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Convergence with Global Trends in the Knowledge Structure and Leading Subfields of Personalized Medicine Research in Iran

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ABSTRACT

Background: Driven by artificial intelligence (AI) and genomics, personalized medicine (PM) is rapidly expanding. Mapping its conceptual structure through co-word analysis identifies research trends, thematic gaps, and priorities. This study mapped the conceptual structure and thematic evolution of PM in Iran from 2005 to 2025 using Web of Science (WoS) data.

Methods: Keyword co-occurrence and network analysis were performed on 623 WoS-indexed documents. Cluster analysis in VOSviewer and strategic diagrams in Excel identified thematic sub-domains and their relationships.

Results: Cluster analysis revealed nine distinct thematic clusters: (1) AI and machine learning in medical imaging and diagnosis; (2) gene editing, omics technologies, and the microbiome's role in treatment; (3) personalized medicine and pharmacogenomics; (4) biomarkers and liquid biopsy in cancer diagnosis; (5) nanomedicine, biosensors, and targeted cancer therapy; (6) tissue engineering, regenerative medicine, and novel drug delivery systems; (7) early detection and management of chronic, inflammatory, and metabolic diseases; (8) nanoparticles, epigenetics, and integrative medicine approaches, including traditional medicine and digital health; and (9) cancer immunotherapy and tumor microenvironment analysis.

Conclusion: Personalized medicine in Iran has a dynamic, interdisciplinary, and evolving structure. Pharmacogenomics serves as the key infrastructure and driving engine, supporting the driving triangle of biomarkers and liquid biopsy, AI in medical imaging, and regenerative medicine with novel drug delivery. Cancer immunotherapy is a specialized, mature domain, while gene editing (CRISPR), nanomedicine, and the microbiome shape future frontiers. Clinical translation requires accelerating mature technologies, establishing national genomic databases, and strengthening interdisciplinary synergies to achieve precise, patient-centered, preventive treatments.

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INTRODUCTION

Personalized medicine (PM), first described conceptually in 1999, is a novel and revolutionary approach to healthcare aimed at fine-tuning diagnosis, prognosis, and treatment for each patient individually (1). This field represents a fundamental paradigm shift from the traditional one-size-fits-all model to a targeted healthcare approach, incorporating periodic, individualized, participatory, and predictive measures based on individuals' unique genetic, environmental, and lifestyle characteristics (2, 3). Nowadays, personalized medicine is expanding into most areas of

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clinical management, becoming a crucial standard for the adoption of new interventions; an approach that has generated high hopes for enhancing patients' quality of life, improving treatment effectiveness, reducing adverse effects, and optimizing costs and time in healthcare delivery (1, 2).

In the scientific literature and knowledge structure of this field, the terms personalized medicine and precision medicine are often used interchangeably, and considering both concepts is essential for a comprehensive elucidation of this new scientific direction (4, 2). Although personalized medicine initially emerged from pharmacogenetic and pharmacogenomic knowledge, a tangible shift towards the use of the term precision medicine gradually occurred (4). By employing specialized terms such as phenotype, endotype, and biomarker, precision medicine seeks to describe diseases more precisely and divide a heterogeneous disease into more homogeneous subgroups, thereby facilitating the provision of specific and targeted treatments (5). Therefore, in exploring the knowledge structure of this domain, both terms, personalized medicine and precision medicine, constitute complementary dimensions of a single paradigm in healthcare.

Rapid advancements in fourth industrial revolution technologies, such as big data, artificial intelligence (AI), machine learning (ML), deep learning (DL), and radiomics, have been the primary drivers of the ever-increasing growth and structural evolution of personalized medicine (6, 7). The integration of advanced computational methods, genomic analysis, and multi-omics data integration has created a profound transformation in clinical decision support systems, diagnostic imaging, and drug discovery (8, 9). The scope of application for this approach is expanding rapidly; so much so that, beyond the dominance of oncology-related topics and decision-making for individualized cancer treatments (10, 3), it has extended into emerging fields such as personalized regenerative medicine and cell therapy utilizing various stem cell sources, including induced pluripotent stem cells (iPSCs) (4), and even prevention and therapy in fetal medicine via prenatal organoids (1).

A review and analysis of global bibliometric literature indicates extraordinary dynamism and exponential growth in research outputs within this field over the past two decades (8, 3). Williams et al. reported an exponential growth of publications in this domain, primarily focusing on genetics and specific treatments. This upward trend has accelerated unprecedentedly in recent years (3); Virk et al. also confirmed the growth of research publications in this field (10). Furthermore, Adam et al. noted a 34.3 % increase in publications in this field solely in the year 2024 (8). In studies focusing on AI and ML in personalized medicine, Al-Dekah demonstrated a staggering annual growth rate of 42.1 % (6). In more specialized areas such as early breast cancer diagnosis, Pedük confirmed a clear acceleration in research post-2020, along with increased international collaboration and a proliferation of open-access publications (8).

Understanding the intellectual structure, identifying core topics, and tracking the evolution of keywords constitute a significant part of scientometric and semantic analyses in this context (8, 11). To accomplish this mapping of knowledge structures, a review of the literature demonstrates that co-word analysis and network analysis have been utilized as effective tools across various fields of science, including information literacy (12), financial literacy (13), digital literacy (14), Throbbing Headaches (15), general concepts of literacy and decision-making (16, 17), and neuroscience (18) to map knowledge structures. Applying these same proven methodologies to the medical domain, through a 10-year analysis of Web of Science (WoS) data (2009 to 2018) using co-word analysis, Lyu et al. demonstrated that the intellectual structure of precision medicine encompasses broad themes that are overall unbalanced. They identified recurring core keywords, including biomarkers, genomics, cancer, therapy, genetics, drug, targeted therapy, pharmacogenomics, pharmacogenetics, and molecular as the core areas and main body of knowledge (19). In this regard, Adam et al. revealed three main clusters: diagnostics and medical imaging, genomic and multi-omics data integration, and personalized treatment strategies (8). Additionally, Khakimova et al. showed that citing articles expand the key terms of the cited articles, creating a stable terminological map for identifying knowledge development trends (11). However, Williams et al. highlighted a significant thematic gap, demonstrating that despite the dominance of genetic and oncological research, little attention has been paid to social and environmental determinants of health and health disparities (3).

As the review of the research background indicates, international research in the fields of personalized and precision medicine is rapidly moving towards maturity, the integration of AI technologies, and comprehensive biological analyses (6, 9, 19). Nevertheless, despite the comprehensive mapping of global scientometric landscapes (7, 10, 11), assessing the engagement, orientation, and extent of participation of Iranian researchers with this knowledge wave requires further investigation. Analyzing Iranian indexed publications in the Web of Science (WoS) database can determine whether domestic research has evolved in alignment with international hotspots such as deep learning, biomarkers, and multi-omics data or suffers from imbalances and knowledge gaps. The insights derived from this structural evaluation provide an evidence-

based knowledge framework to guide policy decisions, optimize the allocation of research budgets, and prioritize interdisciplinary collaborations toward the practical implementation of personalized medicine in the country (8, 19). Therefore, the present study aims to analyze the conceptual structure, identify core and emerging areas, and map the thematic evolution of Iranian research in the field of personalized medicine indexed in the WoS database from 2005 to 2025.

METHODOLOGY

Study Design and Data Retrieval Strategy

This study adopted a bibliometric, co-occurrence, and network analysis design to investigate the scientific landscape of personalized medicine. Data retrieval was conducted on August 25, 2026, using the advanced search section of the Web of Science (WoS) database. The search strategy incorporated the following query:

TS=("Personalized medicine" OR "Precision medicine" OR "Personalized healthcare" OR "Personalized Treatment") AND CU=(Iran) AND PY=(2005-2025)

The document types were limited to original research articles, review articles, proceeding papers, and early access publications. A total of 1,970 documents met these predefined inclusion criteria and were retrieved for analysis. Following data retrieval, the bibliographic records were exported in Excel format, and the required fields were extracted with full records and cited references in plain text format for subsequent data preprocessing.

Data Preprocessing and Concept Standardization

Data processing and concept extraction were executed using BibExcel software. Natural language processing (NLP) techniques within the software were applied to extract core concepts based on author keywords, yielding an initial pool of 9,969 concepts. To ensure data integrity, standardization and unification of concepts were performed, leaving 5,395 unique concepts. To construct a representative co-occurrence matrix that captures the overall schema of the field's main concepts, a cut-off threshold of 5 was selected. This threshold was established using Bradford's one-third law (20). Applying Bradford's law to determine the cut-off point in the keyword co-occurrence matrix serves as a systematic, evidence-based method for screening massive textual data; it identifies and retains core keywords shaping the knowledge structure while filtering out low-frequency, peripheral keywords that obscure map interpretation. Following a series of software commands, a symmetric co-occurrence matrix in plain text format with dimensions of 229 × 229 was created, with the diagonal cell values set to zero.

Network Visualization and Cluster Analysis

The co-occurrence matrix was converted into a similarity matrix utilizing the association strength index and subsequently imported into VOSviewer software. Within VOSviewer, the data were transformed into a correlation matrix to measure the association strength between the retained concepts matching the threshold, providing a measure of concept similarity based on relative co-occurrence frequencies (21, 22). The software's default Louvain clustering algorithm, utilizing the standard Newman-Girvan modularity criterion along with the Visualization of Similarities (VOS) algorithm, was employed for network mapping and clustering.

To map the conceptual structure, a strategic diagram was drawn using the centrality and density scores of the extracted thematic clusters based on the framework of Callon et al (23). This standard framework defines the role of each thematic cluster across four strategic quadrants using centrality and density, enabling the identification of current thematic statuses and potential evolutionary paths. The strategic diagram describes internal relationships and correlations between different clusters, aligning with the approach introduced by Mellers et al. to enhance the visualization of maturity and cohesion within a research field (24).

RESULTS

Publication output trend

Figure 1 displays the publication output trend in the Personalized medicine domain within the Web of Science (WoS) database.

Figure 1 illustrates the trend of scientific document publication in the personalized medicine domain in the Web of Science database between 2005 and 2025. According to this diagram, the scientific output of this field, which underwent a slow process with a very low production volume in the first decade (2005–2014), gradually increased from 2015 and entered an exponential growth phase from 2021. The highest scientific output belongs to the years 2024 and 2025, indicating that personalized medicine has become one of the priorities and highly engaged research fields in the global health arena in recent years.

Frequency distribution of personalized medicine concepts based on keyword co-occurrence

The frequency distribution of the most used concepts in the studied period is shown in table 1.

Table 1 shows the frequency distribution of the most used concepts in the personalized medicine domain during the studied period and reveals the knowledge structure pattern of this realm. The concept of Personalized medicine, with a frequency of (373), has been the focus of research and has the highest repetition. In the subsequent ranks, the dominance of advanced computational technologies is evident;

Fig 1. Publication of personalized medicine between 2005 and 2025.

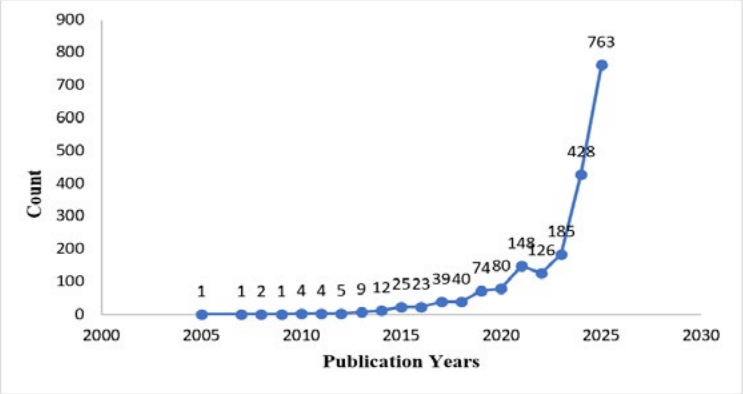


Table 1. Most used concepts in the personalized medicine domain by frequency.

NO.	Concept	Frequency	NO.	Concept	Frequency
1	Personalized medicine	373	11	Colorectal cancer	**45**
2	Artificial intelligence (AI)	125	12	Diagnosis	**43**
3	Machine learning (ML)	124	13	Pharmacogenomics	**40**
4	Biomarker	102	14	Nanoparticle	**37**
5	Cancer	100	15	Regenerative medicine	**34**
6	Drug delivery	72	16	Cancer therapy	**34**
7	Breast cancer	62	17	Tissue engineering	**33**
8	MicroRNA	62	18	Biosensor	**33**
9	Immunotherapy	61	19	3D printing	**33**
10	Deep learning	59	20	Targeted therapy	**32**

such that the concepts of Artificial intelligence (125), Machine learning (124), and Deep learning (59) collectively account for a major portion of knowledge production, indicating a transition in this field towards data-driven and automated analyses. Simultaneously, the biological-molecular foundation of this approach is strengthened by concepts such as Biomarker with a frequency of (102), MicroRNA with (62), and Pharmacogenomics with (40). From a clinical application perspective, the frequency pattern clearly highlights the dominance of neoplastic diseases; general and specific cancer concepts including Cancer (100), Breast cancer (62), and Colorectal cancer (45), alongside novel therapeutic approaches such as Immunotherapy (61), Targeted therapy (32), and Cancer therapy (34), all indicate the clinical focus of this field on precision oncology. In addition, the notable frequency of intertwined concepts of technology and treatment, such as Drug delivery (72), Nanoparticle (37), Regenerative medicine (34), Tissue engineering (33), 3D printing (33), and Biosensor (33), indicate the accelerated integration of engineering approaches and smart drug delivery with personalized medicine. Overall, this frequency distribution presents a cohesive picture of a field whose driving engine is artificial intelligence and biomarkers, and whose dominant applied context is the targeted diagnosis and treatment of cancer.

Knowledge topography: Nine conceptual clusters in the personalized medicine domain

To determine the number of clusters, the clustering analysis section of the VOSviewer software was used, the images of which are displayed in Figure 2 and Table 2. As shown in this image, the concepts of the personalized medicine domain in the studied time frame fall into nine clusters.

The results from Figure 2. The keyword co-occurrence map shows that the concepts in the personalized medicine domain are grouped into nine clusters.

Concept Trends in Iranian health policy research based on overlay visualization. Figure 3 presents the overlay visualization map showing concept evolution

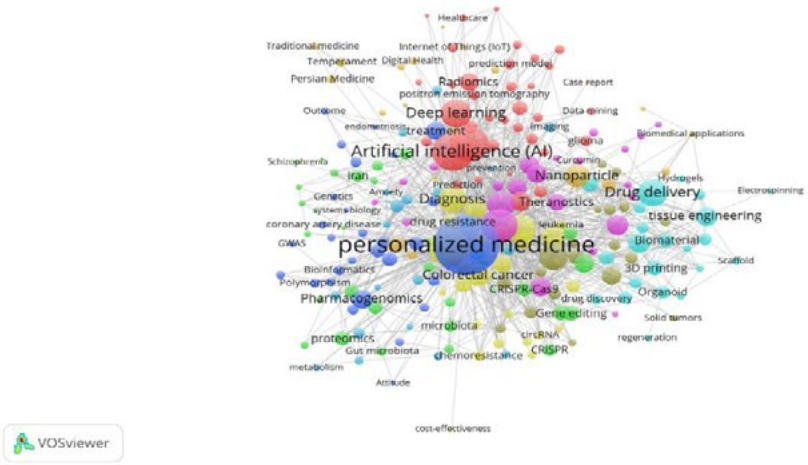


Fig 2. Co-word map of documents in the personalized medicine domain..

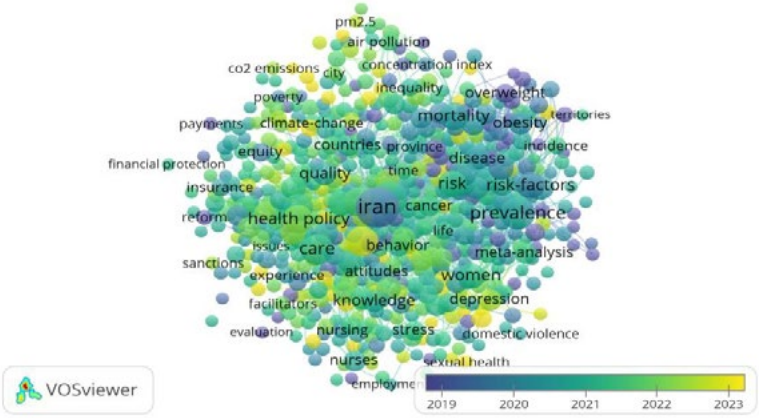


Fig 3. Co-word map of health policy literature based on overlay visualization.

over time. Overlay visualization is used to illustrate temporal developments in the field.

As shown in this map, nodes shifting toward yellow represent recent research trends (radiomics, liquid biopsy, extracellular vesicles, artificial intelligence, hydrogels, biomedical applications, infertility, nanomaterials, etc.). Conversely, concepts prominent in earlier decades appear in darker shades.

Table 2 displays the names of the clusters and their important sub-branches, along with the weight of each sub-branch.

Table 2 displays the nine main clusters and key sub-branches of the personalized medicine domain along with the weight of each concept, indicating the breadth and interconnectedness of this field. The main axis of this table is Cluster (3), i.e., Personalized medicine and Pharmacogenomics, which, with a weight of (1380) for the concept of Personalized medicine, emphasizes the importance of individualized treatments and the role of genetics in them. In the context of novel diagnostic technologies, Cluster (1) Artificial intelligence and machine learning in medical imaging and Cluster (4) Biomarkers and liquid biopsy in cancer diagnosis hold prominent positions. The molecular and cellular approach is also evident in Clusters (2) Gene editing, omics technologies, and the role of microbiome in treatment, and Cluster (8) Nanoparticles, epigenetics, and integrative medicine approaches. Furthermore, cancer treatment has been addressed from various angles, including through Nanomedicine, biosensors, and targeted cancer therapy (Cluster 5) and Cancer immunotherapy and tumor microenvironment analysis (Cluster 9). In the section on engineering and drug delivery technologies, the cluster Tissue engineering, regenerative medicine, and novel drug delivery systems (Cluster 6) is located. Finally, the cluster Early detection and management of chronic, inflammatory, and metabolic diseases (Cluster 7) complements this perspective. Overall, this table shows that personalized medicine is a profound intersection of artificial intelligence, nanotechnology, and genetics with clinical applications in the targeted diagnosis and treatment of diseases, especially cancer.

Strategic position of research clusters

After forming the matrix for each of the clusters and importing it into the UCINET software, the centrality

Table 2. Names of clusters and sub-branches of the personalized medicine domain.

No.	Cluster name	Main concepts & Concept weight
1	Artificial intelligence and machine learning in medical imaging and diagnosis	Artificial intelligence (AI) (562), Machine learning (ML) (502), Deep learning (304), Glioblastoma multiforme (GBM) (148), Radiomics (130), Magnetic resonance imaging (MRI) (78), Multiple sclerosis (MS) (66), Systematic review (64), Chemotherapy (56), Ovarian cancer (54), Brain cancer (48), Glioma (48), Positron emission tomography (44), Prediction model (44), Molecular imaging (40), Neural networks (40), Alzheimer's disease (38), Prediction (38), Internet of Things (IoT) (36), Convolutional neural network (CNN) (34), Survival (32), Classification (30), Parkinson's disease (30), Vaccine (30), Oral cancer (28), Overall survival (28), Radiotherapy (26), Data mining (24), Diagnostic imaging (24), Healthcare (22), Prostate cancer (20), Recurrence (20), Nuclear medicine (14), Adverse events (12), Artificial neural network (ANN) (12), Medical education (8),
2	Gene editing, omics technologies, and the role of microbiome in treatment	Cancer therapy (128), Gene editing (94), Gene Therapy (94), Proteomics (82), CRISPR-Cas9 (76), Metabolomics (72), Genomics (66), Clinical translation (64), CRISPR (60), Iran (60), Meta-analysis (54), Microbiota (54), Early diagnosis (44), Microbiome (38), Probiotics (38), Dysbiosis (34), Gut microbiota (34), Neurological disorders (26), Bipolar disorder (24), Neurodegenerative diseases (24), Transcriptomics (24), Heart failure (20), Attention-deficit/hyperactivity disorder (ADHD) (18), Metabolic syndrome (18), Sex differences (18), Neuroimaging (14), Stem cell therapy (12), Autism (8), Schizophrenia (8), Decision Making (6), Risk factors (6),
3	Personalized medicine and pharmacogenomics	Personalized medicine (1380), Pharmacogenomics (142), Treatment (130), Covid-19 (78), Next generation sequencing (NGS) (74), Diabetes mellitus (70), Single nucleotide polymorphism (60), Oncology (50), Epilepsy (40), Oxidative stress (40), Sars-cov-2 (40), Bioinformatics (36), Polymorphism (36), Drug repurposing (32), Genetic (32), Genetic variation (30), Coronary artery disease (28), Gene (28), Seizure (28), Variant (28), Exome sequencing (26), Gene expression (26), Outcome (22), Genetics (20), Gwas (18), Infertility (18), Endometriosis (12), Systems biology (12), Attitude (8),
4	Biomarkers and liquid biopsy in cancer diagnosis	Biomarker (548), MicroRNA (288), Diagnosis (262), Colorectal cancer (200), Exosome (170), Prognosis (152), Long non-coding RNAS (LNCRNAS) (122), Gastric cancer (102), Non-coding RNAS (98), Liquid biopsy (88), Extracellular vesicles (EVS) (84), Drug resistance (76), Circulating tumor cells (CTCS) (72), Hematologic malignancies (68), Chemoresistance (50), Leukemia (44), Pancreatic cancer (42), Therapeutic targets (34), Circrna (30), Multi-omics (30), Combination therapy (28), Acute myeloid leukemia (24), Diagnostic (22), Signaling pathways (20), Cost-effectiveness (8),
5	Nanomedicine, biosensors, and targeted cancer therapy	Cancer (422), Breast cancer (252), Nanomedicine (152), Targeted therapy (142), Biosensor (138), Non-small cell lung cancer (128), Nanotechnology (118), Theranostics (106), Cancer diagnosis (40), Point-of-care (30), Cancer immunotherapy (28), Detection (28), Tumor (28), Curcumin (24), Nanobiosensors (24), Cancer biomarkers (20), Doxorubicin (20), Nanomaterials (20), Nanosensors (20), Photothermal therapy (20), Biosensing (16), Photodynamic therapy (16), Melanoma (14),
6	Tissue engineering, regenerative medicine, and novel drug delivery systems	Drug delivery (288), Regenerative medicine (154), Tissue engineering (148), Microfluidics (92), 3D printing (84), Biomaterial (78), Stem cell (74), Organoid (68), 3D bioprinting (60), Cell therapy (58), Mesenchymal stem cells (52), Gene delivery (48), Organ-on-a-chip (46), Drug discovery (42), Chitosan (38), Bone tissue engineering (24), Drug screening (24), Hydrogels (24), Scaffold (24), Biocompatibility (22), Regeneration (18), Electrospinning (10),
7	Early detection and management of chronic, inflammatory, and metabolic diseases	Inflammation (70), Cardiovascular disease (66), Autoimmune disease (56), Early detection (54), Obesity (50), Clinical trials (48), Depression (44), Imaging (40), Inflammatory bowel disease (40), Type 2 diabetes (38), Natural language processing (32), Bariatric surgery (28), Mental health (28), Neoplasms (28), Therapeutics (28), Bibliometric analysis (24), Anxiety (22), Rheumatoid arthritis (22), Metabolism (20), Prevention (18), Psoriasis (18), Chronic obstructive pulmonary disease (16),
8	Nanoparticles, epigenetics, and integrative medicine approaches (traditional medicine and digital health)	Nanoparticle (204), Epigenetics (102), Targeted drug delivery (70), DNA methylation (36), Temperament (34), Controlled drug release (30), Persian Medicine (30), Digital Health (26), Surgery (24), Traditional medicine (22), Medicine (20), Qualitative research (18), Asthma (16), Biomedical applications (16), Assisted reproductive technologies (ART) (14), Male infertility (12), Stroke (12), Wound healing (12), Mhealth (8), Case report (6), Rehabilitation (6),
9	Cancer immunotherapy and tumor microenvironment analysis	Immunotherapy (274), Tumor microenvironment (124), Cancer treatment (86), Apoptosis (64), Angiogenesis (58), Immune checkpoint inhibitors (52), Metastasis (52), Triple-negative breast cancer (50), Single-cell sequencing (48), CAR-T cell (42), Therapy (42), Hepatocellular carcinoma (38), Autophagy (36), PD-L1 (34), Cancer vaccine (32), Nanocarriers (28), Tumorigenesis (26), Monoclonal antibodies (22), Solid tumors (20),

and density scores of the clusters were determined, and the strategic diagram was plotted. It should be noted that the origin of the diagram was set at 12.7 and 0.520 based on the average centrality and density of the clusters, respectively. The density and centrality scores of the clusters are shown in Table 3.

Cluster 4 has the highest centrality with a value of 23.36 and the highest density with a value of 0.973. This means that there is a strong relationship within the co-occurrence network of concepts in this cluster,

and also, the highest centrality in terms of influence, connection with other topics, and linkage exists in Cluster 4.

As seen in Diagram 1, the strategic diagram is divided into four parts, each forming a quadrant of the diagram. Clusters located in the first quadrant are cohesive and central to the researched field. These main clusters focus on a large part of the network. Clusters in the second quadrant are still cohesive but have lost centrality, each representing smaller, specialized parts of the researched field. In the third quadrant, clusters dissipate; the clusters in this quadrant are the emerging or declining parts of the network, and finally, the fourth quadrant contains clusters that have not yet matured but have the potential to become main parts (24, 25).

According to the strategic diagram, in the first quadrant, the clusters Artificial Intelligence and Machine Learning in Medical Imaging and Diagnosis (1), Biomarkers and Liquid Biopsy in Cancer Diagnosis (4), and Tissue Engineering, Regenerative Medicine, and Novel Drug Delivery Systems (6) are the main thematic clusters of this field. These clusters are cohesive, central to the researched field, and focus on a large part of the network.

The cluster Cancer Immunotherapy and Tumor Microenvironment Analysis (9) is located in the second quadrant of the strategic diagram. The clusters Gene Editing, Omics Technologies, and the Role of Microbiome in Treatment (2), Nanomedicine, Biosensors, and Targeted Cancer Therapy (5), Early Detection and Management of Chronic, Inflammatory, and Metabolic Diseases (7), and Nanoparticles, Epigenetics, and Integrative Medicine Approaches (Traditional Medicine and Digital Health) (8) are the emerging or declining parts of the network. The fourth quadrant displays clusters that have not yet matured but have the potential to become main parts; in this study, the cluster Personalized Medicine and Pharmacogenomics (3) is placed in this section.

DISCUSSION

Based on the data in Table 3 and the strategic

Table 3. Density and centrality of clusters resulting from the co-word analysis of the personalized medicine domain.

No.	Cluster name	Density	Centrality
1	Artificial Intelligence and Machine Learning in Medical Imaging and Diagnosis	21.56	0.602
2	Gene Editing, Omics Technologies, and the Role of Microbiome in Treatment	7.806	0.26
3	Personalized Medicine and Pharmacogenomics	13.793	0.493
4	Biomarkers and Liquid Biopsy in Cancer Diagnosis	23.36	0.973
5	Nanomedicine, Biosensors, and Targeted Cancer Therapy	10.957	0.498
6	Tissue Engineering, Regenerative Medicine, and Novel Drug Delivery Systems	18.636	0.887
7	Early Detection and Management of Chronic, Inflammatory, and Metabolic Diseases	4.909	0.234
8	Nanoparticles, Epigenetics, and Integrative Medicine Approaches (Traditional Medicine and Digital Health)	4.381	0.219
9	Cancer Immunotherapy and Tumor Microenvironment Analysis	9.368	0.52

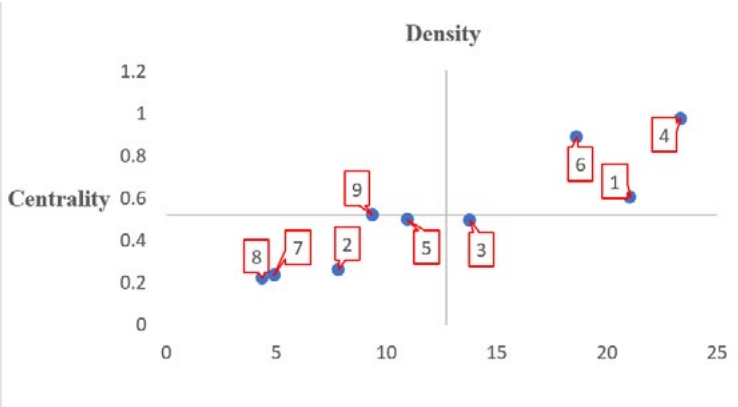


Diagram 1. Strategic diagram of the personalized medicine domain.

diagram, the analysis and discussion regarding the four quadrants are presented as follows:

The analysis of the strategic diagram shows that the first quadrant hosts three pivotal clusters: Artificial Intelligence and Machine Learning in Medical Imaging and Diagnosis (1), Biomarkers and Liquid Biopsy in Cancer Diagnosis (4), and Tissue Engineering, Regenerative Medicine, and Novel Drug Delivery Systems (6). The placement of these clusters in the first quadrant means that their density and centrality scores are above average, and as a result, these three domains are recognized as the cohesive, developed, and primary linking core in the co-word network of personalized medicine. Among these, Cluster 4, with the highest centrality and high density, is the most pivotal and cohesive research core of the entire field. The high weight of concepts such as Biomarker (548), MicroRNA (288), and Liquid biopsy (88) indicates that minimally invasive and molecular diagnostic methods, especially in colorectal and gastric cancers, form the main foundation of personalized medicine knowledge and have established the highest connection rate with other concepts in the network. On the other hand, Cluster 1, with a centrality of (21.056) and a density of (0.602), plays the computational and algorithmic arm role of this field. The prominent presence of concepts such as artificial intelligence, machine learning, deep learning, and Radiomics in this cluster is evidence that intelligent processing of imaging data (such as MRI and PET) in the diagnosis of intractable diseases has become a mainstream, mature, and structured stream in research. Finally, Cluster 6, with a density of 0.887 and a centrality of 18.636, completes the therapeutic and applied aspect of this quadrant. Concepts such as Drug delivery, Regenerative medicine, Tissue engineering, and emerging technologies like 3D bioprinting and Organ-on-a-chip demonstrate that therapeutic approaches based on personalized biological structures have achieved high theoretical and practical cohesion. In other words, the main foundations and drivers of personalized medicine rest on the triangle of advanced molecular diagnosis (Cluster 4), intelligent analysis of imaging data (Cluster 1), and targeted therapeutic design and tissue regeneration (Cluster 6), and these three domains constitute the mainstream drivers of knowledge in this arena.

The second quadrant only hosts Cluster 9, titled (Cancer Immunotherapy and Tumor Microenvironment Analysis). Its placement in this quadrant indicates that this cluster is in a good position in terms of internal cohesion and structural development, but compared to the clusters in the first quadrant, it has less centrality and linking power with other macro-domains of the network. In other words, this cluster represents a highly specialized, mature, and self-sufficient research domain in personalized medicine, where the topics within it are highly interdependent, However, its transversal connections with the entire network are not yet as extensive as the main clusters. Analyzing the prominent sub-branches of this cluster in Table 2 clearly elucidates the reason for this position. Concepts such as Immunotherapy, Tumor microenvironment, Immune checkpoint inhibitors, CAR-T cells, and PD-L1 indicate a very specific and focused knowledge chain on the molecular biology and immunology of cancer. These concepts form highly advanced and targeted therapeutic approaches that primarily focus on the mechanisms of inhibiting or stimulating the immune system against specific tumors. Although advanced technologies like Single-cell sequencing and cancer vaccines are present in this cluster, their function is more directed toward solving intra-domain problems of immunotherapy rather than linking disparate sections of the network. Therefore, Cluster 9 acts as a specialized and prominent niche in novel cancer treatments, which, while possessing a cohesive and well-established research literature, plays a specialized and separate part in the comprehensive map of personalized medicine.

The third quadrant encompasses clusters that have scored lower than the network average in both centrality and density. In bibliometric analyses, this quadrant represents emerging or declining topics; domains that, on the one hand, have not yet achieved internal and structural cohesion, and on the other hand, have not established extensive connections and influence over the entire personalized medicine network. In this study, four clusters (Clusters 2, 5, 7, and 8) are located in this quadrant, indicating the breadth of developing or interdisciplinary topics. The cluster Nanomedicine, Biosensors, and Targeted Cancer Therapy (5) is on the verge of entering the mature clusters in the first quadrant. The presence of widely used concepts such as Theranostics, Biosensor, and Nanotechnology indicates that this domain is a key and promising emerging technology that is rapidly growing and moving towards becoming one of the main pillars of the field. Cluster 2 (Gene Editing, Omics Technologies, and the Role of Microbiome in Treatment), despite the high appeal and importance of concepts such as Gene editing, CRISPR-Cas9, and Microbiome, has low density and limited centrality. This indicates that the clinical applications of CRISPR and the microbiome in personalized medicine have not yet turned into an integrated and structured paradigm, and research in this domain is scattered across numerous branches. Cluster 7 (Early Detection and Management of Chronic, Inflammatory, and Metabolic Diseases), due to covering a wide range of heterogeneous diseases (such as cardiovascular diseases, obesity, depression, and autoimmune diseases), has not been able to create high internal cohesion and is positioned as a general

and scattered domain on the periphery of the network. Cluster 8 (Nanoparticles, Epigenetics, and Integrative Medicine Approaches (Traditional Medicine and Digital Health)) has the weakest centrality and density scores in the entire network. The combination of heterogeneous topics like Epigenetics, Persian Medicine, and Digital Health in this cluster indicates a nascent, interdisciplinary, and peripheral domain that has not yet been able to find a clear structural position in the mainstream literature of personalized medicine. In other words, the third quadrant shows that advanced concepts such as gene editing, epigenetics, the microbiome, and nanomedicine, despite their abundant theoretical importance, are still in the development, testing, and emergence phase, and require integrative research and focus on specific clinical applications to become mainstream and cohesive streams of knowledge.

The fourth quadrant is dedicated to clusters that have a centrality higher than the average but a density lower than it. This quadrant represents basic, transversal topics with high potential. Due to their extensive transversal connections, these clusters play a linking and key role in the network. However, due to the breadth of their concepts and the diversity of their application domains, their intra-group relations have not yet reached complete cohesion. The clusters in this quadrant are the future drivers of the network, possessing a high potential to transfer to the first quadrant in the future. In the present study, Cluster 3, titled (Personalized Medicine and Pharmacogenomics), is positioned as the sole cluster in this strategic quadrant. This cluster has a very strong influence and linking power with other sections of the network, and its density is situated very close to the average. This cluster contains the most key and frequent concept of the entire research, namely the term personalized medicine itself. In addition, the foundational tools and concepts of Pharmacogenomics, Next generation sequencing (NGS), Single nucleotide polymorphism, and Bioinformatics are located in this cluster. These genetic and omics tools are infrastructural technologies upon which all other clusters, including AI diagnostics, liquid biopsy, and immunotherapy, depend to achieve their goals; therefore, this cluster is the heart of the network and the bridge connecting various concepts. Furthermore, the presence of highly diverse and heterogeneous clinical topics alongside foundational concepts, ranging from emerging infectious diseases like Covid-19 to metabolic diseases like Diabetes mellitus, neurological diseases such as Epilepsy, cardiovascular diseases (Coronary artery disease), Infertility, and even Drug repurposing, has caused the concepts within the cluster to be dispersed across multiple clinical branches, preventing them from forming a dense internal cohesion. Overall, the position of Cluster 3 in the fourth quadrant demonstrates that pharmacogenomics and basic genetics act as the foundation and main underlying driving engine of the entire personalized medicine domain. Given the very small gap between this cluster's density and the threshold, it is expected that with further integration of bioinformatics methods and the standardization of pharmacogenomics applications in the clinic, this cluster will soon transfer to the first quadrant and be recognized as the most established main pillar of this field.

CONCLUSION

The research results indicate that the personalized medicine domain possesses a dynamic, four-part, multidimensional, and evolving structure; such that pharmacogenomics and basic genetics (Cluster 3 in the fourth quadrant), as the foundation and underlying driving engine, feed the entire network and provide the necessary substrate for the establishment of the field's driving triangle, namely minimally invasive molecular diagnostics (Cluster 4), intelligent AI-based imaging analysis (Cluster 1), and regenerative medicine and novel drug delivery (Cluster 6) in the first quadrant. Simultaneously, the domain of immunotherapy and tumor microenvironment (Cluster 9 in the second quadrant), as a specialized, mature, and self-sufficient hub, undertakes the advancement of targeted cancer treatments, while highly promising domains such as nanomedicine, gene editing (CRISPR-Cas9), epigenetics, and the microbiome (Clusters 2, 5, 7, and 8 in the third quadrant), although currently having an emerging, developing, and somewhat scattered nature, shape the frontiers of knowledge and the future development paths of this field. This structural perspective proves that the future and main leap of personalized medicine relies on the interdisciplinary integration of the pharmacogenomics substrate with artificial intelligence algorithms and emerging diagnostic-therapeutic technologies, so that existing knowledge can transition from the research phase to tangible and integrated clinical applications.

Study Limitations

A key limitation of this study is its exclusive reliance on the Web of Science database for data retrieval. Consequently, relevant publications indexed in other major international and regional databases, such as PubMed, Scopus, and the Islamic World Science Citation Center (ISC), were not included, which may exclude pertinent domestic studies published outside WoS.

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Availability of data and materials

The data of study are available upon reasonable request.

Conflicts of interest

The author declares that there is no conflict of interest in this article.

Ethics Approval and Consent to Participate

This study was a bibliometric analysis based on publicly available secondary data extracted from the ISC database and did not involve human or animal subjects. Therefore, ethical approval and informed consent to participate were not required.

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REFERENCES

1.De Sousa RM, Marinaro M, D'Ariano G, De Coppi P, Gerli MF. Prenatal organoids for personalised medicine. Semin Pediatr Surg. 2026:151676. https://doi.org/10.1016/j.sempedsurg.2026.151676

2.Pandey A, Gupta SP. Personalized medicine: a comprehensive review. Orient J Chem. 2024;40(4):933–44. https://doi.org/10.13005/ojc/400403

3.Williams JR, Lorenzo D, Salerno J, Yeh VM, Mitrani VB, Kripalani S. Current applications of precision medicine: a bibliometric analysis. Per Med. 2019;16(4):351–9. https://doi.org/10.2217/pme-2018-0089.

4.Arjmand B, Goodarzi P, Mohamadi-Jahani F, Falahzadeh K, Larijani B. Personalized regenerative medicine. Acta Med Iran. 2017;55(3):144–9.

5.Sipka S. Precision and personalized medicine. Orv Hetil. 2016;157(44):1739–41. https://doi.org/10.1556/650.2016.30564.

6.Al-Dekah AM. Systematic bibliometric and visualized analysis of global research trends, impact, emerging areas, and hotspots of artificial intelligence in personalized medicine. Naunyn Schmiedebergs Arch Pharmacol. 2026;399(3):4193–214. https://doi.org/10.1007/s00210-025-04732-5.

7.Sohn E, Noh KR, Lee B, Kwon OJ. Bibliometric network analysis and visualization of research and development trends in precision medicine. In: 2018 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM); 2018; Barcelona, Spain. p. 727–30. https://doi.org/10.1109/ASONAM.2018.8508350.

8.Adam KM, Ali EW, Elangeeb ME, Abuagla HA, Elamin BK, Ahmed EM, et al. Intelligent care: a scientometric analysis of artificial intelligence in precision medicine. Med Sci (Basel). 2025;13(2):44. https://doi.org/10.3390/medsci13020044.

9.Pedük Ş. Mapping the future of early breast cancer diagnosis: a bibliometric analysis of AI innovations. Discov Oncol. 2025;16(1):1870. https://doi.org/10.1007/s12672-025-03495-y.

10.Virk R, Ririe AK, Lashari U, Yousif Mohamed MM, Rafique T, Iqbal H, et al. Personalized medicine: evaluating the role of genomic data in tailoring cancer treatments. A bibliometric perspective. J Neonatal Surg. 2025;14(19S):906–45. https://www.jneonatalsurg.com/index.php/jns/article/view/5145.

11.Khakimova A, Rahim F, Zolotarev O. Bibliometric and semantic analysis of the global research on biomarkers in personalized medicine. Open Biomark J. 2022;12(1). https://doi.org/10.2174/18753183-v12-e220926-2022-3.

12.Li Y, Chen Y, Wang Q. Evolution and diffusion of information literacy topics. Scientometrics. 2021;126(5):4195–224.https://doi.org/10.1007/s11192-021-03925-y.

13.Shollapur MR, Hulagabali SC, Kolle SR. Global research on financial literacy: a bibliometric analysis. DESIDOC J Libr Inf Technol. 2023;43(3):157–63. https://doi.org/10.14429/djlit.43.03.18436.

14.Park H, Kim H, Park H. A scientometric study of digital literacy, ICT literacy, information literacy, and media literacy. J Data Inf Sci. 2021;6(2):116–38. https://doi.org/10.2478/jdis-2021-0001.

15.Rahimi S, Soheili F, Aminiinia Y, Danesh F. Identifying emerging areas and map scientific structure of throbbing headaches. Health Inf Manag. 2020;17(4):189–98. https://doi.org/10.22122/him.v17i4.4132.

16.Rahimi S, Soheili F, Khasseh AA. An analysis of literacy research in Iran: the conceptual structure of

literacy in Islamic World Science Citation Center. Libr Inf Sci. 2025;27(4):195–220. https://doi.org/10.30481/lis.2024.474041.2189.
17.Rahimi S, Soheili F, Yazdanbakhsh K. Thematic trends analysis in decision-making research in Islamic World Science and Technology Monitoring and Citation Institute (ISC): a bibliometric study. J Decis Oper Res. 2024;9(4):1099–112. https://doi.org/10.22105/dmor.2025.496852.1901.
18.Rahimi S, Soheili F, Yazdanbakhsh K. Discovering current trends and identifying future research directions in neuroscience. Scientometrics Res J. 2025;11(2):327–46. https://doi.org/10.22070/rsci.2025.20132.1788.
19.Lyu X, Hu J, Dong W, Xu X. Intellectual structure and evolutionary trends of precision medicine research: co-word analysis. JMIR Med Inform. 2020;8(2):e11287. https://doi.org/10.2196/11287.
20.Bradford SC. Sources of information on scientific subjects. Engineering. 1934;137:85–6. https://www.scirp.org/reference/referencespapers?referenceid=3027930.
21.Van Eck NJ, Waltman L. How to normalize cooccurrence data? An analysis of some well-known similarity measures. J Am Soc Inf Sci Technol. 2009;60(8):1635–51.https://doi.org/10.1002/asi.21075.
22.Van Eck NJ, Waltman L. Software survey: VOSviewer, a computer program for bibliometric mapping. Scientometrics. 2010;84(2):523–38. https://doi.org/10.1007/s11192-009-0146-3.
23.Callon M, Courtial JP, Laville F. Co-word analysis as a tool for describing the network of interactions between basic and technological research: the case of polymer chemistry. Scientometrics. 1991;22:155–205. https://doi.org/10.1007/BF02019280.
24.Melcer E, Nguyen THD, Chen Z, Canossa A, El-Nasr MS, Isbister K. Games research today: analyzing the academic landscape 2000–2014. In: Proceedings of the 10th International Conference on the Foundations of Digital Games; 2015; Pacific Grove, CA, USA. http://www.fdg2015.org/papers/fdg2015_paper_41.pdf.
25.Khasseh AA, Soheili F, Sharif Moghaddam H, Mousavi Chelak A. Intellectual structure of knowledge of iMetrics: a co-word analysis. Inf Process Manag. 2017;53(3):705–20.https://doi.org/10.1016/j.ipm.2017.02.001.