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A Systematic Review and Meta-Analysis for Dental Implant Recognition Using Machine Learning: Models, Diagnostic Performance, and Clinical Evidence

Cristhian Hinostroza-De-La-Peña[1], Carlos Arroyo-Pérez[1], Johnny Astete-Llerena[2], Fabrizio Del Carpio Delgado[3], Luz Elena Nolasco Valenzuela[4], Flavio Amayo-Gamboa[5], Blanca Cecilia López-Ramírez[6,*]

[1] Universidad Nacional Mayor de San Marcos, Peru

[2] Universidad Tecnológica del Perú, Peru

[3] Universidad Nacional de Moquegua, Peru

[4] Universidad San Ignacio de Loyola, Peru

[5] Universidad Nacional de Trujillo, Peru

[6] Tecnológico Nacional de México/IT Roque, Mexico

{cristhian.hinostroza, carroyop}@unmsm.edu.pe, jastete@utp.edu.pe, fdelcarpiod@unam.edu.pe, luz.nolascov@epg.usil.pe, famayo@unitru.edu.pe, bllopez@itroque.edu.mx

Abstract. Dental implant recognition using Machine Learning has gained increasing relevance in digital dentistry; however, the rapid expansion of publications and the heterogeneity of approaches, metrics, and validation contexts make it difficult to accurately identify which strategies demonstrate greater robustness and what gaps persist in the literature. In this context, the objective of this study was to analyze the state of the art of Machine Learning applied to dental implant recognition, with emphasis on its methodological approaches, scientific collaboration patterns, conceptual definitions, and dominant thematic lines. To this end, a systematic review and meta-analysis were conducted based on an adaptation of the Kitchenham approach and the PRISMA guidelines, using structured search equations in Scopus, PubMed, IEEE Xplore, Cochrane Library, and Wiley Online Library; after the screening, eligibility, and quality assessment processes, 65 primary studies were included. The results show the predominance of Transfer Learning and Supervised Learning as central methodological strategies, a co-authorship network fragmented into relatively closed communities, a conceptual concentration on implant detection and classification and surgical planning, and a thematic map in which AI Dentistry appears as a specialized core, while most topics remain in a marginal condition. In conclusion, the field exhibits relevant technical advances, but still requires greater methodological standardization, external validation, and conceptual articulation to consolidate its clinical applicability.

Keywords. Machine Learning, dental implant recognition, deep learning, denture recognition, systematic review, meta-analysis.

1 Introduction

The use of machine learning algorithms to identify dental implants from radiographic images has

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become increasingly relevant in digital dentistry. Advances in artificial intelligence have enabled the development of systems capable of analyzing radiographic patterns and supporting clinicians in the recognition of implant systems.

However, the rapid growth of publications in this field has generated a heterogeneous body of literature, making it difficult to determine which approaches are truly effective and which aspects still require more robust evidence. First, various studies have explored the use of convolutional neural networks and deep learning architectures for the analysis of medical images, particularly in the diagnosis of cardiovascular diseases.

These advances have demonstrated the potential of deep learning in the automatic interpretation of clinical images, which has subsequently driven its application in other medical fields, such as dental imaging and dental implant recognition.

Authors [1,7,9] indicate that models based on CNNs and architectures such as U-Net enable the segmentation of clinical images and the detection of pathological patterns with high levels of accuracy in disease classification tasks. Likewise, several studies have focused on the analysis of electrocardiographic (ECG) signals using deep learning techniques, with the aim of improving the automatic detection of cardiac anomalies. In this regard, studies [5,16,17] highlight that deep neural networks can extract relevant features from ECG signals and facilitate automated clinical diagnostic processes with high predictive performance.

In a complementary manner, other studies have developed artificial intelligence models aimed at improving diagnostic accuracy through optimized neural network architectures. Authors [4,6,13] propose different deep network configurations that allow the classification of cardiovascular diseases based on biomedical data, demonstrating significant improvements in the ability to recognize complex clinical patterns.

On the other hand, several works have addressed the prediction of cardiovascular diseases using structured clinical data and medical databases, applying machine learning algorithms and data mining techniques. In this line, studies [10,11,18] report that the use of machine learning models applied to clinical records enables the identification of risk factors and early prediction of cardiac pathologies.

Similarly, some researchers have explored hybrid models that combine deep learning with other analytical techniques or multiple sources of clinical information. Authors [12,14,20] indicate that the integration of data from biomedical signals, clinical records, and statistical analysis improves the robustness of cardiovascular prediction and diagnostic models. Finally, other recent contributions have examined the use of intelligent systems and advanced deep learning techniques for the automated analysis of multimodal medical information. In particular, studies [2,8,15] show that artificial intelligence applied to mobile devices, clinical text analysis, and biomedical pattern recognition can expand the diagnostic capabilities of intelligent medical systems. Additionally, further studies [19,21] continue to deepen the comparative evaluation of deep learning models for the detection of anomalies and pathological patterns in clinical records and medical images.

Several systematic reviews have shown that artificial intelligence and deep learning models applied to dental radiographs achieve high levels of accuracy in the identification and classification of dental implants. Authors [73,74,79] report that deep learning algorithms can achieve accuracies above 95%, reaching values close to 98% in the classification of dental implant systems from radiographic images, which demonstrates their potential to support clinical diagnosis and therapeutic decision-making. Likewise, other studies have analyzed the performance of deep learning models in the automatic detection of dental implant brands and types in two-dimensional radiographs. In this context, studies [71,77] indicate that deep learning algorithms can reach accuracy levels close to 99%, showing high sensitivity and specificity in implant identification and in the detection of peri-implant pathologies.

In addition, several reviews have examined the role of artificial intelligence in different applications of dental implantology, including diagnosis, treatment outcome prediction, and implant design optimization. Authors [70,76,82] highlight that AI techniques have shown promising results across multiple stages of implant treatment, although methodological limitations and risks of bias still restrict their independent clinical adoption. On the other hand, some studies have emphasized the need to integrate artificial intelligence technologies to improve diagnostic processes and treatment planning in implantology. In this regard, authors [78,81] indicate that dental implant identification remains a significant clinical challenge, and therefore the development of AI-based tools can contribute to optimizing therapeutic planning, although more robust datasets and stricter standardization processes are still required.

Although previous systematic reviews have confirmed the high potential of artificial intelligence and deep learning for identification, classification, and diagnostic support in dental implantology, the current state of the art still presents a substantial knowledge gap: there is no review that simultaneously and systematically integrates the methodological approaches used to design, train, and evaluate models, the distribution of publications by quartile, co-authorship and scientific collaboration patterns, the conceptual definitions used to describe the application of Machine Learning in this domain, and the thematic lines structuring the field. This absence limits a broader and more strategic understanding of the literature, as existing reviews have mainly focused on diagnostic performance or specific clinical applications, without offering an articulated view of the methodological maturity, intellectual structure, and bibliometric configuration of the area. In this context, the present review differs from previous systematic reviews because it not only synthesizes evidence on model accuracy or performance, but also proposes a comprehensive characterization of the field from a methodological, bibliometric, conceptual, and thematic perspective, thereby providing a distinctive contribution to identify dominant trends, persistent gaps, and future research opportunities in Machine Learning applied to the Recognition of Dental Implants. The objective of this study is to conduct a systematic literature review to analyze the state of the art of Machine Learning techniques applied to dental implant recognition, identifying methodological trends and predominant approaches in recent research.

This paper is organized as follows. First, the Introduction presents the objective of the study, the context of the problem, and the main research background. Second, the Background section reviews the relevant conceptual and theoretical foundations. Third, the Methodology section describes the procedures followed for conducting the systematic review, based on an adapted Kitchenham approach [66] and the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. Fourth, the Results and Discussion section analyzes the findings obtained. Subsequently, the Conclusions section summarizes the main contributions of the study and outlines potential directions for future research. Finally, the Acknowledgments and References sections are presented.

2 Background

2.1 Machine Learning

Machine Learning (ML) can be defined as the discipline that systematically studies algorithms and mathematical models that enable computational systems to learn to perform specific tasks based on patterns present in data, without requiring explicit programming [67]. In this context, it has been noted that identification and classification systems based on machine learning have considerable potential to improve clinical practice [84].

Likewise, data constitute the fundamental element that underpins current technologies and research activity, particularly in the fields of machine learning and deep learning, where models depend on large volumes of information to optimize their performance [75]. Similarly, several studies highlight the sustained growth of research in this area in recent years [80]. Consequently, the application of machine learning has been prioritized across multiple domains of knowledge [72]. This is because various researchers have developed scientific studies in which artificial intelligence algorithms based on machine learning are implemented, successfully integrating them into different real-world use cases [2].

Additionally, among artificial intelligence technologies, machine learning is particularly suitable for tasks such as classification, object detection, and prediction, achieving in some cases performance comparable to or even exceeding that of humans. In the dental field, these techniques have been applied to interpret radiographs for diagnostic purposes, estimate clinical prognoses, classify tumors, and address various problems related to oral health [6]. Finally, this progress can be explained by the fact that, over the last decade, artificial intelligence—particularly deep learning techniques and neural networks—has evolved significantly, enabling its widespread adoption in medicine and dentistry [30].

2.2 Dental Implant Recognition

Dental Implant Recognition is defined as the process of identifying and classifying different implant systems present in periapical radiographs using computational techniques, such as convolutional neural networks [23]. In a complementary manner, it is also described as the procedure aimed at recognizing and categorizing various dental implant systems based on specific characteristics, such as diameter, length, shape, coating, and surface material, as well as their structural properties [32].

Dental implants are composed of different components, including fixtures, abutments, superstructures, and screws, whose internal designs and compatible tools vary depending on the manufacturer and the system used [25]. These devices exhibit a high success rate as substitutes for missing teeth. Furthermore, the demand for this type of treatment remains high and continues to grow steadily [2].

As a consequence of this increasing demand, numerous manufacturers have entered the market, resulting in more than 300 implant brands currently available and continuously expanding. Each of these brands offers multiple variants that differ in aspects such as length, diameter, surface texture, and other structural characteristics [5].

Over time, dental implants may present biological or mechanical complications, making periodic clinical follow-up necessary. In this context, accurate identification of the implant system can become particularly complex, especially when clinical information must be shared across different countries, due to the lack of a standardized interregional network for this purpose [6].

Finally, it has been noted that when adequate clinical records are not available, dental implant identification based solely on professional experience can be time-consuming and costly [42]. The complete process of implant placement, from initial intervention to final restoration, may take up to one year and exceed $4000 per unit. Moreover, since an implant consists of multiple components, its replacement can be complex when the specific type of implant used is not precisely known [78].

2.3 Application of Machine Learning in the Recognition of Dental Implants

Machine Learning (ML) contributes to dental implant recognition through the automated analysis of radiographs using computational mechanisms such as feature extraction, pattern recognition, and the use of deep learning architectures, especially convolutional neural networks, which enable the identification and classification of implant systems based on their distinctive morphological features.

This interaction is theoretically grounded in the principles of supervised learning, computer vision, and medical image analysis; however, its implementation faces challenges related to the limited availability of labeled clinical data, variability in the quality of radiographic images, and the high diversity of existing implant designs.

Nevertheless, the integration of ML in dental implant recognition is driving the development of more automated and accurate diagnostic approaches within digital dentistry, which justifies the systematic review of the scientific literature presented in the following sections.

3 Research Methodology

The Systematic Literature Review (SLR) constitutes a widely used methodological approach for conducting comprehensive analyses and systematically addressing specific research questions, following the guidelines proposed by Kitchenham [66]. In this context, the methodology employed in this study corresponds to an adaptation of the approach originally proposed by Kitchenham, incorporating complementary elements considered relevant to strengthen the review process, such as the PRISMA methodology and the use of structured search equations. These

Table 1. Search equations by source

Source	Search Equation
Scopus	TITLE-ABS-KEY ("machine learning" OR ml OR "artificial intelligence" OR "neural networks" OR "deep learning") AND TITLE-ABS-KEY ("dental implants" OR "dentures" OR "artificial teeth" OR "oral implant" OR "tooth implant" OR "implant dentistry")
PubMed	("machine learning"[Title/Abstract] OR ml[Title/Abstract] OR "artificial intelligence"[Title/Abstract] OR "neural networks"[Title/Abstract] OR "deep learning"[Title/Abstract]) AND ("dental implants"[Title/Abstract] OR "dentures"[Title/Abstract] OR "artificial teeth"[Title/Abstract] OR "oral implant"[Title/Abstract] OR "tooth implant"[Title/Abstract] OR "implant dentistry"[Title/Abstract])
IEEE Xplore	("All Metadata":"machine learning" OR "All Metadata":ml OR "All Metadata":"artificial intelligence" OR "All Metadata":"neural networks" OR "All Metadata":"deep learning") AND ("All Metadata":"dental implants" OR "All Metadata":"dentures" OR "All Metadata":"artificial teeth" OR "All Metadata":"oral implant" OR "All Metadata":"tooth implant" OR "All Metadata":"implant dentistry")
Cochrane Library	("machine learning" OR ml OR "artificial intelligence" OR "neural networks" OR "deep learning"):ti,ab,kw AND ("dental implants" OR "dentures" OR "artificial teeth" OR "oral implant" OR "tooth implant" OR "implant dentistry"):ti,ab,kw
Wiley Online Library	((title:("machine learning" OR ml OR "artificial intelligence" OR "neural networks" OR "deep learning") OR keywords:("machine learning" OR "ml" OR "artificial intelligence" OR "neural networks" OR "deep learning")) AND (title:("dental implants" OR "dentures" OR "artificial teeth" OR "oral implant" OR "tooth implant" OR "implant dentistry") OR keywords:("dental implants" OR "dentures" OR "artificial teeth" OR "oral implant" OR "tooth implant" OR "implant dentistry")))

aspects are not explicitly part of Kitchenham's original framework [66], but they contribute to improving the rigor, transparency, and reproducibility of the study selection process.

The growing interest in and expansion of artificial intelligence in recent years have driven its incorporation into multiple research areas with the aim of optimizing processes and addressing complex problems, with the healthcare sector being one of the domains where its adoption has shown significant development.

In this context, and considering the advancement of studies related to the application of Machine Learning in the Recognition of Dental Implants, it was deemed appropriate to conduct a systematic literature review to analyze the current state of knowledge in this field. Accordingly, the present study is aimed at answering the following research questions (RQ) and achieving the corresponding objectives.

3.1 Research Questions

Research Questions (RQ) must be formulated clearly and precisely, as they constitute the central axis guiding the process of selecting relevant papers within the systematic review. In this sense, these questions served as a guide to identify studies addressing the application of Machine Learning and its impact on the Recognition of Dental Implants. The research questions considered in this study are as follows:

RQ1: What methodological approaches are reported in the literature for the design, training, and evaluation of models based on Machine Learning?

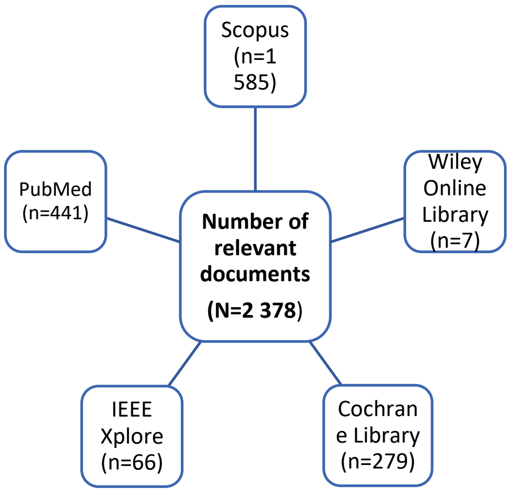

Fig. 1. Number of documents found by source

RQ2: What quartile classification levels are presented by scientific journals that have published studies related to Machine Learning in dental implant identification, according to recognized indexing systems?

RQ3: Which researchers recurrently participate as co-authors in publications related to Machine Learning in dental implant identification, and what patterns of inter-institutional or intra-group collaboration can be observed in these studies?

RQ4: What definitions have been used in studies addressing the application of Machine Learning in dental implant identification?

RQ5: What thematic lines or areas of focus are identified in research exploring the application of Machine Learning in dental implant identification?.

3.2 Sources of Information

Scientific databases of recognized international prestige were selected, and specific search equations were formulated for each of the following research sources: Scopus, PubMed, IEEE Xplore, Cochrane Library, and Wiley Online Library.

3.3 Search Equations

In order to conduct a systematic and focused search of relevant literature, structured search equations were defined using Boolean operators and specific keywords. These equations enabled the precise identification of the most relevant studies on the research topic across various scientific databases. The search equations used in each source are presented in Table 1.

3.4 Identified Studies

The studies identified through the application of the search equations across the different databases can be observed in Figure 1.

3.5 Exclusion Criteria

In order to ensure the relevance, quality, and thematic coherence of the studies considered in this research, exclusion criteria were defined to discard those papers that did not align with the objectives of the analysis. These criteria contribute to ensuring a rigorous selection of the literature, consistent with the methodological parameters established for the systematic review:

– EC1: Books, book chapters, theses, systematic reviews, bibliometric reviews, and conference papers were excluded.

– EC2: Papers older than six years were excluded.

– EC3: Papers not written in English were excluded.

– EC4: Studies without full-text availability were excluded.

– EC5: Papers not related to the subareas of the study were excluded.

– EC6: Papers with non-relevant keywords were excluded.

– EC7: Duplicate papers were excluded.

After applying the exclusion criteria to the identified studies, the result shown in Figure 2 was obtained, which presents the PRISMA diagram and the different stages of the filtering process used to determine the final papers included in the review.

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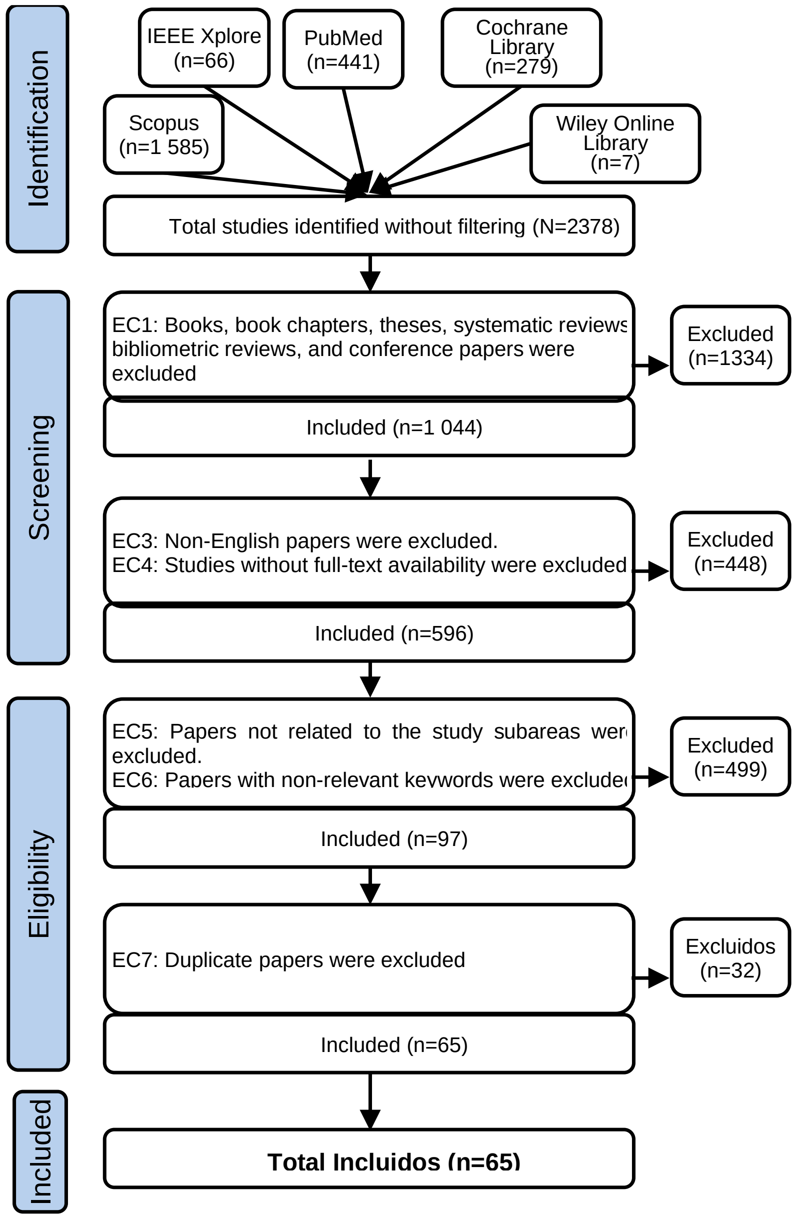

Fig. 2. PRISMA diagram

3.6 Quality Assessment

At this stage, the selected papers were analyzed through the application of seven quality assessment criteria (QA). During this final phase of the selection and filtering process, the definitive list of included studies was obtained, incorporating a quality evaluation that ensured each research study described in the papers was clear, consistent, and methodologically valid. The list of quality criteria (QA) considered in the analysis is presented below:

– QA1: Is the research objective explicitly and clearly stated?

Table 2. Quality assessment results

Ref	Type	QA1	QA2	QA3	QA4	QA5	QA6	QA7	Score
[1]	Journal	2	1	1	2	3	2	3	14
[2]	Journal	3	3	2	2	2	1	2	15
[3]	Journal	2	3	2	2	1	1	3	14
[4]	Journal	2	1	2	3	1	2	3	14
[5]	Journal	1	2	3	1	1	1	3	12
[6]	Journal	2	2	2	2	3	3	3	17
[7]	Journal	2	1	3	1	2	1	3	13
[8]	Journal	1	1	2	3	3	2	3	15
[9]	Journal	1	1	3	3	3	2	2	15
[10]	Journal	3	1	2	2	3	2	3	16
[11]	Journal	2	1	1	3	1	1	3	12
[12]	Journal	1	3	2	3	3	1	3	16
[13]	Journal	2	2	3	3	2	1	3	16
[14]	Journal	1	1	1	3	3	2	2	13
[15]	Journal	3	3	1	2	2	2	2	15
[16]	Journal	2	3	2	2	1	2	3	15
[17]	Journal	1	2	3	1	2	3	2	14
[18]	Journal	1	3	2	1	2	1	2	12
[19]	Journal	2	3	1	2	1	2	3	14
[20]	Journal	2	3	2	2	3	1	1	14
[21]	Journal	1	3	2	2	2	3	1	14
[22]	Journal	1	1	1	3	3	3	3	15
[23]	Journal	2	3	2	1	2	1	3	14
[24]	Journal	3	2	2	3	3	2	2	17
[25]	Journal	1	1	1	2	3	2	2	12
[26]	Journal	3	1	2	3	3	1	2	15
[27]	Journal	1	2	2	2	3	1	2	13
[28]	Journal	2	2	2	2	1	3	2	14
[29]	Journal	1	2	1	2	3	1	2	12
[30]	Journal	1	1	2	2	3	1	2	12
[31]	Journal	2	2	3	3	1	1	1	13
[32]	Journal	2	2	3	1	2	1	3	14

– QA2: Is the methodology described with sufficient clarity?

– QA3: Does the document present a clear, coherent, and well-organized academic structure?

– QA4: Does the study explicitly specify the dataset used?

– QA5: Are the conclusions consistent with the stated objectives?

– QA6: Does the study explicitly examine and report its main limitations?

[33]	Journal	3	2	1	3	2	1	1	13
[34]	Journal	2	3	2	2	1	3	3	16
[35]	Journal	3	1	1	2	2	3	3	15
[36]	Journal	2	3	3	2	3	3	1	17
[37]	Journal	1	1	2	1	3	3	2	13
[38]	Journal	2	2	3	3	3	2	3	18
[39]	Journal	1	2	2	1	3	2	1	12
[40]	Journal	2	3	1	3	1	1	1	12
[41]	Journal	3	1	1	2	2	3	3	15
[42]	Journal	3	3	1	3	1	3	3	17
[43]	Journal	3	3	2	2	1	2	2	15
[44]	Journal	2	2	3	2	1	2	1	13
[45]	Journal	3	2	3	1	1	2	1	13
[46]	Journal	2	1	2	2	2	2	2	13
[47]	Journal	3	2	3	3	3	3	3	20
[48]	Journal	3	2	2	1	1	1	2	12
[49]	Journal	2	2	2	3	3	1	3	16
[50]	Journal	2	1	2	3	3	1	2	14
[51]	Journal	2	1	3	1	1	3	3	14
[52]	Journal	2	2	1	1	2	3	3	14
[53]	Journal	3	2	3	2	3	1	2	16
[54]	Journal	2	2	2	2	2	2	3	15
[55]	Journal	2	3	3	1	2	1	2	14
[56]	Journal	3	3	2	1	3	2	1	15
[57]	Journal	1	2	1	2	3	3	1	13
[58]	Journal	3	1	1	3	1	2	2	13
[59]	Journal	1	2	2	1	3	1	3	13
[60]	Journal	1	2	3	2	1	1	2	12
[61]	Journal	1	2	3	2	2	1	1	12
[62]	Journal	3	3	2	2	3	1	3	17
[63]	Journal	3	2	2	3	1	1	2	14
[64]	Journal	3	1	1	2	3	3	3	16
[65]	Journal	3	2	2	2	2	3	2	16

– QA7: Are the research results presented and identified clearly and systematically?

For each paper evaluated comprehensively, the seven quality criteria were applied using a scoring scale from 1 to 3, where 1 represents low quality, 2 medium quality, and 3 high quality. A minimum acceptance threshold of 11 points was established; therefore, any paper that did not reach this value was excluded from the analysis.

After applying this evaluation to the 65 selected papers, it was verified that all primary studies exceeded the established minimum threshold. Consequently, it was possible to definitively determine which publications would be included in the study, whose results are presented in Table 2

Table 3. Synthesis of findings by methodological category

Method Category	Methods used	Performance	Limitations	References	Qty. (%)
Clinical Prediction & Decision Support Systems	Bayesian network; random forest; AdaBoost; multilayer perceptron; logistic regression; multiple linear regression; CNN-based classifiers	Accuracy: 72.8%-94.48%; RMSE: 0.1085; AUC: 0.6786-0.975; Sensitivity: 37.33%-90.49%	Limited sample sizes; retrospective designs; exclusion of psychological/ genetic factors; lack of external validation; modest sensitivity in biomarker models	[2] [12] [35] [45] [49] [57] [63] [64]	8 (11.4)
Cloud-Based & Automated ML Platforms	AutoML Vision; cloud-based CNN; virtual patient creator platform	Accuracy: 98.1%; Dice: 0.92±0.02; RMS: 0.08-0.11 mm; Processing time: <30 s vs 621 s	Limited implant types; lack of algorithm transparency; minor refinements needed in 70-80% cases; excludes complex multi-implant cases	[14] [25]	2 (2.9)
Deep Learning - Convolutional Neural Networks (CNN)	ResNet (18/ 34/ 50/ 101/ 152); VGG-16; MobileNet; LeNet-5; Inception V3; automated DCNN; 3D CNN	Accuracy: 84.00%-99.7%; AUC: 0.954-0.9999; F1: 0.85-0.9967; Detection AUC: 0.984	Limited implant brands/ types; retrospective single-center datasets; manual image cropping; potential overfitting with small datasets; generalizability concerns across devices	[20] [23] [30] [32] [51] [53] [55] [58] [59]	9 (12.9)
Deep Learning - Object Detection & Instance Segmentation	DETR; YOLO (v3/ v4/ v5/ v7/ v8); Faster R-CNN; Mask R-CNN; SSD; Dental-YOLO	Precision: 0.777-0.991; Recall: 0.89-0.995; mAP: 20.40%-99.46%; F1: 0.82-0.993; Mean IoU: 0.813-0.916	Small testing sets; ambiguity in bounding box standards; lower performance for specific anatomical regions; exclusion of images with artifacts limits generalizability	[5] [8] [21] [22] [39] [43] [47] [60] [65]	9 (12.9)
Explainable AI & Visualization Methods	Grad-CAM; Attention Branch Network (ABN); attention maps; feature visualization	Accuracy: 93.7%-99.08%; AUC: 0.986-0.9999; Precision: 0.867-0.9914	Limited to specific CNN architectures; visualization does not guarantee causal interpretation; small ROI may restrict feature extraction; single-center data limits generalizability	[20] [49] [51] [53]	4 (5.7)

3.7 Data Extraction Strategy

At this stage, a systematic data extraction process was carried out based on the selected papers in order to address the research questions. From each study, bibliometric and methodological variables were recorded, including title, URL, source, publication year, country, ISSN, publication type, journal, authors, institutional affiliation, quartile, H-index, number of citations, methodology, abstract, and keywords; however, it should be noted that not all papers reported all these elements or addressed all research questions.

For the organization, management, and processing of the information, the Mendeley Desktop tool was used to facilitate the management of papers and the efficient and systematic generation of bibliographic citations, thereby reducing the likelihood of human error. Additionally, the RAj tool, developed by Dr. Javier Gamboa Cruzado, was used to accelerate the processing and analysis of the extracted data during the review.

4 Results and Discussion

In this section of the paper, the results obtained are presented and discussed, placing them within the context of the existing literature and the objectives established in the study.

4.1 Overview of the studies

Table 3 synthesizes the methodological approaches identified in the literature on Machine

Hybrid & Ensemble Methods	CNN + SVM/ RF/ DT; U-Net + ANN + RF; improved AdaBoost; ensemble with GA optimization; hybrid periapical+panoramic model	Accuracy: 82%-98%; AUC: >0.86; F1: 0.85-0.9304; Correlation: >93%	Assumes validity of underlying theories (e.g., mechano-regulation); prediction accuracy unexamined outside training range; synthetic data generation risks overfitting; no external validation	[2] [26] [29] [48] [64]	5 (7.1)
Multi-Criteria Decision Making & Fuzzy Logic (MCDM/ SVNS)	CoCoSo; AHP; Single-Valued Neutrosophic Sets (SVNSs)	Statistically validated through case study and sensitivity analysis	Does not account for social influences in voluntary consumer context; may not suit institutional IT integration requirements; limited to chatbot selection domain	[1] [4] [13] [15] [19] [24] [27] [31] [33] [38] [40] [42] [44] [52] [61] [62]	16 (22.9)
Optimization & Simulation with AI (FEA+BESO+DL)	BESO; FEA; CNN-based surrogate; conditional variational U-Net; AI-driven 3D model generation	Compliance error: 0.29%; Shape error: 11.26%; Computation time: 6.5h→45s; Accuracy: 82%; Correlation: >93%	Simplified geometries; limited morphological variability; 2D axisymmetric assumptions; clinical parameter measurement requirements; performance metrics not fully reported	[3] [11] [26] [28] [54] [56]	6 (8.6)
Radiomics & Feature-Based Machine Learning	Hu moments; eigenvalues; radiomic feature extraction; ComBat harmonization; naive Bayes; RF; gradient boosting	Accuracy: 67%; AUC: 0.746-0.751; Sensitivity: 66.0%; Specificity: 58.04%-68.4%; DSC: 0.78-0.89	Small datasets; single-center data; moderate diagnostic accuracy; overlapping biomarker levels between conditions; manual annotation variability	[6] [45] [57]	3 (4.3)
Time Series & Sequential Modeling	LSTM; Optuna hyperparameter tuning; DARTs library; wear loss time series prediction	RMSE: 6.23-88.56 µm; MAE: 7.47-70.71 µm; MAPE: 12.43%-23.02%	Single-sample LSTM limits generalizability; potential artifacts from material deformation; limited to in vitro conditions; no clinical validation	[17]	1 (1.6)
Transfer Learning & AutoML Strategies	Transfer learning with fine-tuning; pre-trained models (VGG16/ ResNet50/ Xception); AutoML Vision; data augmentation pipelines	Accuracy: 95.28%-98.1%; Precision: 96.3%; Recall: 96.1%; F1: 96.2%; AUC: 0.9351-0.9877	Limited implant types; high-quality manually selected images may not reflect clinical reality; lack of algorithm transparency; potential reduced accuracy with non-standardized images	[23] [25] [29] [32] [58] [59] [65]	7 (11.1)

Learning in Dental Implant Recognition, organizing them by categories, methods used, reported performance, limitations, and relative weight in the literature. This structuring allows for the identification of dominant methodological trends, as well as gaps and imbalances in the research. The Qty. (%) column facilitates the interpretation of each pattern according to its representativeness within the analyzed corpus.

Method Category: The distribution reveals a predominance of Multi-Criteria Decision Making and Fuzzy Logic (22.9%), followed by CNN and Object Detection (12.9% each), and Clinical Prediction Systems (11.4%).

This pattern indicates that the field is divided between approaches focused on radiographic recognition using deep learning and more general decision-making frameworks.

The high presence of CNNs is explained by the visual nature of the problem, where implant morphological features are better detected through convolutional architectures. In contrast, categories such as Radiomics (4.3%) or Time Series (1.6%)

Table 4. Number of papers by author and source

Author	Cochrane Library	IEEE Xplore	PubMed	Scopus	Wiley Online Library	Total
Jae-Hong Lee	0	0	1	3	0	4
Dong Wu	0	0	1	2	0	3
Katsusuke Yamashita	0	0	0	3	0	3
Kazumasa Yoshii	0	0	0	3	0	3
Reinhilde Jacobs	0	0	0	3	0	3
Shintaro Sukegawa	0	0	0	3	0	3
Takeshi Hara	0	0	0	3	0	3
Alberto Traverso	0	2	0	0	0	2

Table 5. Impact of publications by author

Author	N° Papers	N° Citations	Citations/ Paper	Avg H-Index
Jae-Hong Lee	4	141	35	214.0
Dong Wu	3	3	1	289.7
Katsusuke Yamashita	3	80	27	316.0
Kazumasa Yoshii	3	80	27	316.0
Reinilde Jacobs	3	66	22	176.0
Shintaro Sukegawa	3	80	27	316.0
Takeshi Hara	3	80	27	316.0
Alberto Traverso	2	19	10	222.0
Andre Dekker	2	19	10	222.0
Bahaeelden M. Elgarba	2	33	17	168.5
Benjamin Haibe-Kains	2	19	10	222.0

remain marginal, likely due to the limited availability of longitudinal data or biomarkers.

Methods used: The methods are dominated by deep learning architectures (ResNet, VGG, MobileNet, YOLO, Faster R-CNN), complemented by transfer learning, data augmentation, and traditional classifiers such as random forest or logistic regression. This combination reflects a technical adaptation to visual recognition in radiographs and CBCT images. Hybrid approaches (7.1%) aim to improve robustness by combining automatic feature extraction with classical models or multiple image sources.

Performance: The reported results indicate high performance, with accuracies reaching up to 99.7%, AUC values up to 0.9999, and F1-scores up to 0.993 in classification or detection tasks. However, these figures are derived from heterogeneous experimental configurations (datasets, classes, validation strategies), which limits direct comparisons. In general, the best results are observed in controlled datasets or those with a limited number of classes, whereas performance decreases as clinical variability increases.

Limitations: The most recurrent limitations include small datasets, retrospective designs, lack of external validation, and limited diversity of implants or clinical centers. These constraints can be explained by the difficulty of obtaining expert-

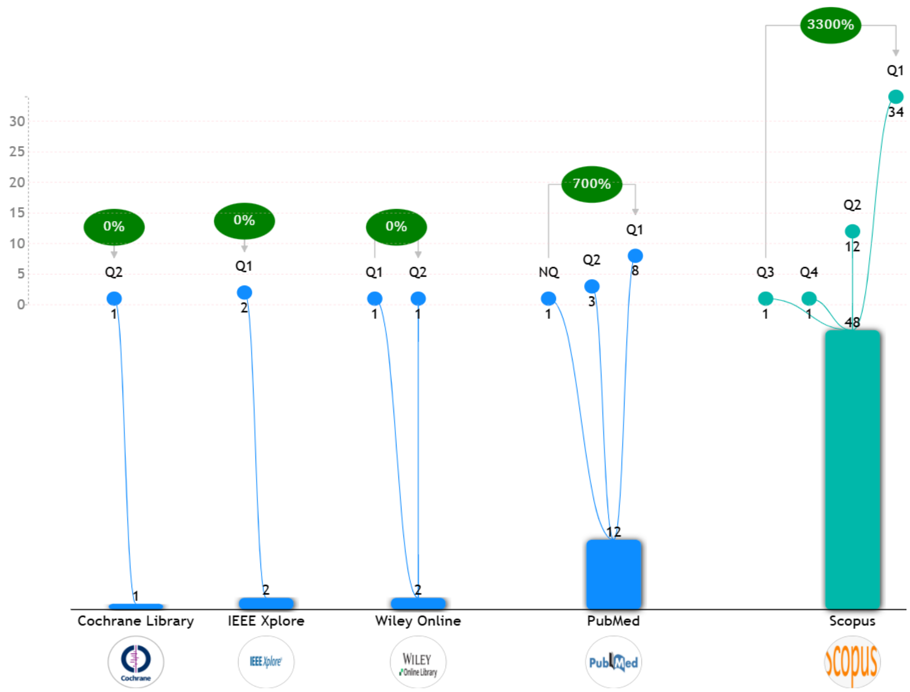

Fig. 3. Papers classified by source and quartile

Table 6. Impact of publications by source

Source	Avg H-Index	Total Papers	Total Citations	Citations/ Paper
Scopus	135.81	48	633	13
PubMed	162.67	12	143	12
IEEE Xplore	290.00	2	42	21
Wiley Online	87.00	2	21	11
Cochrane Library	83.00	1	12	12
Total	143.20	65	851	13

annotated radiographs and by the morphological similarity between implants from different manufacturers. In simulation-based or radiomics approaches, additional issues arise, such as simplified assumptions or moderate diagnostic metrics.

Qty. (%): The column confirms an uneven structure: although MCDM (22.9%) is the most represented category, approaches directly related to radiographic recognition are concentrated in CNN and object detection (12.9%). Categories such as Transfer Learning (11.1%) and Clinical Prediction (11.4%) reflect an expansion toward clinical support and computational efficiency. In contrast, areas such as radiomics or temporal modeling remain peripheral.

Ibraheem [73] reported that artificial intelligence models applied to radiographic images can achieve high levels of performance in dental implant identification and classification, with accuracy values ranging from approximately 67% to 98.5%, with most studies reporting accuracy rates above 90%.

Table 7. Impact of publications by country

Country	Number of Papers	Percentage of Papers (%)	Total Citations	Percentage of Citations (%)	H-Index	Citations per Paper
Korea	13	11.7%	242	17.0%	2111	18.6
Japan	9	8.1%	187	13.1%	1425	20.8
China	8	7.2%	41	2.9%	1351	5.1
Canada	5	4.5%	25	1.8%	790	5.0
Italy	5	4.5%	17	1.2%	713	3.4
Belgium	4	3.6%	85	6.0%	643	21.3
India	4	3.6%	39	2.7%	409	9.8
Turkey	4	3.6%	18	1.3%	303	4.5
Brazil	3	2.7%	33	2.3%	471	11.0
Egypt	3	2.7%	33	2.3%	398	11.0
Iran	3	2.7%	10	0.7%	125	3.3
Saudi Arabia	3	2.7%	63	4.4%	562	21.0
Spain	3	2.7%	20	1.4%	495	6.7
Sweden	3	2.7%	66	4.6%	528	22.0
Switzerland	3	2.7%	2	0.1%	408	0.7
Taiwan	3	2.7%	13	0.9%	386	4.3
US	3	2.7%	28	2.0%	281	9.3

The results indicate that the field has primarily advanced in radiographic classification and detection through deep learning. However, issues related to clinical generalization and metric standardization persist. Future research should prioritize multicenter datasets, external validation, and multimodal approaches. It is also necessary to integrate explainability and real clinical support. Without these advancements, many systems will remain experimental prototypes rather than consolidated clinical tools.

The information presented in Table 4 shows the distribution of authors according to the indexing sources in which they published their studies, while Table 5 presents their impact indicators, including number of papers, total citations, citations per paper, and average H-index. This organization is relevant because it allows for a complementary analysis of the authors' presence in the main scientific dissemination channels and the level of academic visibility achieved by their contributions.

The findings show that several authors concentrate their production almost exclusively in Scopus, as is the case of Katsusuke Yamashita, Kazumasa Yoshii, Reinhilde Jacobs, Shintaro Sukegawa, and Takeshi Hara, suggesting that this database functions as the main space for validation and circulation of knowledge in this field, likely due to its broader coverage of interdisciplinary journals in dentistry, medical imaging, and artificial intelligence. Jae-Hong Lee stands out both for his presence in more than one source—PubMed and Scopus—and for reporting 4 papers and 141 citations, indicating a trajectory with greater dissemination diversification and higher cumulative impact, possibly supported by a sustained research agenda aligned with highly visible scientific topics. In addition, some authors with three publications achieve up to 27 citations per paper and H-index values of 316.0, such as Katsusuke Yamashita, Kazumasa Yoshii, Shintaro Sukegawa, and Takeshi Hara, which shows that in this domain academic influence does not depend solely on publication volume, but also on integration into consolidated thematic networks and the publication of methodologically relevant studies in highly visible sources.

Unlike existing reviews, which have focused on methodological aspects, technological applications, or clinical outcomes, the available literature has rarely systematically examined the distribution of authors according to indexing sources together with their academic impact indicators. In this sense, the absence of comparable reviews reveals a specific gap in the literature, as most previous studies have prioritized

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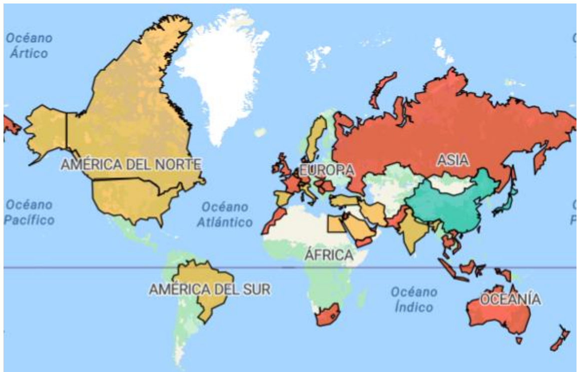

Fig. 4. Distribution of papers by country

Table 8. Machine Learning methodologies used in the analyzed studies

Methodology	Reference	Qty. (%)
Cross Validation	[5] [9] [18] [24] [29] [39] [51] [52] [53] [57] [64]	11 (18.03)
Supervised Learning	[1] [2] [6] [28] [29] [44] [48] [50] [51] [52] [53] [54] [57]	13 (21.31)
Transfer Learning	[1] [6] [19] [20] [21] [23] [24] [29] [30] [32] [34] [42] [51] [58] [59] [65]	16 (26.23)
Data Augmentation	[1] [4] [5] [8] [19] [24] [29] [34] [38] [40] [41] [43] [46] [47] [51] [52] [58] [59] [65]	19 (31.15)
Hyperparameter Optimization	[14] [31]	2 (3.28)

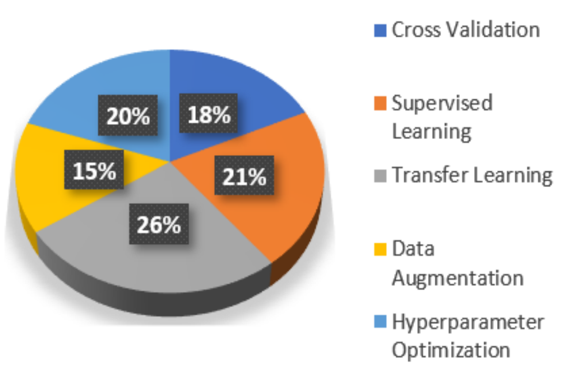

Fig. 5. Consolidated criteria for machine learning methodologies

the analysis of methods, datasets, or domain-specific applications. Consequently, the present study extends the scope of existing reviews by incorporating a complementary dimension aimed at simultaneously analyzing scientific dissemination channels and the bibliometric visibility of authors, thereby providing a more comprehensive perspective on the structure of knowledge production and positioning in this research field.

These results suggest that, in other knowledge-intensive sectors, the combination of strategic concentration in high-visibility sources and consistent thematic production may strengthen the positioning of authors and research teams, enhancing their recognition in areas such as digital health, data analytics, or advanced manufacturing. Likewise, this pattern may be extrapolated to other geographical regions and time periods to examine how the distribution of publications by source influences scientific impact, collaboration dynamics, and dissemination strategies in emerging fields.

Figure 3 and Table 6 present the distribution of the analyzed papers according to indexing source, quartile, and associated bibliometric metrics, including number of publications, total citations, average H-index, and citations per paper. This information is relevant because it enables the evaluation of the quality, scientific visibility, and editorial concentration of the corpus of studies included in the systematic review.

Scopus concentrates the largest number of papers, with 48 publications and 633 total citations, suggesting that this database acts as the main channel for scientific dissemination in research related to Machine Learning in dental implant recognition, likely due to its broader interdisciplinary coverage and the predominant indexing of biomedical and engineering journals. PubMed shows a lower number of papers but maintains a high average H-index (162.67), indicating that, although its publication volume is lower, these studies tend to be concentrated in biomedical journals with higher scientific impact, reflecting the clinical nature of the research topic. In turn, IEEE Xplore presents the highest average H-index (290), despite having only two papers, which may be explained by the highly specialized and technological nature of engineering publications, where papers often appear in journals or conferences with strong impact in the fields of artificial intelligence and medical image processing.

In the absence of prior studies, existing reviews in the field have mainly focused on methodological aspects or technological applications, while the integrated analysis of the distribution of studies by indexing source, quartile, and bibliometric metrics has received limited attention. In this context, the lack of comparable reviews reveals an analytical gap in the literature, particularly in the joint evaluation of editorial quality and scientific visibility of the corpus. Consequently, the present study extends the literature by incorporating this bibliometric dimension, providing a more structured perspective on the positioning and dissemination of knowledge in this research field.

These results suggest that future research in artificial intelligence applied to healthcare may benefit from interdisciplinary publication strategies that integrate biomedical and engineering journals, thereby expanding the scientific reach and international visibility of findings. Likewise, the concentration of publications in specific databases highlights the relevance of replicating this type of bibliometric analysis in other geographical regions and time periods to better understand the global evolution of research in clinical artificial intelligence and its transfer to technological and business sectors.

Figure 4 shows the geographical distribution of the papers included in the systematic review, visually representing the countries of origin of the publications through a georeferenced map. Table 7 complements this information by presenting bibliometric indicators by country, including number of papers, relative percentage, total citations, H-index, and citations per paper, allowing for the simultaneous evaluation of scientific productivity and academic impact at the national level.

It is important to note that the results obtained in the present study are consistent with those reported by Ibraheem [73], as both identify South Korea as the country with the highest number of papers on this topic. Although this convergence is limited to the geographical dimension of scientific production, it is relevant because it reinforces the idea that this country occupies a central position in the development of research on Machine Learning applied to dental implant identification.

These results suggest that the development of artificial intelligence applications in dentistry could benefit from international scientific collaboration strategies that integrate highly productive research centers with those exhibiting higher relative impact, thereby promoting technological transfer across regions. Likewise, the observed geographical pattern indicates that future studies could explore the temporal evolution of this distribution and its replicability in other medical or industrial sectors where image analysis through machine learning is becoming a strategic tool for innovation.

4.2 Response to the Research Questions

In this section, the results obtained from the systematic literature review are presented in order to address the research questions posed. The analysis integrates methodological, bibliometric, and thematic evidence related to the use of Machine Learning in dental implant recognition.

To this end, the findings are organized around five research questions (RQ1–RQ5), addressing the methodological approaches used, the distribution of publications by quartile, patterns of collaboration among researchers, the definitions employed in the studies, and the main thematic lines of the field.

4.2.1 RQ1: What Methodological Approaches Are Reported in the Literature for the Design, Training, and Evaluation of Models Based on Machine Learning?

Table 8 synthesizes the methodologies used in the analyzed studies for the design, training, and evaluation of Machine Learning-based models, indicating the associated references and their relative frequency in the literature. Figure 5 complements this information through a graphical representation of the percentage distribution of these methodologies, facilitating the identification of methodological adoption patterns and their relative weight within the analyzed corpus.

Transfer Learning represents the most frequent methodology, accounting for 26% of the total, suggesting that researchers widely rely on pre-trained models to overcome the limited availability of labeled radiographic datasets, thereby reducing

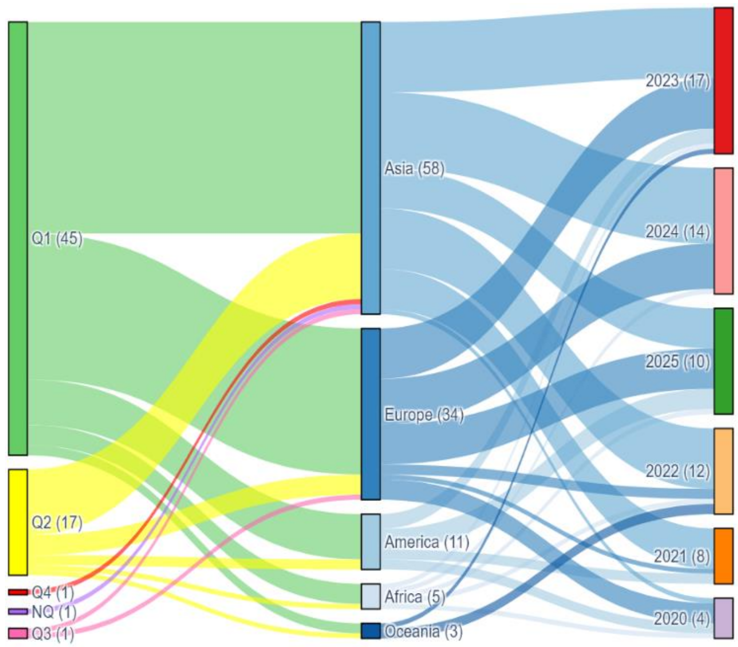

Fig. 6. Distribution of papers by quartile, continent, and year

Table 9. Distribution of papers by quartile, year, and continent

Quartile	NQ		Q1							Q2							Q3		Q4		Total
Continent	**2024**	**Total**	**2020**	**2021**	**2022**	**2023**	**2024**	**2025**	**Total**	**2020**	**2021**	**2022**	**2023**	**2024**	**2025**	**Total**	**2025**	**Total**	**2023**	**Total**	
Asia	1	1	0	4	9	10	13	6	42	1	4	3	3	1	1	13	1	1	1	1	58
Europe	0	0	4	1	0	8	9	7	29	0	0	2	2	0	0	4	1	1	0	0	34
America	0	0	2	1	0	2	0	4	9	0	1	0	1	0	0	2	0	0	0	0	11
Africa	0	0	1	0	0	1	0	1	4	0	0	1	0	0	0	1	0	0	0	0	5
Oceania	0	0	0	0	2	0	0	0	2	0	0	0	1	0	0	1	0	0	0	0	3

both computational costs and training time required to develop clinically applicable models. Supervised Learning (21%) and Hyperparameter Optimization (20%) also show significant presence, indicating that the field maintains a strong dependence on supervised learning schemes combined with fine-tuning strategies to improve the predictive performance of models under variations in medical images.

Cross Validation (18%) and Data Augmentation (15%) appear with lower relative frequency, which may be attributed to the fact that, although they are fundamental techniques for statistical robustness and artificial dataset expansion, their implementation largely depends on data availability and the type of architecture used, which may explain their lower presence compared to approaches focused on reusing pre-trained models.

The results obtained indicate that the present study shows partial agreement with those reported by Bonfanti-Gris and collaborators [77], who identify cross validation as one of the most widely used validation methodologies; however, in the present review, the predominant method corresponds to split dataset. Although Tsegaye

Table 10. Impact of publications by quartile

Quartile	N° Papers	N° Citations	Citations per Paper	H-index
Q1	45	501	11	7894
Q2	17	335	20	1388
NQ	1	14	14	0
Q3	1	1	1	25
Q4	1	0	0	1
Total	65	851	13	9308

Table 11. Impact of publications by continent

Continent	N° Papers	N° Citations	Citations per Paper	H-index
Asia	58	735	13	8458
Europe	34	441	13	5374
America	11	86	8	1542
Africa	5	126	25	593
Oceania	3	39	13	595

and colleagues [83] point out that hyperparameter tuning constitutes the most commonly used strategy, they also acknowledge the presence of cross validation, which is consistent with the findings of this systematic review. Consequently, these differences reveal the coexistence of multiple validation approaches, a situation that, while reflecting methodological flexibility, also highlights significant heterogeneity in evaluation protocols. In this regard, it is important to note that Abbott and collaborators [68] had already reported considerable variability in AI platforms, datasets, and evaluation procedures in dental diagnostic research, reinforcing the need to advance toward greater methodological standardization. Overall, these findings are aligned with broader systematic evidence indicating the predominance of deep learning-based approaches in artificial intelligence applications within dental implantology, particularly in image analysis tasks such as implant identification and anatomical classification, as reported by Vázquez-Sebrango and other authors [82].

These results suggest that data-intensive sectors relying on visual information—such as AI-assisted medical diagnosis, intelligent manufacturing, or automated inspection—may benefit from methodological strategies based on Transfer Learning when labeled data availability is limited. Likewise, the combination of supervised learning with hyperparameter optimization highlights the importance of robust methodological frameworks that can be adapted to different geographical contexts, time periods, or industrial domains where Machine Learning models must be tailored to specific local data characteristics.

4.2.2 RQ2: What Quartile Classification Levels are Presented by Scientific Journals That Have Published Studies Related to Machine Learning in Dental Implant Recognition, According to Recognized Indexing Systems?

Figure 6 represents the distribution of papers according to quartile, continent, and year of publication, while Tables 9, 10, and 11 complement this visualization by detailing the frequency of papers by quartile and their bibliometric impact both by quartile and by continent. This set of results is relevant because it allows not only the evaluation of the editorial hierarchy of the journals in which studies on Machine Learning in dental implant recognition are disseminated, but also the relationship between indexing quality, temporal evolution, and the geographical concentration of scientific impact.

According to the identified pattern, publications are predominantly concentrated in Q1 journals (45 papers) and, to a lesser extent, Q2 journals (17 papers), while NQ, Q3, and Q4 show marginal representation. This distribution suggests that the field has been primarily positioned within high-impact editorial channels, likely due to its combination of strong clinical relevance and technological innovation, two attributes that are highly valued by top-tier journals. Based on the presented evidence, Asia accounts for the highest volume of production (58 papers) and the largest number of citations (735), followed by Europe (34 papers and 441 citations), indicating that the consolidation of the field largely depends on regional ecosystems with strong research capacity, technological infrastructure, and integration between dentistry, medical imaging, and artificial intelligence. Furthermore, the highest temporal concentration of publications is observed between 2023 (17), 2024 (14), and 2025 (10), with

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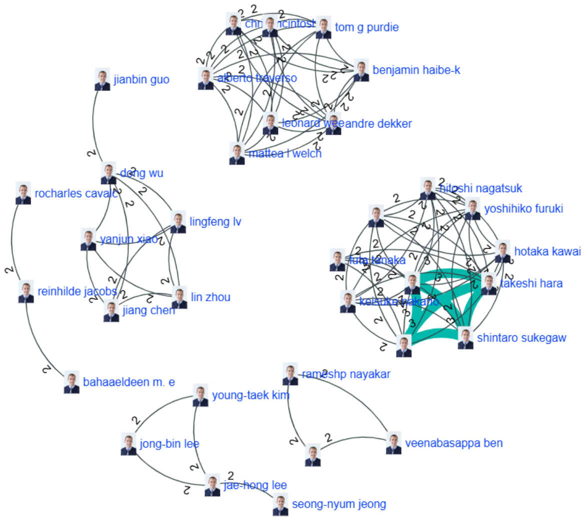

Author1	Author2	Weight
katsusuke yamashita	benjamin yoshii	3
katsusuke yamashita	shintaro sukegawa	3
katsusuke yamashita	benjami hara	3
benjamin yoshii	shintaro sukegawa	3
benjamin yoshii	benjami hara	3
shintaro sukegawa	benjami hara	3
alberto traverso	andre dekker	2
alberto traverso	benjamin haibe-kains	2
alberto traverso	chris mcintosh	2
alberto traverso	benja a jaffray	2
alberto traverso	leonard wee	2
alberto traverso	mattea l welch	2
alberto traverso	tom g purdie	2
andre dekker	benjamin haibe-kains	2

Fig. 7. Bibliometric co-authorship network

a persistent predominance of Q1 publications, suggesting a recent expansion of the topic in high-quartile journals. This trend may be explained by the increasing methodological maturity of the models, the cumulative availability of radiographic evidence, and the growing interest in automated solutions applicable to specialized clinical contexts.

Unlike previous reviews, which have primarily focused on evaluating the diagnostic performance of Machine Learning models, the literature has not explicitly addressed the quartile classification of journals publishing research on dental implant identification. In this regard, the present study contributes to filling this gap by incorporating a bibliometric analysis that characterizes the distribution of such publications according to recognized indexing systems.

These findings suggest that, in other data-intensive sectors involving image analysis and decision support—such as radiology, advanced manufacturing, industrial quality control, or precision agriculture—the combination of algorithmic innovation and practical applicability may also facilitate publication in high-quartile journals, particularly in regions with well-established scientific ecosystems. Furthermore, the observed distribution highlights the relevance of replicating this analysis across different time periods and geographical regions to determine whether the current concentration in Asia and Europe persists, shifts, or expands, which would have strategic implications for international collaboration policies, journal targeting, and the scientific positioning of the field.

4.2.3 RQ3: Which Researchers Recurrently Participate as Co-Authors in Publications Related to Machine Learning in Dental Implant Identification, and What Patterns of Inter-Institutional or Intra-Group Collaboration Can be Observed in These Studies?

Figure 7 presents the bibliometric co-authorship network that describes the collaborative relationships among researchers publishing on Machine Learning in Dental Implant Identification, while Table 12 complements this visualization by reporting co-authorship weights and structural centrality indicators. Additionally, Figure 8 illustrates the organization of the network into communities detected using the Louvain algorithm. This set of evidence is relevant because it enables a simultaneous analysis of the relational structure of the field, which is characteristic of bibliometric networks, and the way in which this structure is partitioned into Louvain communities, thereby revealing patterns of scientific collaboration, thematic cohesion, and knowledge organization.

Based on the presented evidence, the bibliometric co-authorship network does not exhibit

Table 12. Structural indicators of authors in the co-authorship network

Author	Degree	Strength	Clustering Coefficient	Betweenness
katsusuke yamashita	0.27	21.00	0.65	0.00
kazumasa yoshii	0.27	21.00	0.65	0.00
shintaro sukegawa	0.27	21.00	0.65	0.00
takeshi hara	0.27	21.00	0.65	0.00
hitoshi nagatsuka	0.24	16.00	0.69	0.00
hotaka kawai	0.24	16.00	0.69	0.00
keisuke nakano	0.24	16.00	0.69	0.00
kiyofumi takabatake	0.24	16.00	0.69	0.00
yoshihiko furuki	0.24	16.00	0.69	0.00
alberto traverso	0.21	14.00	0.67	0.00
andre dekker	0.21	14.00	0.67	0.00
benjamin haibe-kains	0.21	14.00	0.67	0.00
chris mcintosh	0.21	14.00	0.67	0.00
david a jaffray	0.21	14.00	0.67	0.00
leonard wee	0.21	14.00	0.67	0.00
mattea l welch	0.21	14.00	0.67	0.00

a uniform structure, but rather a system composed of six Louvain communities with a modularity of 0.66 and Strong quality, indicating that scientific collaboration in this domain tends to be organized into relatively autonomous clusters of researchers who share methodological agendas or institutional affiliations. According to the observed distribution, the cluster Japanese collaboration in implantology represents the largest community with 10 authors, within which Katsusuke Yamashita, Kazumasa Yoshii, Shintaro Sukegawa, and Takeshi Hara stand out, as they exhibit the highest values of degree (0.27) and strength (21.00), as well as co-authorship ties with a weight of 3. This suggests the presence of a highly cohesive core where recurrent collaboration strengthens scientific output and thematic specialization. According to the pattern identified in the bibliometric network, other communities such as Medical Machine Learning Consortium (8 authors) and Chinese collaboration in dental implants (6 authors) reflect intermediate collaborative groupings. In contrast, the betweenness value of 0.00 observed among the analyzed authors indicates a low level of intermediation between Louvain communities; this suggests that knowledge exchange occurs primarily within each community rather than across them, resulting in a relatively segmented research structure in which international or inter-institutional collaboration flows remain limited.

In the reviewed literature, no review studies were identified that specifically analyze the recurrent participation of researchers or the patterns of scientific collaboration in studies on Machine Learning applied to dental implant identification. This absence highlights a gap in the bibliometric analysis of the field, as most existing reviews have primarily focused on the diagnostic performance of models. In this context, the present study extends the understanding of the field by incorporating the analysis of co-authorship networks and scientific collaboration dynamics that shape research production in this domain.

These findings demonstrate that the combined analysis of bibliometric networks and Louvain communities constitutes a valuable methodological approach for understanding how research ecosystems are structured in emerging fields. This approach can be applied to other knowledge-intensive sectors such as biotechnology, digital health, clinical analytics, or biomedical engineering. Furthermore, it enables the identification of connectivity gaps between scientific communities across different geographical regions or time periods, providing strategic insights for the design of international consortia, inter-institutional cooperation programs, and research policies aimed at enhancing the integration of scientific knowledge.

4.2.4 RQ4: What Definitions Have Been Used in Studies Addressing the Application of Machine Learning in Dental Implant Identification?

Table 13 synthesizes the conceptual definitions employed in the literature to describe the application of Machine Learning in Dental Implant

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Cluster Name	Modularity	Quality	N° Authors
Chinese collaboration in dental implants	0,66	Strong	6
Collaboration in biomaterials for dental implants	0,66	Strong	3
International collaboration in dental implants	0,66	Strong	3
Japanese collaboration in implantology	0,66	Strong	10
Korean collaboration in dental implants	0,66	Strong	4
Medical machine learning Consortium	0,66	Strong	8
Total			34

Fig. 8. Author clusters based on Louvain Communities

Identification, organizing them into five analytical categories derived from the analysis of the reviewed studies. Additionally, Figure 9 presents the percentage distribution of these categories, enabling the visualization of the predominant conceptual approaches in the field and facilitating the identification of the functional areas in which this technology has been most extensively conceptualized.

According to the observed distribution, the category Implant Detection & Classification accounts for the largest proportion of definitions with 48 cases (45%), suggesting that the literature has primarily conceptualized Machine Learning as a tool focused on the automatic recognition and classification of radiographic images. This predominance may be explained by the increasing availability of medical imaging datasets and the high performance of supervised learning models in visual classification tasks. Similarly, the category Surgical Planning & Guided Surgery ranks second with 37 cases (34%), indicating a significant tendency to conceptualize these technologies as decision-support tools in clinical contexts, particularly in the assessment of bone density and the determination of implant immediate loading feasibility. Based on the reported results, the categories Prosthetic Rehabilitation & Design (10%) and Therapeutic Monitoring & Prognosis (9%) show intermediate participation, while Forensic Identification (2%) appears marginal. This suggests that applications related to forensic identification or legal contexts have received less scientific attention, likely due to the limited availability of forensic datasets and the lower direct clinical demand compared to diagnostic and surgical contexts.

It is worth noting that the findings of Bonfanti-Gris et al. [77] indicate that AI-based diagnostic systems can support clinicians by facilitating the identification of unknown implants and enabling earlier detection of peri-implant pathologies through radiographic analysis. In line with this, Tyagi et al. [69] highlight that Machine Learning techniques, particularly deep learning models based on convolutional neural networks, demonstrate strong capability in analyzing dental radiographic images and supporting diagnostic decision-making across various dental specialties. Furthermore, the evidence synthesized by Alfaraj et al. [85] confirms that these models, especially CNNs, have achieved robust performance in implant identification tasks and other radiographic diagnostic processes, reinforcing their growing role as clinical decision-support tools in dental implantology.

These results indicate that definitions of Machine Learning in dental implant identification have been primarily constructed around diagnostic and clinical planning applications, opening opportunities to extend their conceptualization toward other domains such as biomedical engineering, digital dentistry, medical device manufacturing, or predictive analytics in healthcare systems. Moreover, the proposed categorization may be applied in future comparative studies across different geographical regions or time periods to assess the conceptual evolution of the field and to guide the development of more integrative methodological frameworks in clinical and technological applications based on artificial intelligence.

Table 13. Definitions categorized by analytical approach

Category	Definition	Reference	Qty. (%)
Implant Detection & Classification	“It involves the use of algorithms and computational models that enable a system to learn from data and progressively improve its performance in tasks such as prediction, radiographic image classification, prognosis, and tumor classification.”	[1][2][4-13][15][17-25][29][31-36][38-43][47-49][56-65]	48 (45)
Surgical Planning & Guided Surgery	“It involves the use of algorithms and computational models to evaluate bone density and classify implants as ‘YES’ or ‘NO’ to determine their suitability for immediate loading.”	[1][2][4-15][19][26-27][31][37-44][53-58][60-64]	37 (34)
Therapeutic Monitoring & Prognosis	“It consists of the evaluation and prediction of implant success through the use of data mining and machine learning tools.”	[9][11][14][21][22][41][45][46][57][64]	10 (9)
Prosthetic Rehabilitation & Design	“It involves the development of systems that can learn from clinical and imaging data to automate the design of crowns and other prosthetic components.”	[7][9][11][14][27][33][36][46][50][54][55]	11 (10)
Forensic Identification	“It consists of the process of recognizing and distinguishing different dental implants present in human remains, which is essential when identifying obsolete or exotic implant systems.”	[1][5]	2 (2)

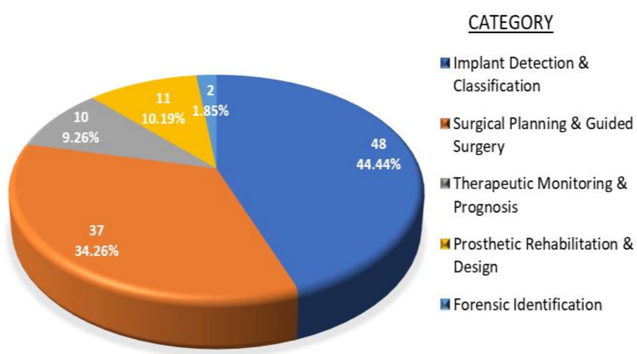

Fig. 9. Distribution of definitions by category

4.2.5 RQ5: What Thematic Lines or Areas of Focus are Identified in Studies Exploring the Application of Machine Learning in Dental Implant Identification?

Figure 10 presents the thematic map derived from keyword co-occurrence analysis, while Table 14 summarizes the bibliometric metrics associated with each identified theme, including centrality and density, which enable the simultaneous evaluation of their relevance and level of development within the field of study. In this context, each theme is positioned according to its centrality (horizontal axis), representing the degree of connection with other thematic areas, and its density (vertical axis), reflecting the level of internal development and cohesion, thereby allowing the identification of the main research lines related to Machine Learning in Dental Implant Identification.

The theme AI Dentistry exhibits the highest density (0.94) but a moderate centrality (0.23), indicating that it constitutes a highly developed and

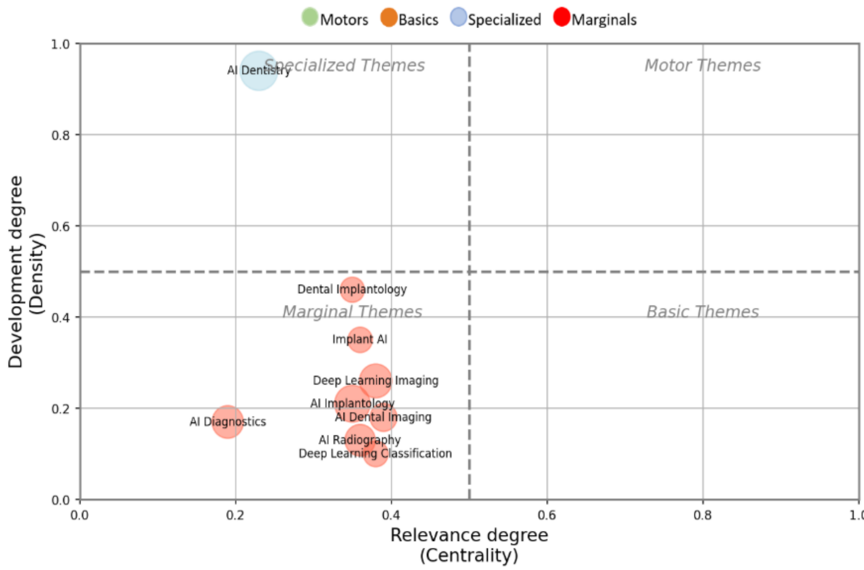

Fig. 10. Thematic map of research on Machine Learning and Dental Implant Recognition

Table 14. Thematic categories and bibliometric metrics

Theme	Density	Centrality	Category
AI Dentistry	0.94	0.23	Specialized
Dental Implantology	0.46	0.35	Marginal
Implant AI	0.35	0.36	Marginal
Deep Learning Imaging	0.26	0.38	Marginal
AI Implantology	0.21	0.35	Marginal
AI Dental Imaging	0.18	0.39	Marginal
AI Diagnostics	0.17	0.19	Marginal
AI Radiography	0.13	0.36	Marginal
Deep Learning Classification	0.1	0.38	Marginal

specialized topic within the field. This pattern suggests that research has established a solid conceptual foundation around the application of artificial intelligence in dentistry, although its transversal integration with other thematic areas remains relatively limited. Most themes, such as Dental Implantology, Implant AI, Deep Learning Imaging, AI Implantology, and AI Dental Imaging, are positioned within the Marginal category, with moderate centrality values (between 0.35 and 0.39) but relatively low densities. This indicates that these areas maintain connections with multiple research lines, yet still exhibit an incipient level of conceptual and methodological development. Themes such as AI Diagnostics, AI Radiography, and Deep Learning Classification display the lowest densities within the analyzed set, suggesting that these lines are emerging subfields undergoing consolidation, likely driven by recent advances in computer vision and deep learning techniques applied to automated radiographic image analysis.

These findings are consistent with those reported by Bonfanti-Gris et al. [77], who highlight implant classification as the most frequently addressed topic in the literature, while also identifying additional applications such as dental diagnostics. Similarly, Vázquez-Sebrango et al. [82] identify implant classification as the predominant thematic core, followed by diagnostic applications and the classification of oral structures. In the same vein, the category Implant Detection & Classification, identified in this review as the most developed (45% of the analyzed definitions), aligns with the findings reported by Ibraheem [73], where implant classification represents the primary focus of AI applications in dental implantology. Consequently, this convergence suggests a relative consolidation of this research line within the field. Nevertheless, Khattak et al. [86] emphasize that, although image-based detection and classification tasks demonstrate higher technical maturity and performance, multivariate predictive applications still exhibit more heterogeneous results due to biological complexity and dataset variability. Overall, these findings reinforce the need to advance toward greater methodological standardization and prospective validation to strengthen the clinical generalizability of Machine Learning models in dental implantology.

These results indicate that thematic lines related to Machine Learning in dental implant identification are still undergoing a process of conceptual expansion, opening opportunities to integrate these approaches with other areas such as AI-assisted diagnostics, digital dentistry, computer-aided design, or advanced clinical analytics. Furthermore, the thematic map analysis based on keywords may be applied to other technological and biomedical sectors, as well as across different geographical contexts or time periods, to identify the evolution of scientific agendas and to guide research strategies toward emerging areas with high development potential.

5 Conclusions and Future Research

In light of the findings obtained, it can be concluded that the field of Machine Learning applied to Dental Implant Recognition has reached a significant level of technical sophistication, yet has not achieved full methodological and conceptual maturity. First, and in line with RQ1, the predominance of approaches such as Transfer Learning, supervised learning, and hyperparameter optimization confirms that current research is structured around highly efficient architectures for visual tasks, although still dependent on optimization schemes aimed at mitigating the limited availability of large and diverse clinical datasets. In other words, the development of the field has been driven more by the technical adaptability of pre-trained models than by the existence of homogeneous methodological standards, which partly explains the persistence of heterogeneity across studies.

Second, in accordance with RQ3, the organization of scientific production into relatively closed bibliometric communities suggests that knowledge generation follows a logic of local specialization rather than robust international integration. While this configuration may foster thematic depth within each cluster, it simultaneously limits the transversal circulation of methods, validation criteria, and shared comparative frameworks. From a critical perspective, this implies that the advancement of the field depends not only on algorithmic performance but also on the ability to articulate more interconnected collaborative ecosystems.

Third, in line with RQ4, the concentration of definitions around detection, classification, and surgical planning reveals that Machine Learning has been primarily understood under a functional and instrumental logic, focused on solving immediate diagnostic problems within digital implantology. Although this orientation has been effective in producing applicable evidence, it has also constrained the development of a broader conceptual framework that integrates the role of AI in the evolution of implantological practice.

Complementarily, RQ5 showed that, although a clearly identifiable specialized core exists, most thematic lines still exhibit low density and only moderate centrality, indicating that the domain remains in a process of consolidation. From a theoretical standpoint, this suggests that the field is in a transitional phase between demonstrating technological feasibility and structuring a more stable and articulated scientific agenda. Moreover, the results support the argument that the high accuracy reported by many studies should not be interpreted in isolation as a proxy for clinical maturity, as persistent challenges remain regarding external validation, metric comparability, image diversity, and dataset representativeness.

Consequently, the contribution of this review lies not only in synthesizing performance outcomes or frequency distributions, but also in demonstrating that the technical strength of the field coexists with methodological, conceptual, and collaborative fragilities. From this perspective, the present review distinguishes itself by offering an integrative analysis that connects bibliometric results, conceptual definitions, methodological approaches, and thematic structure, thereby moving beyond a perspective exclusively focused on diagnostic accuracy. Overall, the findings indicate that Machine Learning in dental implant recognition constitutes a promising and expanding domain; however, its consolidation as a real clinical support tool will depend on simultaneous progress in methodological standardization, conceptual integration, multicenter validation, and more open scientific collaboration. This interpretation is consistent with current challenges in AI-driven dentistry, where the lack of standardized benchmarks, limited validation in real-world settings, and the need for greater explainability remain substantial barriers to sustained clinical translation.

Future research should prioritize the development of multicenter, diverse, and standardized datasets, as well as homogeneous external validation protocols that enable more rigorous model comparison and improved clinical generalizability. Additionally, it will be essential to advance toward approaches with greater explainability, transparency, and integration into real clinical workflows, evaluating not only accuracy but also practical utility, professional acceptance, and regulatory compatibility. Finally, collaborative studies should be promoted, including federated approaches where appropriate, to connect currently fragmented scientific communities and facilitate the evolution of the field from technically promising prototypes toward clinically robust and sustainable tools.

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**Corresponding author is Blanca Cecilia López-Ramírez.*