications [9], [10] underscoring his significant contribution to the field of study. Other authors such as Abiola-Oke E, Ahmad N, Akhavan F, Ala A, Alamri S, Almashaqbeh Ha, Ameen N Y, and Andriani L have each contributed with one publication [4], [11], [12], [13], [14], [15], [16], [17], reflecting diverse and active collaboration in the research field.

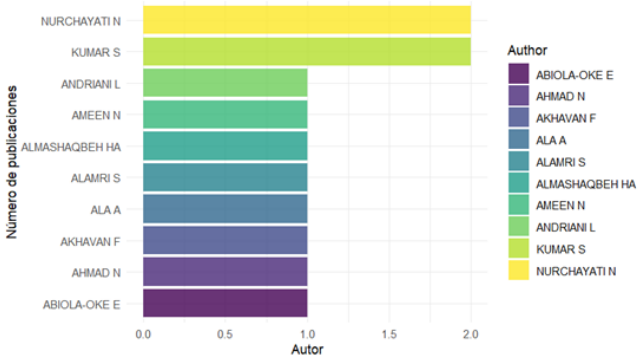

Fig. 4. Most productive authors.

D. Analysis of Technologies Used in Research and Comparison with Traditional Methods (Q1 and Q10)

After synthesizing the research based on the first PICO sub-question 'What technologies were used in the reviewed research?' referred to as (Q1), we found the following matches to create Table VI.

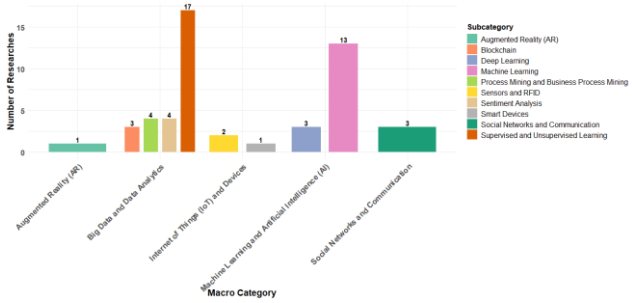

Fig. 5. Technologies by categories and subcategories found in the articles.

TABLE VI. COINCIDENCES OF TECHNOLOGIES FOUND BY RESEARCH

Category	Reference
Big Data and Data Analysis	[12], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39]
Internet of Things (IoT) and Devices	[40], [41], [42]
Machine Learning and Artificial Intelligence (AI)	[9], [10], [11], [13], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54]
Augmented Reality (AR)	[4]
Social Networks and Communication	[55], [56], [57]

Additionally, we reinforced the analysis of the information from Q1 with the sub-question Q10 'Is there any comparison between the technology and traditional methods?' to subdivide into a higher sublevel that provided information for Fig. 5, which we can see more clearly in Table VII.

TABLE VII. TECHNOLOGIES BY CATEGORIES AND SUBCATEGORIES FOUND IN THE ARTICLES

Category	Subcategory	Reference
Big Data and Data Analysis	Sentiment Analysis	[19], [21], [23], [32]
	Process Mining and Business Process Mining	[12], [16], [22], [28]
	Supervised and Unsupervised Learning	[14], [17], [18], [20], [24], [25], [26], [27], [30], [31], [33], [34], [35], [36], [38], [39]
	Blockchain	[28], [40], [42]
Internet of Things (IoT) and Devices	Sensors and RFID	[41], [42]
	Smart Devices	[40]
Machine Learning and Artificial Intelligence (AI)	Machine Learning	[7], [8], [9], [11],[41], [43], [45], [46], [48], [49], [50], [51], [52]
	Deep Learning	[44], [46], [57]
Augmented Reality (AR)	Augmented Reality (AR)	[4]
Social Networks and Communication	Social Networks and Communication	[55], [56], [57]

These tables provide a detailed summary of the technologies identified in the reviewed studies, organized by technology and subcategory. Table VI presents the distribution of publications across different technological categories, while Table VII details the specific subcategories within each technology and the number of associated publications. This analysis highlights the predominance of Big Data and Machine Learning in current research. It is important to note that multiple technologies were found in several studies, but the predominant technology in each case was considered for the construction of these tables.

E. The Role of Emerging Technologies in Identifying and Exploiting New Market Opportunities (Q3)

To contribute to our research, we consider the following PICO sub-question: What role do emerging technologies play in identifying and exploiting new market opportunities? (hereafter referred to as Q3). This question can be applied to a company and a loyalty program, as both aim to increase the company's revenue. As shown in Fig. 6, the publications are also mentioned in Table VIII.

TABLE VIII. CONTRIBUTIONS OF TECHNOLOGIES TO THE BENEFIT OF COMPANY REVENUES

Benefit	Reference
Improvement of Customer Experience	[4], [12], [15], [17], [23], [24], [30], [31], [35], [40], [45], [53], [56], [57]
Fraud Prevention	[9]
Inventory Optimization	[11], [32], [42], [52]
Behavior Analysis	[20], [35], [40], [57]
Decision Support	[22], [28], [42], [49]
Customer Satisfaction Prediction	[12], [35], [36], [47]
Avoiding Supply Chain Disruptions	[26]
Improvement of Payment Methods and Channels	[19]
Enhancement of Customer Interaction	[20]
Anticipation of Needs	[48], [56]
Identification of Additional Products	[55]
Recommendations from Satisfied Users	[25]
Process Efficiency	[21], [28], [42]
Cost Reduction	[21], [42], [52]
Customer Retention	[14], [24], [52]
Sales Increase	[4]
Productivity Improvement	[28], [45]
Creation of Specific Product Lists	[46]
Improvement of Visibility	[42]
Enhancement of Service Accuracy	[21]
Personalization of Offers	[46]
Market Development	[20]
Improvement of Customer Interaction	[20]
Provision of Key Information	[23], [31]
Not Mentioned	[10], [13], [16], [18], [27], [29], [33], [34], [37], [38], [39], [41], [43], [44], [50], [51], [54]

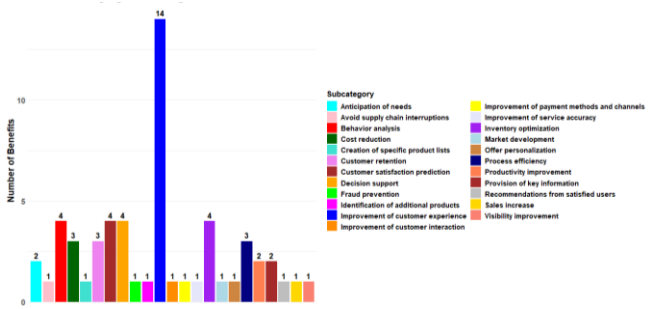

Fig. 6. Benefits of technology in increasing company revenues.

Fig. 7 shows the percentage distribution of the benefits provided by emerging technologies in identifying and exploiting new market opportunities. It highlights that some categories are particularly relevant to our research, such as big data analysis and market data analysis and personalization, representing 29.73% and 24.32% of the publications, respectively. Additionally, it is important to note that studies classified as "not mentioned" do not address the topic specified in the PICO sub-question Q3 and were therefore excluded from the specific benefits analysis. Table IX shows distribution of research by categories with reference to new market opportunities.

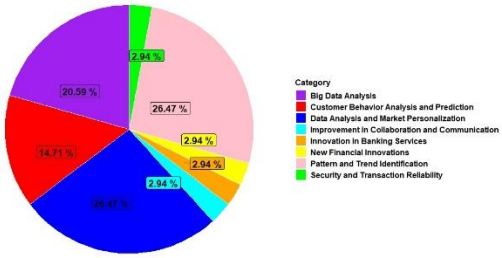

Fig. 7. Emerging technologies in the identification and exploitation of new market opportunities.

TABLE IX. DISTRIBUTION OF RESEARCH BY CATEGORIES WITH REFERENCE TO NEW MARKET OPPORTUNITIES

Benefit	References
Data Analysis and Market Personalization	[4], [11], [19], [23], [24], [31], [40], [52]
Security and Reliability in Transactions	[9]
Customer Behavior Analysis and Prediction	[12], [15], [20], [26], [56]
Analysis of Large Data Volumes	[21], [35], [36], [47], [48], [55], [57]
Innovation in Banking Services	[38]
Pattern and trend identification	[14], [18], [22], [25], [28], [35], [39], [42], [53]
Improvement in collaboration and communication	[42]
New financial innovations	[34]
Not mention	[10], [13], [16], [17], [27], [28], [29], [30], [32], [33], [37], [41], [43], [44], [45], [46], [49], [50], [51], [54]

F. Impact of Emerging Technologies on User Experience: Benefits Analysis (Q4, Q9, Q12)

In Fig. 8, the categories are distributed in bubbles, each focusing on different aspects of user experience according to the

reviewed studies. The categories include Personalization and Recommendations, Security and Privacy, Convenience and Ease of Use, Optimization and Efficiency, Analysis and Prediction, and Customer Satisfaction and Loyalty. Each bubble represents the number of publications addressing each benefit, clearly visualizing how emerging technologies impact user experience; the publications are also synthesized in Table X.

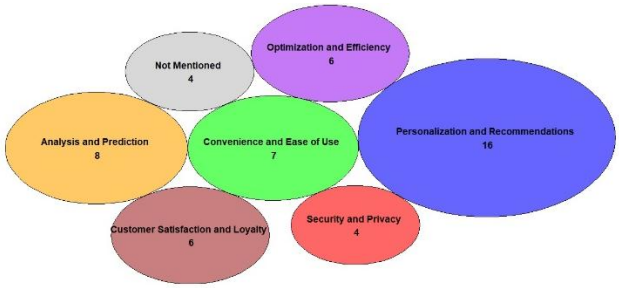

Fig. 8. Contribution of emerging technologies in relation to user experience.

TABLE X. USER EXPERIENCE CATEGORIES BY TECHNOLOGIES

Benefit	References
Personalization and Recommendations	[4], [11], [14], [15], [19], [23], [30], [35], [38], [40], [45], [46], [48], [55], [56], [57]
Security and Privacy	[9], [18], [26], [34]
Convenience and Ease of Use	[25], [27], [28], [31], [39], [49], [53]
Optimization and Efficiency	[12], [21], [33], [42], [54]
Analysis and Prediction	[10], [22], [29], [32], [37], [43], [47], [50]
Customer Satisfaction and Loyalty	[17], [20], [24], [36], [41], [52]
Not mention	[13], [16], [44], [51]

This information was synthesized based on three PICO sub-questions, with the main one being: What aspects of the user experience benefit the most from using emerging technologies? (hereafter referred to as Q4). Additionally, other questions relevant to the user experience were considered, such as the PICO sub-question: Is there any measurement of customer satisfaction with implementing the technology? (Q9), and the question: Is there information on customer reactions to technologies compared to traditional methods? (Q12). These sub-questions help deepen the synthesis of how emerging technologies influence the user experience.

IV. DISCUSSION

This section provides an overview of the research findings. It compares the identified emerging technologies to traditional customer loyalty practices, highlighting how each approach impacts user experience and loyalty. In the search for emerging technologies and their potential focus on customer loyalty, we found that the selected articles are mostly grouped around Big Data and Data Analysis [19], [37], [39], [48]. This reflects companies' perception of the importance of Big Data in evaluating customer satisfaction by integrating indicators such as perceived quality, perceived value, customer complaints, and customer loyalty. However, it is also crucial to consider other equally relevant emerging technologies, such as Machine Learning [9], [33], [39] and Process Mining [12], [25]. These technologies offer innovative and complementary approaches to Big Data and could even surpass its impact on customer loyalty.

We also found that it is essential for companies to achieve better revenue by improving customer satisfaction, which leads to greater loyalty. This is achieved by using different technologies to enhance the user experience in various ways, whether by providing greater perceived value, predicting factors that could generate dissatisfaction, or identifying and mitigating factors that negatively influence customer experiences [12], [15], [24], [30], [31], [53]; leading to an increase in customers. However, we must not forget important issues such as inventory optimization [25], [38], [41], [44], which represents considerable savings for the company, and above all, increased sales [4], which is usually the main reason of businesses existence.

Additionally, we should explore other perspectives, such as the comparison between efficiency and quality in the customer-company relationship. Our research shows that technologies like Big Data and Machine Learning enable automated and scalable personalization, providing precision and agility, albeit with less human interaction. In contrast, customer satisfaction and loyalty in the Peruvian footwear sector highlight the loyalty achieved through an emotional and direct connection with the customer based on in-store experiences and personalized attention [56]. This raises the question of whether the efficiency of technology can replace the emotional connection, especially in sectors that rely on a close relationship to strengthen customer loyalty.

Emerging technologies, such as those mentioned in our research, enable companies not only to enhance the personalization of their processes, services, or products but also to identify new market opportunities through data analysis and the analysis of customer preferences and behaviors. This goes further, creating a cycle of continuous improvement in the customer experience that results in greater satisfaction and loyalty, which translates into growth opportunities for companies [4], [9], [23], [24], [31], [35]. However, it is crucial to consider that the analysis method must be thoroughly validated to ensure it is suitable for what needs to be analyzed [51], [56].

On the other hand, loyalty programs in the retail sector present key differences in personalization and customer experience. While we highlight that technologies such as Big Data and Machine Learning allow for large-scale and real-time personalization, the retail loyalty study suggests that personalized incentives achieve a direct emotional connection, creating a more stable loyalty bond [59]. This difference is relevant for those seeking to balance technical personalization with emotional connection in loyalty strategies.

Our results align with previous studies that emphasize the importance of technology in customer loyalty. For example, previous research has shown that Big Data and Machine Learning can significantly improve a company's ability to personalize its offerings, as well as increase customer satisfaction and experience [4], [9], [12]. It is worth highlighting research that provides important information on Machine Learning models, which have proven effective in improving the prediction and management of customer satisfaction compared to deep learning models. We do not claim these are the best

models, but they showed the best predictions in the reviewed studies. The Random Forest, Naive Bayes, and SVM models stand out for several key factors. Random Forest effectively handle data imbalance through oversampling techniques, significantly improving its accuracy, reaching 92%, Additionally, the model identified delivery time, total order value, and shipping cost as key determinants of customer satisfaction [56]. On the other hand, Naive Bayes proved very effective in customer segmentation, achieving a positive response rate of 78% [16]. Finally, SVM improved its performance using oversampling techniques to handle data imbalance, resulting in a positive response rate of 82% in customer classification and churn prediction [29].Additionally, the model identified delivery time, total order value, and shipping cost as key determinants of customer satisfaction [56] [58]. On the other hand, Naive Bayes proved very effective in customer segmentation, achieving a positive response rate of 78% [16]. Finally, SVM improved its performance using oversampling techniques to handle data imbalance, resulting in a positive response rate of 82% in customer classification and churn prediction [29].

V. CONCLUSION

This systematic literature review study achieved its goal of evaluating how emerging technologies affect customer loyalty during digital transformation. The main findings show that technologies such as Big Data, IoT, Machine Learning, and Artificial Intelligence improve customer retention and satisfaction, surpassing traditional practices in personalization and user experience.

For future research, it is recommended that the range of years be expanded, more languages be included, whether the inclusion of another scientific database, and practical studies that show concrete results of the application of these technologies be focused on. Additionally, it would be beneficial to explore documents in additional databases and review research that is restricted access to obtain a broader view.

Going forward, the development of new emerging technologies, such as quantum computing, explainable artificial intelligence (XAI) and hyper-personalization based on advanced deep learning models, is expected to further transform customer loyalty. These innovations will enable highly personalized and automated experiences, optimizing the interaction between businesses and consumers. Organizations should be prepared to adopt these technologies strategically, ensuring their effective integration into loyalty strategies and guaranteeing a sustainable competitive advantage in a constantly evolving digital environment.

In conclusion, technology plays a crucial role for companies today, especially in customer loyalty. These technologies improve and personalize processes, services, and products and help identify new market opportunities. However, it is essential to choose the right technologies and methods and thoroughly validate their results to ensure they adequately meet the company's needs. Companies should consider integrating these technologies into their loyalty strategies in a planned and structured manner, ensuring effective implementation and thus gaining a sustainable competitive advantage.

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