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Disruptive Computational Technologies in Electronic Medical Records Management

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Abstract:

Purpose – *The adoption of disruptive computing technologies in hospital administration services has transformed the landscape of medical data and information handling. Electronic medical records (EMRs) contain patients' health data generated in medical practices. This data can be converted into health information that pertains to individual patient health status, monitoring patient well-being, processing payments and financial transactions, providing statistics and demographics, and facilitating quality control of medical services.*

Design/methodology/approach – *This narrative literature review summarizes the current theoretical and practical frameworks for electronic medical record systems (EMRS), database structures, and information searching and retrieval strategies. The resources have been published in peer-reviewed journals indexed in PubMed, Scopus, Web of Science, and iCite databases.*

Findings – *EMR data stored in relational databases (RDB) are managed by RDB management systems (RDBMS) using structured query language (SQL) or not only SQL (NoSQL). Their efficient operation and content accuracy can be achieved by applying rules that ensure the atomicity and consistency of each transaction with the database, the isolation and synchronized control of the database, and the durability of the system against failures or errors. Current disruptive computational technologies, deep learning algorithms, artificial neural networks, recurrent neural networks (RNN), convoluted neural networks (CNN), and generative large language models (LLM) artificial intelligence (AI) systems can be utilized in these systems to uncover knowledge by answering complex health information queries.*

Originality/value – *Implementing AI systems in EMR RDBMS will enhance computer-assisted decision-making for various healthcare stakeholders, including medical practitioners, patients, and caregivers. From a clinical perspective, these systems may contribute equally to evidence-based and precision medicine. We will discuss the best practical and ethical considerations for their routine application.*

Index Terms — Electronic Medical Record, Electronic Medical Record System, Electronic Patient Record, Health Information Science, Computer-Assisted Medical Decision Making.

I. Introduction

The practice of maintaining medical records is a widely accepted clinical practice, documented in ancient Egyptian and Greek papyri as early as the 16th and 5th centuries BC, respectively [1, 2]. These case reports, particularly those from the Hippocratic Corpus, were shared among physicians in both the Arabic and Western worlds, establishing the foundations of medical pathology. Since the early 19th century AD, physicians have systematically documented clinical histories in their notebooks [3]. Initially, hospital staff and administrative personnel adopted and managed this process for inpatient cases by recording admissions and discharges. However, they gradually included additional data, such as patients' symptoms, physical examinations, drug administration, and surgical or other interventions. This administrative hospital bookkeeping has proven to offer additional educational value, particularly for teaching hospitals [4]. The copying of selected case reports from medical records involved transferring medical and surgical volumes to the hospitals' libraries [5].

Nevertheless, a clear distinction exists between medical data and health information. Both data and information are fundamental concepts in librarianship and information science, often used interchangeably in scientific literature. They serve as essential building blocks for producing knowledge after logical interpretation. However, these concepts are distinct, each with different organization, meaning, and roles.

Biomedical data refers to raw, unorganized, and unprocessed text, numbers, graphics, images, sounds, or videos that provide qualitative descriptions, figures, or quantitative data. These data exist independently in biomedicine, representing snapshots of clinical, laboratory, or experimental processes that describe biological parameters both objectively and subjectively without interpretation. The latter directly relates to the subjective description of a clinical case and diagnosis by the physician or the patient's self-report of symptoms and suffering. Although medical data possesses direct didactic, educational, and training value, it lacks context, reference, and meaning [5]. To acquire these aspects, appropriate processing or analysis is necessary, transforming medical data into health information.

Health information is essential for healthcare providers to follow up on patients' health and deliver effective care. When aggregated, it can also help to understand population health trends and the effectiveness of medical interventions. It can improve healthcare by monitoring common patterns in illnesses, treatments, and outcomes. Clinical audits, service ratings, and useful statistics are all components of health information for healthcare organizations, hospitals, or insurance agencies.

Here, we will discuss the evolution of adopting disruptive computational technologies in healthcare over the past four and a half decades.

II. Related Work

The scientific value of the patient's medical record, beyond its administrative practical importance, has been well recognized and detailed in statistical reports from hospitals since the early 19th century [4]. It was the promise of high-throughput analytical power and communication that initiated the era of computer applications in medicine. From the perspective of information scientists, regarding hardware, software, and algorithm generation, computer applications in medicine are not fundamentally different from those in other fields of knowledge. However, medical informatics significantly surpasses computer applications in medicine, as it is positioned at the core of biomedical research and the generation of health information. The practical application of this disruptive technology includes communication and registration, data storage and retrieval, automation and computation, decision-making, image processing and pattern recognition, process control, systems regulation, simulation, and model building [6]. Notably, this exact framework, as described by the medical informatics pioneers in 1984, remains unchanged to this day.

The transition from a paper-based system to the computing era required significant financial investments, infrastructure changes, training, and familiarization with new systems for all stakeholders: physicians, nurses, paramedics, other healthcare providers, administrative personnel, patients, families, and caregivers. The digitization of current and past medical records was monumental in scale. Despite the challenges, by the mid-1980s, the introduction of computer-based patient records replaced the use of paper and the physical storage of medical records in hospitals. Soon, the use of electronic medical records (EMRs) by medical institutions became so common in the US that it was broadly implemented within a decade, leading to revisions in commentaries on standard healthcare services [7]. The need to adopt standard, structured metadata formats to effectively describe EMR data was urgent. Metadata can be descriptive, detailing a data resource for discovery and identification; structural, illustrating the composition of complex entities and how their elements are coordinated; or administrative, providing information on managing a resource, such as creation time, file type, and other relevant technical information.

Guidelines for electronic patient registries were introduced to evaluate patient outcomes in an organized manner, utilizing observational clinical examination methods, uniform delivery of laboratory-observed measurements, and descriptive definitions of diseases, conditions, symptoms, and therapeutic interventions. The patient registry database delineates the files derived from such a registry [8]. The impact of these technologies extended beyond the narrow hospital environment to be applied to nursing homes [9].

Medical informatics can be applied to these datasets to infer health information from structured biomedical data. Considering the scope of the collection and the objectives of the medical informatics analysis, three distinct types can be identified. When the analysis focuses on the primary reason for collecting the data, it is known as primary data analysis. If the purpose of the analysis differs, it is termed secondary data analysis. Tertiary analysis involves annotation, filtering, and data interpretation to draw comprehensive functional, quality, and post-analytical logical conclusions. For example, blood pressure readings can be used primarily to diagnose hypertension in individual patients. However, if a patient's postoperative pressure measurement intervals are recorded, this can be used secondarily to indicate the quality of nursing services in a hospital. The broader association of blood pressure readings with clinical genetics, such as next-generation sequencing analysis, provides a means for complex interpretation of genetically heterogeneous disorders, including hypertension [10].

Thirty years ago, it was clear that maintaining electronic medical records (EMRs) in-house did not promote cross-organizational communication and information exchange. The data stored and aggregated in institutional silos of electronic medical record systems (EMRSs) were difficult to share or reuse for clinical or research purposes. Hypertext-based design improved computational capabilities by branching the content, index, and keyword references [11]. The introduction of web technology marked a communication breakthrough that paved the way for the desilofication of health information. Naturally, unifying coding standards for medical data has been and remains essential for aligning the information derived from different electronic medical record systems (EMRSs) created by various vendors [12].

Since the turn of the century, numerous disruptive technologies have emerged in computer science and medical informatics, such as mobile edge computing, telemedicine, smart mobile devices, web 2.0, the semantic web, the Internet of Things (IoT), cloud-edge computing, data encryption, blockchain, machine learning, and generative artificial intelligence (AI) models. The following sections will examine the literature on the impact of these technologies on in-house and outsourced electronic medical record management and analysis.

III. Methodology

A thorough investigation of multiple bibliographic databases was conducted to explore the computational technologies used in medical informatics that develop electronic medical or health records (EMRs or EHRs), clinical and laboratory analyses, medical imaging, biomedical research, epidemiology, patient-centered care, clinical decision-making, and collaboration among healthcare providers.

A. *Research Questions*

This study aims to address specific questions regarding the application of disruptive computational technologies in routine electronic medical records management:

- RQ1: What are the research areas involved, and what are the topics of research focus?
- RQ2: What computing technological advances are utilized in healthcare?

B. *Search Strategy Design*

Four bibliographic databases were used in the search strategy:

- PubMed (https://pubmed.ncbi.nlm.nih.gov/),
- Web of Science (https://www.webofscience.com/),
- Scopus (https://www.scopus.com/), and
- iCite (https://icite.od.nih.gov/).

The applied keywords of interest included: "electronic medical record systems," "relational databases management systems," "electronic patient record," and "computation" within the Title, Abstract, Keywords, or Topics, without institutional or country affiliation, or chronological restrictions. Additional keywords were utilized for post hoc investigations of specific subjects: "medical information system(s)," "mobile edge computing," "telemedicine," "mobile healthcare," "emergency medicine," "personalized medicine," "evidence-based medicine," "epidemic(s)," "pandemic(s)," "COVID-19," "smart mobile devices," "web 2.0," "social media," "blogging," "microblogging," "semantic web," "ontologies," "Internet of Things," "cloud computing," "data encryption," "blockchain," "machine learning," "deep learning," "artificial intelligence," and "Large Language Model(s)," or "generative artificial intelligence." All bibliographic research was conducted in accordance with the formatting requirements of the relevant bibliographic database, employing advanced query syntax, Boolean operators, field codes, and auxiliary filters such as publication date range, subject area, document type, keywords, affiliation, and language. PubMed and iCite interrogation yield the same research results; however, the contexts of the PubMed and iCite databases, as well as their deliverables, differ. PubMed results comprise titles, abstracts, and bibliographic metadata, whereas iCite results encompass bibliometric metadata, including paper influence, translation into applied clinical practices, and open citations. All search results were extracted and downloaded as comma-separated values (CSV) or text files. The last time the databases were accessed was on June 6, 2025.

C. *Data Analysis*

The collected data was combined and delivered in worksheets for further analysis. VOSviewer version 1.6.20 was utilized for bibliographic analysis and visualization of trends. Full counting was employed to calculate the link strength. Descriptive statistics and Latent Dirichlet Allocation (LDA) topic modeling were applied. The iCite translation module was used to estimate the levels of clinically applied research articles, which are more closely related to human subjects compared to animal models or molecular/cellular biology research patterns, based on the number of Medical Subject Headings (MeSH) terms that fall into each category.

IV. Results

A total of 75,593 documents were identified, of which 30,988 remained after duplicates were removed. Among these, 9,522 papers were included based on their relevance to the research query (Figure 1). Relevance estimation was conducted by sorting the retrieved records according to the presence of query terms in their titles, abstracts, or keywords. More than half of these publications have been issued from 2021 to the present (Figure 2).

Research Areas	Record Count	% of 9,522 docs
Health Care Sciences Services	6631	69.639
Mathematical Computational Biology	5785	60.754
Computer Science	4148	43.562
Mathematics	3648	38.311
Medical Informatics	3228	33.9
Communication	2139	22.464
General Internal Medicine	1903	19.985
Information Science Library Science	1746	18.336
Science Technology Other Topics	1712	17.979
Pharmacology Pharmacy	1454	15.27
Cardiovascular System Cardiology	1370	14.388
Engineering	1331	13.978
Geriatrics Gerontology	1271	13.348
Public Environmental Occupational Health	1234	12.959
Radiology Nuclear Medicine Medical Imaging	1133	11.899

Table 1. The top 15 research areas within the bibliographic portfolio using Web of Science.

A. *Research areas and topics involved*

The research areas related to the adoption of disruptive computer technologies in biomedicine (Table 1) highlight the multidisciplinary nature of this process.

Topics	Record Count	% of 9,522 docs
Computational Biology	4030	42.323
Human Medicine Medical Sciences	3261	34.247
Computer Applications	1745	18.326
Medical Sciences	1349	14.167
Models And Simulations	1260	13.233
Mathematical Biology	1199	12.592
Human Medicine	941	9.882
Pharmacology	786	8.255
Cardiovascular Medicine	766	8.045
Methods And Techniques	659	6.921
Allied Medical Sciences	597	6.27
Oncology	528	5.545
Infection	509	5.346
Clinical Immunology	481	5.051
Information Studies	444	4.663

Table 2. The top 15 topics identified in the bibliographic portfolio, according to the Web of Science.

The research areas related to the adoption of disruptive computer technologies in biomedicine (Table 1) highlight the multidisciplinary nature of this process. The objective is to enhance healthcare services, but achieving this requires collaborations with computational biology, computer science, mathematics, medical librarianship, and information science. In terms of applications, medical informatics emphasizes the communication of general internal medicine and pharmacological evidence, particularly in cardiology, geriatrics, public environmental occupational health, medical imaging, epidemiology, oncology, psychology, immunology, neurosciences, pediatrics, pulmonology, genetics, endocrinology and metabolism, gastroenterology, hematology, surgery, urology, critical care medicine, and obstetrics and gynecology. Beyond the confines of applied clinical research, EMR computational algorithmic applications are involved in sociology and business economics, in-house logistics, and the outsourcing of healthcare services and their financial administration.

Nearly 80% of the papers are original research investigations, with 10% of them being conference proceedings, 8% being reviews, and 2% being applied clinical trials of computational applications. Although this finding suggests poor penetration of disruptive computational technologies in medical practice, the iCite analysis of the bibliography indicates that from 1980 to the present, nearly all reports relate to human patients and not to animal experimental models or basic molecular biology research, as reflected by the number of related MeSH terms reported in papers. Indeed, this observation is consistent with the topics analysis (Table 2), which investigates the topics reported in the bibliographic portfolio. Human medicine is the leading concept in 90% of the papers in the collection, closely followed by computational methodologies. Among the specific concepts, models and simulations lead at 13%, followed by pharmacology and cardiology, both at 8%, and oncology, the epidemiology of communicable human diseases, and immunology, all at 5%. Metabolism, gastroenterology, neurology, the epidemiology of non-communicable human diseases, and pulmonary medicine each account for 4%. Molecular biology accounts for 3.4% of the investigations.

According to MeSH qualifiers, the bibliographic portfolio consists of 17% methods, 16% diagnosis, 14% epidemiology, 12% statistics, 6% standards, 6% therapy, 5% drug therapy, 4.5% organization administration, 4% prevention and control, 3.5% adverse effects, 3% etiology, 2.5% complications, and 2% genetics, trends, classification, diagnostic imaging, psychology, pathology, and mortality. The MeSH headings attributed to the research papers included in the study are 61% about humans, 40% about electronic health records, 26% about algorithms, 23% concerning female human population, 20% males, 15% middle aged people, 13% adults, 11% retrospective studies, 10.5% machine learning, 7% natural language processing, 6% databases, and 5% risk factors.

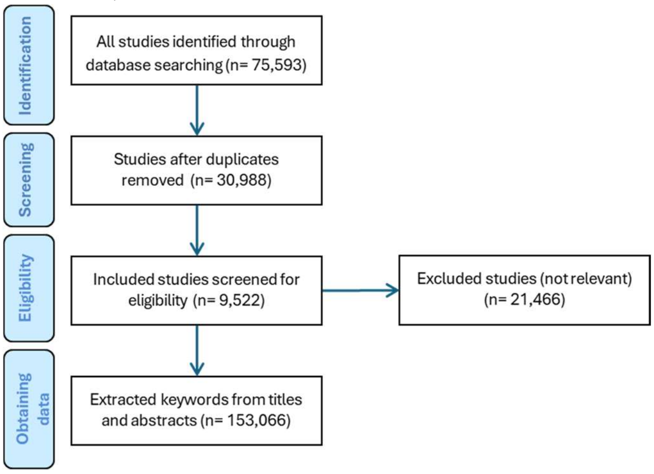

***Fig. 1.** Literature review and keyword extraction study design. All documents were retrieved from PubMed, Web of Science Core Collection, and Scopus bibliographic databases.*

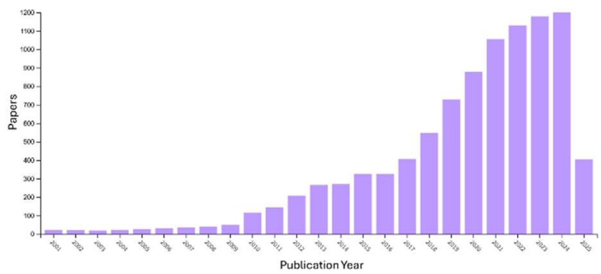

***Fig. 2**. Publication years of the bibliographic portfolio.*

B. Computational technologies in healthcare

The bibliographic portfolio, which includes titles and abstracts, was imported into VOSviewer for further analysis. In total, 153,066 keywords were extracted that appeared at least once in the corpus of included papers.

The VOSviewer analysis generated visualizations of keyword networks based on the number of occurrences, links, average publication year, and average citations. This data was extracted into visual illustrations in Portable Network Graphics (PNG) format and presented in tabular text files (TXT). The tabular text files were imported into spreadsheet software (Microsoft Excel®) for further analysis. These datasets were examined for specific questions regarding technologies, applications, or stakeholders.

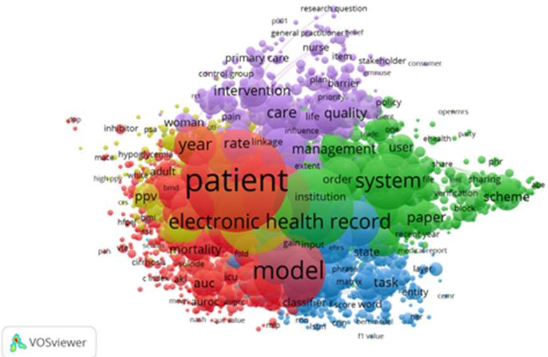

Fig. 3. *Network visualization of keywords with at least 20 times of co-occurrence in the bibliographic portfolio. A full count was considered, including multiple occurrences within a record. The term "patient" dominates in occurrences, followed by "electronic health record," "data," "algorithm," and "system."*

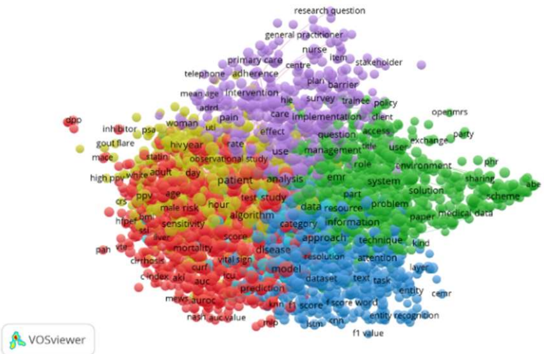

Fig. 4. *Network visualization of keywords with at least 20 times of co-occurrence in the bibliographic portfolio. A full count was considered, including multiple occurrences within a record. The size variation in occurrences for each circle has been reduced in $^{1}/_{10}$ to improve the resolution. There are six clusters of terms in red (cluster 1, 750 terms), green (cluster 2, 667 terms), blue (cluster 3, 509 terms), yellow (cluster 4, 404 terms), purple (cluster 5, 381 terms), and cyan (cluster 6, 63 terms).*

When examining the specific disruptive computational technologies utilized in healthcare and EMR management, the most interesting concepts, based on their frequency and relationships in the bibliographic portfolio, are:

- Machine Learning (ML) entails the analysis of patient data and medical images for various tasks, including disease diagnosis, risk stratification, medical image analysis, clinical decision support, optimization of clinical trials, modeling of longitudinal patient data, and administrative automation. It also tackles challenges such as data inconsistencies, incompleteness, irregular or temporal data, the risk of information leakage, bias, and feedback loops [13, 14].

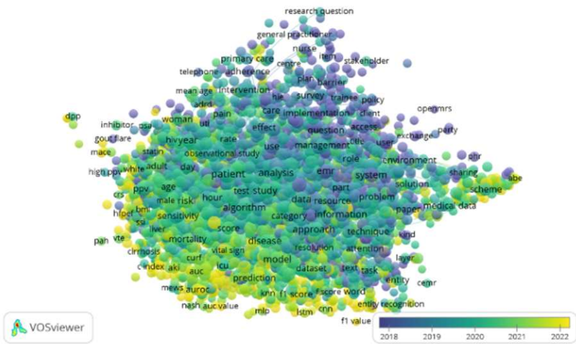

Fig. 5. *Network visualization of keywords with at least 20 times of co-occurrence in the bibliographic portfolio. A full count was considered, including multiple occurrences within a record. The terms are colored from dark blue to green and yellow according to the average year of publication of the papers to which they are referred. Cluster 5 appears in papers published on average in 2018, while the rest of the clusters appear in papers published on average between 2020 and 2024.*

Term	Occurrences	Average publication year	% of 9,522 docs
patient	1025121	2019.90	99.89%
model	511414	2020.82	99.32%
study	453277	2020.23	99.75%
risk	186439	2020.76	97.22%
year	216659	2020.12	96.76%
hospital	139681	2018.99	95.75%
outcome	149830	2020.40	97.04%
prediction	116289	2021.11	91.38%
machine	108678	2021.28	94.23%
treatment	115075	2019.81	96.11%
area	116703	2020.65	97.19%
score	115177	2020.41	92.68%
machine learning	94156	2021.70	94.27%
age	108563	2020.42	91.35%
cohort	93885	2020.73	89.51%
level	82931	2019.27	94.34%
day	91129	2019.92	88.07%
factor	81038	2019.93	91.28%
covid	79584	2022.25	73.22%
variable	75284	2020.54	88.57%

Table 3. The top 20 terms of cluster 1 concepts identified in the bibliographic portfolio, as determined by VOSviewer.

- Natural Language Processing (NLP) automates clinical documentation, extracts and structures clinical information, classifies and summarizes clinical notes, recognizes named entities (NER), detects clinical conditions early, enhances research analytics, monitors activities of daily living (ADL), and addresses the risk of performance variability, which poses challenges for full integration into clinical workflows and leads to variability in performance [15, 16].

- Artificial Intelligence (AI) is used to analyze patient-generated health data (PGHD), provide clinical decision support, enhance personalized medicine, automate administrative tasks, identify errors, validate data, perform predictive analytics, and assist in drug development. However, there are drawbacks, including the variability of EMR entries, data volume, complexity of biological systems, challenges in making generalizations, and the potential for bias to be introduced during training [17, 18].

Term	Occurrences	Average publication year	% of 9,522 docs
data	602094	2019.74	99.96%
system	274442	2017.26	98.59%
electronic medical record	168663	2017.78	98.74%
time	175291	2019.41	98.49%
emr	146276	2017.72	94.95%
research	133969	2019.59	97.22%
application	108775	2019.37	95.71%
development	110968	2019.67	98.02%
paper	86259	2018.66	89.98%
process	100826	2019.14	93.73%
framework	93645	2020.22	89.73%
challenge	88669	2020.21	92.90%
technique	84693	2020.14	92.68%
network	75949	2020.00	90.45%
management	81082	2019.59	92.39%
review	75238	2019.99	89.62%
scheme	52820	2020.02	57.50%
technology	61551	2019.12	82.34%
problem	66476	2018.61	88.18%
need	70626	2019.36	92.50%

Table 4. The top 20 terms of cluster 2 concepts identified in the bibliographic portfolio, as determined by VOSviewer.

- Blockchain is utilized for storing encrypted EMRs in a decentralized ledger, allowing patients to manage their personal information via smart contracts. It facilitates transparent auditing of healthcare services, fraud prevention, and remote patient monitoring. However, there are caveats, including incompatibilities with personal data legislation in some countries, challenges in handling large volumes of healthcare data, and substantial implementation costs [19, 20].
- Clinical Decision Support Systems (CDSS) provide diagnostic assistance, optimize medication and treatment planning, offer real-time alerts for critical cases, deliver reminders, implement clinical guidelines, assist with patient triage in emergencies, monitor radiation doses, support nursing decisions, and enable mobile decision support. However, challenges include data incompleteness, physician alert fatigue, ethical concerns regarding accountability for failures, and algorithmic bias [21, 22].

Term	Occurrences	Average publication year	% of 9,522 docs
electronic health record	283813	2020.74	99.68%
ehr	272636	2020.73	99.13%
approach	219923	2019.79	98.92%
information	194449	2018.91	98.52%
performance	159915	2020.47	97.95%
disease	142497	2020.39	96.79%
accuracy	133963	2020.59	96.86%
dataset	119926	2020.94	94.63%
feature	115154	2020.53	94.84%
type	110079	2019.28	95.39%
evaluation	75611	2019.18	93.76%
task	68893	2019.74	82.19%
report	62488	2017.98	83.60%
natural language processing	63107	2020.45	87.13%
nlp	64857	2020.45	78.55%
detection	66445	2020.08	88.10%
term	59561	2019.36	90.84%
classification	56871	2020.22	85.72%
pattern	58168	2019.45	88.00%
rule	57003	2019.47	82.05%

Table 5. The top 20 terms associated with cluster 3 concepts, as identified in the bibliographic portfolio, according to VOSviewer.

Term	Occurrences	Average publication year	% of 9,522 docs
algorithm	515941	2020.26	99.75%
diagnosis	187050	2020.11	98.45%
case	169907	2019.39	97.33%
sensitivity	122838	2019.74	91.89%
database	113237	2018.67	96.18%
code	98379	2019.64	90.05%
specificity	94273	2019.72	89.62%
record	87165	2018.61	94.52%
population	99998	2019.91	92.39%
individual	83463	2020.69	90.41%
validation	72836	2020.31	93.08%
identification	69037	2019.83	92.83%
ppv	65143	2020.13	66.73%
medication	68972	2019.54	87.31%
condition	70634	2019.89	91.20%
icd	63808	2020.16	74.04%
visit	60999	2019.44	81.22%
positive predictive value	51622	2019.32	80.14%
child	46651	2020.31	68.67%
status	48983	2020.08	84.35%

Table 6. The top 20 terms associated with cluster 4 concepts, as identified in the bibliographic portfolio, according to VOSviewer.

- Support Vector Machines (SVMs) are supervised machine learning algorithms that use kernel functions to transform data into higher-dimensional spaces and classify it by calculating a hyperplane that maximizes the distance between each class. They are used in healthcare for similar purposes as ML, including early disease diagnosis, predicting disease progression, assessing prognostic risk, analyzing medical images, and classifying EMRs. However, there are caveats such as computational complexity, inconsistencies due to incomplete data, and preprocessing issues [23].

Term	Occurrences	Average publication year	% of 9,522 docs
use	204323	2018.50	99.17%
analysis	198563	2019.97	98.95%
tool	140252	2019.87	96.61%
care	146570	2019.00	94.27%
rate	103962	2019.67	93.04%
group	112738	2020.03	93.44%
intervention	126424	2019.56	89.37%
implementation	92173	2017.99	90.23%
value	104631	2019.78	94.02%
number	90961	2019.07	96.25%
quality	91097	2018.05	91.31%
clinician	79632	2019.12	89.91%
physician	76493	2017.23	88.39%
strategy	69260	2020.07	92.65%
impact	65232	2019.70	91.06%
month	86680	2019.34	82.05%
effect	70421	2018.68	88.21%
assessment	62990	2019.81	90.92%
measure	62544	2019.14	89.08%
participant	68911	2019.97	86.73%

Table 7. The top 20 terms of cluster 5 concepts identified in the bibliographic portfolio, as determined by VOSviewer.

Term	Occurrences	Average publication year	% of 9,522 docs
association	68833	2019.61	86.66%
control	58103	2019.55	85.47%
phenotype	47378	2020.34	70.19%
site	48934	2018.84	75.96%
bias	29177	2021.16	69.86%
interaction	27063	2018.71	70.33%
range	27918	2019.72	80.28%
variation	23108	2018.91	70.19%
variant	14408	2019.16	43.87%
electronic medical records	9869	2018.43	57.61%
gene	10381	2018.86	40.74%
trajectory	10619	2021.02	44.30%
variability	10346	2020.67	55.12%
biobank	8327	2019.45	37.56%
eye	6636	2020.44	26.32%
gain	6673	2018.27	44.45%
hypothesis	6811	2018.70	47.33%
meta analysis	7277	2021.09	39.62%
estimator	5112	2021.85	27.47%
simulation study	4905	2020.75	30.43%

Table 8. The top 20 terms of cluster 6 concepts identified in the bibliographic portfolio, as determined by VOSviewer.

- Extreme Gradient Boosting (XGBoost) is a machine learning algorithm used in EMR management for early diagnosis, imputation of missing data, predicting individual risk, defining personalized interventions, and managing large, structured datasets. It employs model-agnostic techniques such as permutation importance, which aligns with clinical intuition. However, it has limitations in interpretation, requires data preprocessing, and poses risks related to generalization and handling temporal data [24].
- Computational medical image analysis employs advanced algorithms that utilize deep learning frameworks, integrating convolutional neural networks (CNNs) and transformer architectures. This combination enables multimodal data fusion, along with the precise extraction and interpretation of anatomical, microscopic, and histological features for image segmentation and classification. This process distinguishes between physiological and pathological regions and categorizes images as normal or diseased, thereby aiding in diagnosis, treatment planning, and patient monitoring. These methodologies can enhance image quality and reconstruction by aligning and registering images from various time points or modalities, such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and Positron Emission Tomography (PET), all recorded in electronic medical records (EMRs). CNN-based models also apply to data from Internet of Medical Things (IoMT) devices, including wearable sensors and cellphone photography, to extract features of physiological or pathological signals during real-time health monitoring. The challenges these technologies face include the heterogeneity of imaging formats, population biases, and clinical mistrust, as they frequently function as "black boxes." [25-27]
- Computational data encryption can secure healthcare data, personal information, and other sensitive content. This may involve: Data-at-Rest Encryption, which utilizes symmetric encryption algorithms like the Advanced Encryption Standard (AES) to ensure that EMRs remain confidential, even if storage media are compromised; Data-in-Transit Encryption, which secures the transmission of EMR data between healthcare stakeholders by employing specific secure protocols such as Transport Layer Security (TLS); Access Control Authentication, which encrypts credentials and session data to ensure that only authorized personnel can decrypt and access patient records; Secure Record Sharing, achieved through asymmetric encryption with public and private key cryptography, enabling the secure sharing of medical records between different healthcare entities; Transparent Data Encryption (TDE), which

encrypts entire databases or specific tables containing patient EMRs; and the Encryption of Portable Devices and Files, ensuring that patient data stored on portable devices or shared as PDF files containing prescriptions or bills is encrypted and password-protected to prevent unauthorized access; Audit and Integrity Verification with cryptographic hash functions like MD5 or SHA to verify the integrity of medical records and detect unauthorized modifications, ensuring data accuracy and trustworthiness. The challenges of encryption include managing multiple keys, interoperability issues, potential data loss due to the loss or corruption of encryption keys, and compliance with national legislation regarding data storage [28, 29].

- Recurrent Neural Networks (RNNs) effectively model sequential and temporal data, making them suitable for clinical event prediction, disease progression modeling, multilabel diagnosis, managing irregular and sparse data, and transferring health information across medical institutions. The challenge is to handle rare events, complications, or uncommon adverse effects [30, 31].
- Large Language Models (LLMs) can enable transformative applications in EMR management by leveraging NLP. LLMs accurately identify clinical entities through semantic textual similarity and inference. They improve understanding of clinical reasoning, support decision-making, and automate the summarization of clinical notes, patient histories, and EMRs. The main challenges include hallucinations and inaccuracies, bias and fairness issues, the interpretability of outputs, and ethical considerations [32, 33].
- Generative artificial intelligence (GenAI) automates clinical documentation, extracts information, and summarizes data while providing clinical decision support. It actively engages patients by offering educational materials and simplifying explanations of clinical conditions and therapies, thereby enhancing compliance and communication with healthcare providers. However, challenges and caveats include data privacy and security risks, potential inaccuracies, incorrect or fabricated information, biases, and computational and resource demands [34, 35].

Disruptive computational technologies collectively provide automation, enhance efficiency, enable high-throughput analysis, facilitate early detection and diagnosis, ensure administrative and audit control of healthcare services, enable patients to manage their personal data, gather health information, and promote rapid communication.

V. Discussion

Since the mid-1980s, the global implementation of computer-based management of Electronic Medical Records (EMRs) has facilitated unprecedented statistical and analytical processing of medical data to produce health information. The term "medical data" encompasses a wide range of qualitative entities, whether on a nominal or ordinal scale, as well as quantitative ones.

Unstructured medical data typically includes narrative descriptions and notes in text form, along with images, audio, or video files, entered directly into EMRs by clinicians, nurses, pharmacists, or bioscientists. Although it is stored in digital databases, it still constitutes blob data. Aside from the inherent complexity of biomedical data, the subjective descriptions of clinical examinations, symptoms, interviews, self-assessments, diagnoses, biopathological or histopathological findings, adverse events, and medical certificates, as well as the introduction of raw audiovisual content, pose significant challenges for systematic analysis.

In contrast to the freedom of expression and the description of unstructured medical data, modern electronic medical record (EMR) management systems provide a stricter framework for entries through predefined selection menus and options. Structured or discrete medical data attains specific values and acquires distinct meaning. The various database fields can be filled through standardized entry selections based on a controlled vocabulary of medical terminology, medical instruments, and measurement systems, utilizing numeric or alphanumeric fields organized into a data entry form that feeds into the EMR database. Dropdown menus assist users in entering structured data related to clinical diagnoses, procedures, medications, and tests across various registration fields. Typically, these systems restrict off-list data entry. If a healthcare stakeholder wishes to include something, such as a medication that is not on the existing list, the inclusion request must be submitted to the administrative authorities of the medical information system. Users of structured medical data systems gain access to:

- Planning medical services
- Organization and routing of clinical procedures
- Continuous access to data
- Document storage and retrieval
- Creation of patient guidelines
- Patient health records
- Management of clinical and laboratory tests
- Issuance of patient certificates and consent forms
- Information on adverse drug reactions
- Patient demographics
- Patient's medical history
- Medical prescriptions
- Guidelines for treating a disease
- Secure communication with medical service providers
- Insurance coverage verification
- Allergy lists
- Data archiving and destruction

- Data retention
- Drug interactions
- Guidelines and protocols
- Vaccination and immunization records
- Help with medical coding
- Standard medical care plans
- Medication lists
- Financial management and fees
- Communication with pharmacies
- Problem log lists
- Generate reports
- Exam referrals
- Good health and prevention criteria.

Structured medical data creates a highly functional computing environment that supports specialized analyses, interoperability, and compatibility with other systems while enhancing security and safety, as patient data is entered into a secure information environment accessible only to authorized users. Furthermore, because the EMR system design adheres to the principles of a knowledge information system, it aids in processing and interpreting collected data for decision-making, action design, and drawing conclusions.

EMR databases encompass repositories of health records, prescriptions, diagnostic tests, case and event reports, descriptions of clinical procedures, hospitalization data, disease certificates, vaccination certificates, scientific experiments, scientific publications, scientific papers, DNA sequencing results, RNA, proteins, structures, vertebrate genomic bases, metabolic and biochemical pathways, human and vertebrate genomes, human genes and diseases, microarrays and gene expression, proteomics, molecular biology, cell organelles, immunology, cell biology, anatomy, physiology, pathology resources, pharmacology, and clinical and pharmacological trials [36]. For many years, efforts have been made to address data heterogeneity and complexity in EMR databases by applying specific vocabulary rules in information exchange and communication. The interpretation of genetic associations, medical imaging, and the integration of medical device data recordings contribute to medical algorithms and professional assessments. However, to date, machine learning and artificial intelligence systems provide methodologies to apply predefined rules in pre-training, enabling advanced computing to curate or extract conclusions from medical data. Health information can be generated in a high-throughput manner by systematically processing medical data under the evaluation of a computer system.

This review centers on international literary perspectives, ideas, and practical applications of disruptive computer technologies in everyday medicine, with a specific emphasis on analyzing EMRs when necessary.

We found that most research papers on this topic are clinical or translational reports focusing on applying existing medical algorithms or developing new analytical ones for various pathologies affecting both sexes, particularly emphasizing middle-aged and elderly populations. Many of these papers utilize retrospective data from hospital EMRs or publicly available biomedical datasets to train machine learning systems, which are then used to analyze real-world clinical data in primary healthcare settings. These systems facilitate risk assessment, provide reproducible and accurate diagnosis, prognosis, and decision support for interventions aimed at preventing adverse effects, as well as tracking epidemiological trends.

All the applied methodologies agree on analyzing trends in computing technological advancements for medical record management over the past thirty years. iCite demonstrates the impact of these technologies in translational research, connecting the laboratory bench to the patient's bedside. Scopus keyword analysis and Web of Science MeSH and concept analyses, along with the VOSviewer map of keywords extracted from paper titles and abstracts, collectively highlight the significance of disruptive computing applications in pharmacology, cardiology, geriatrics, public health, and infectious diseases—where COVID-19 represents the top and most critical global health risk—oncology, and immunology, often in combination when immunological cell therapy is applied against tumors, as well as in neurosciences, pediatrics, pulmonology, genetics, general pathology, endocrinology, gastroenterology, hematology, surgery, urology, critical care medicine, obstetrics and gynecology, rheumatology, and ophthalmology. These applications can be utilized on-site at the premises of a hospital clinic, healthcare services center, or a doctor’s office, during patient administration, emergency or scheduled visits, or remotely through telemedicine or wearable medical device monitoring.

When considering the publication year of the studied papers, we can observe the timeframe of the innovations implemented or the concerns related to them. Informatics topics, such as the use of Extensible Markup Language (XML) in health information systems and electronic medical records, along with picture archiving and communication systems (PACS), the OpenMRS medical record system as open-source software for EMR management, and the application of Health Level Seven (HL7) medical standards in the exchange, integration, sharing, and retrieval of electronic health information, have been reported in papers published on average before 2013. Subsequently, schemes for semantic interoperability, Global Positioning System (GPS) integration, various EMR systems and their uses in adverse drug events (ADEs), as well as compliance with the Health Insurance Portability and Accountability Act to protect sensitive health information from disclosure without patient consent, which was introduced as a federal standard in 1996, were reported in papers with an average publication year of 2015. Topics such as Informatics for Integrating Biology and the Bedside (i2b2) and eHealth, as a generic description of EMRs, electronic prescribing, telehealth, decision support, single nucleotide polymorphisms (SNPs) for genetic association studies, the application of SNOMED Clinical Terms standards, and the Telecare Medical

Information System (TMIS) in health monitoring and medical services over internet or mobile networks at any place and any time, Structured Query Language (SQL) for retrieving stored data and extracting information from Relational Database Management Systems (RDBMS), automatic algorithm implementation, and Phenome-Wide Association Studies (PheWAS), as an inverted Genome-Wide Association Study (GWAS), are discussed in papers with an average publication year of 2018. Machine learning approaches, medical Big Data, Randomized Control Trials (RCTs), classification systems for Potentially Preventable Emergency Department Visits (PPVs) as innovative patient clinical management to avoid complications in outpatient and ambulatory settings, early warning systems, Fast Healthcare Interoperability Resources (FHIR)-based electronic health records, propensity score matching for comparative studies, regression analysis and models, positive and negative predictive values (PPV and NPV, respectively), crucial tools for diagnostic accuracy, patient demographics, elliptic curve cryptography in EMRs, computable phenotype algorithms, Convolutional Neural Networks (CNN) using deep learning approaches in healthcare systems, and Natural Language Processing (NLP) tools in clinical practice are found in papers published on average in 2020. Discussions in papers published on average in 2022 include Artificial Intelligence algorithms (AI algorithms), Artificial Neural Networks (ANN), Support Vector Machines (SVM), applications of the area under the receiver operating characteristic curve (AUC-ROC) to assess AI model performance, F1-score evaluation of machine learning, applications of the Medical Information Mart for Intensive Care (MIMIC-III) critical care database in AI systems, nomograms, precision-recall (PR) curves for simulation prediction models, Extreme Gradient Boosting (XGBoost) models, NLP models, the Internet of Medical Things and Healthcare (IoMT), Protected Health Information (PHI), and clinical concept extraction using transformers such as BERT, RoBERTa, BERTTweet, TwitterBERT, BioClinical_Bert, BioBert, ALBERT, and ELECTRA, along with pretraining strategies like domain-adaptive pretraining (DAPT), source-adaptive pretraining (SAPT), or topic-specific pretraining (TSPT). Finally, papers issued on average in 2024 discuss Large Language Models (LLMs), SHapley Additive exPlanations (SHAP) analysis integrated into machine learning models to address the challenges of black-box predictions or classifications, Generative Pre-trained Transformers (GPT), and ChatGPT.

This study was conducted using three bibliographic and bibliometric databases: NCBI PubMed, Elsevier Scopus, and Clarivate Web of Science. Gray literature or preprints were not included, which represents a limitation. In computer science, preprint server repositories, such as Cornell University arXiv (arxiv.org), are often used to present machine learning or artificial intelligence models, methodologies, and applications. Nonetheless, when these systems interrogate applied clinical data, the results are published in biomedical journals. Therefore, it is expected that the record of published scientific publications aligns well with trends in computational applications for EMR management.

VI. Conclusions

The introduction of innovative computational technologies and automated analytical frameworks in biomedical research and routine clinical practice marks a transformative breakthrough in EMR management. This text summarizes these technologies and their applications, along with their implementation timelines. Machine Learning (ML), Natural Language Processing (NLP), blockchain, Clinical Decision Support Systems (CDSS), Support Vector Machines (SVMs), computational data encryption, Large Language Models (LLMs), and Generative Artificial Intelligence (GenAI) systems are examined in the context of EMR management. These disruptive computational technologies, both individually and collectively, enhance the extraction of health information from medical data and the generation of new biomedical knowledge.

VII. References

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