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Digital Innovations in Patient-Centered Care: The Emerging Role of Natural Language Processing

Bima Ananta Putra[1], Merita Arini[1], and Yoviena Kusuma Terichtia Tamaranny[2]

[1] Master of Hospital Administration, Postgraduate Program, Universitas Muhammadiyah Yogyakarta, Yogyakarta, Indonesia
[2] Master of Women's Health, Postgraduate Program, University College London, London, United Kingdom

Abstract

Patient-Centered Care (PCC) faces critical challenges such as fragmented communication, limited interpretation of patient narratives, and underutilization of real-time feedback. Natural Language Processing (NLP) offers promising solutions by enabling the structured analysis of unstructured data like Electronic Health Records (EHRs), social media content, and patient feedback. This study aims to systematically map the scholarly landscape of NLP applications in PCC between 2015 and 2025, identifying key trends, dominant research themes, and knowledge gaps. A bibliometric analysis was conducted using the Scopus database, with inclusion criteria focused on peer-reviewed, English-language articles in relevant health and technology fields. From an initial set of 645 records, 254 publications met the eligibility requirements. Data cleaning and network analysis were performed using OpenRefine, MS Excel, and VOSviewer, focusing on co-authorship, keyword co-occurrence, and citation density. Results indicate an exponential increase in research output, rising from five publications in 2015 to eighty-one in 2024, largely driven by high-income countries with advanced digital infrastructure. Five thematic clusters emerged: (1) Social Media–Based Patient Communication, (2) Sentiment Analysis for Care Feedback, (3) Clinical Decision Support via NLP, (4) AI-Powered Patient Empowerment, and (5) Modeling Perceived Quality of Care. Implications include the development of real-time, AI-driven feedback loops, multimodal data integration, and culturally responsive chatbot systems. This study also highlights urgent directions for future research, such as building explainable and ethical AI models, integrating diverse data sources, and designing adaptive NLP applications that support longitudinal patient engagement. It offers foundational insights into the evolving role of NLP in enhancing personalized, responsive, and ethically sound PCC.

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Author Email
bimaap052@gmail.com
merita.arini@umy.ac.id
yovienak.terichtia@gmail.com

I. Introduction

Patient-Centered Care (PCC) is a fundamental model in today's healthcare that centralizes patients in every medical process. It has been operationalized as the delivery of care that respects and responds to patient preferences, needs, and values, and these values also dictate every clinical decision [1]. Some of the main features of PCC include respect for patient choice, collaboration between patients and healthcare providers through shared decision-making, comprehensive and coordinated care, and the active involvement of patients and families in the care process [2–4]. Further, PCC emphasizes a person-directed approach aimed at allowing patients to drive physically and emotionally for improved health outcomes [5]. In practice, PCC can be effectively applied through interventions like enhanced patient engagement in direct-care safety, universally accessible health education, and utilization of technologies such as clinical decision support tools [6]. Although Patient-Centered Care (PCC) is a widely accepted ideal, its practical implementation faces persistent barriers. Several key challenges hinder its effectiveness in clinical settings, including suboptimal patient-doctor communication, limitations in analyzing patient experience narratives, and low trust in AI technology due to a lack of transparency and interpretability [7–9].

With the ongoing digitalization of healthcare systems, Natural Language Processing (NLP), an artificial intelligence (AI) subdiscipline, is the central element in processing unstructured data such as Electronic Health Records (EHR) and patient complaints [10]. NLP facilitates the automated extraction of significant clinical information from documents, such as diagnoses and interventions, transforming what was once a manual task into a routine computerized process [11]. Recent advances demonstrate that NLP applied to unstructured EHR data can enhance prognosis and outcome prediction, highlighting its potential to transform clinical decision-making and personalized care [12,13]. NLP is also applied in analyzing patient reviews, identifying common themes and sentiments, and aiding quality improvement programs [14]. NLP also facilitates real-time monitoring of patient-reported information to allow early detection of safety issues and greater responsiveness in the provision of healthcare [15–17]. Compared with

Corresponding author: Bima Ananta Putra, bimaap052@gmail.com, Master of Hospital Administration, Postgraduate Program, Universitas Muhammadiyah Yogyakarta, Jl. Brawijaya, Geblagan, Tamantirto, Kec. Kasihan, Kabupaten Bantul, Yogyakarta 55183, Indonesia.
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manual analysis, NLP allows healthcare organizations to conclude high-volume of textual data more rapidly [18,19]. NLP is used to all facets of PCC, including speech recognition and text conversion technology used to automate narrative reporting, patient complaint, and feedback sentiment analysis to enhance patient experience, development of chatbots to enhance patient-provider communication responsiveness, and emotional needs and patient preference automatic identification for improved personalized care delivery [20–22]. Thus, Natural Language Processing (NLP) is present as a solution in the implementation of PCC by improving the quality of communication, automating clinical documentation, and analyzing narrative data efficiently and transparently to strengthen empathy and personalization of health services [9,23,24].

Despite the simultaneous development of NLP literature and PCC, no comprehensive bibliometric study has been done to mark the overlap of these areas, particularly to examine how NLP supports key areas like patient experience, communication, and shared decision-making in PCC. Previous research suggests that the application of artificial intelligence in palliative care is still in its early stages, and while NLP has shown promise in these settings, a broader and more systematic mapping of its role in the wider PCC context is lacking [25]. A bibliometric approach enables the identification of patterns, collaborations, and research trends that are otherwise difficult to capture in traditional reviews.

This study aims to explore and synthesize the landscape of scholarly literature concerning the application of NLP in Patient-Centered Care (PCC) from 2015 to 2025 by mapping publication trends, identifying dominant research themes, analyzing patterns of international collaboration, and uncovering knowledge gaps through bibliometric analysis. In doing so, it not only provides a structured overview of how NLP technologies have been utilized to enhance communication, feedback processing, decision support, and patient empowerment in PCC contexts but also identifies underexplored domains, thereby offering actionable insights for future research, practice, and healthcare policy development. First, this study offers the initial rigorous bibliometric review of NLP uses in PCC, therefore establishing a structured body of evidence for further research. Second, it highlights untapped regions of crossover between NLP and important vectors of PCC, such as communication, shared decision-making, and patient experience, therefore demarcating concrete research gaps. Third, the research guides practice and healthcare policy by defining how NLP technologies might be applied to strengthen empathy, personalization, and trust in digital health settings.

II. Materials and Method

This bibliometric review was conducted to examine patterns of publication for NLP in PCC from the Scopus database. The use of Scopus is because it has extensive coverage and comprises high-standard, peer-reviewed articles, making it an accepted source of data among researchers [26]. Compared to Web of Science, where author and affiliation data may have inconsistencies due to the absence of adequate mechanisms for distinguishing authors with similar or identical names, Scopus has cleaner metadata [27]. In addition, while PubMed is focused on life sciences and biomedical subjects and therefore yields fewer documents, Scopus covers a broader range of interdisciplinary literature including health informatics, computer sciences, and social sciences that better fits this study's range of interest [28]. This broader scope is particularly essential for capturing the cross-disciplinary nature of NLP applications in patient-centered care, which spans both technical and clinical domains. The differences in citation index coverage across scientific fields further support the appropriateness of using Scopus for this type of analysis [29]. Bibliometric analysis is a research method used to examine global trends in a specific field by analyzing the output of academic publications, and it enables researchers to identify collaboration patterns, productive authors, and emerging research issues [30,31].

Data were collected using a combination of Boolean-based keyword searches targeting NLP applications in PCC within the area of healthcare services. The search was conducted in the TITLE-ABS-KEY field of the Scopus database using a predefined Boolean query. The complete search string is presented in Table 1, allowing for full transparency and replicability of the search process. Filters were employed to show only English-language publications and to exclude documents on irrelevant topic matter. A time period of ten years was chosen for this study, as the past decade has witnessed an explosive spurt in digital transformation within the healthcare sector. The endpoint of 2025 was chosen intentionally, as data collection was conducted in early 2025 and included all documents indexed in Scopus up to the time of retrieval. Therefore, 2025 is not a future projection but a representation of the most current publication trends available at the time of analysis. It is characterized by the global rollout of digital solutions aimed at improving operational efficiency, organizational resilience, and patient care quality, as observed in recent literature [32–34]. The search terms used are shown in Table 1.

An initial search using the specified keywords yielded 645 documents, as depicted in Fig. 1. The flow diagram, adapted from Işık [35], outlines the screening process. The Scopus database automatically removes duplicate records, so no additional deduplication was required. Several exclusion criteria were then applied to refine the dataset: publications outside the range of 2015–2025 (n=26), subject areas not related to medicine, computer science, engineering, health professions, nursing, pharmacology, toxicology and pharmaceutics, immunology and microbiology, psychology, or dentistry (n=42), document types other than articles and conference papers (n=174), publications not in the final stage (n=7), non-journal sources (n=108), and non-English language articles (n=5). The “final stage” designation was determined using Scopus’s built-in filter

Corresponding author: Bima Ananta Putra, bimaap052@gmail.com, Master of Hospital Administration, Postgraduate Program, Universitas Muhammadiyah Yogyakarta, Jl. Brawijaya, Geblagan, Tamantirto, Kec. Kasihan, Kabupaten Bantul, Yogyakarta 55183, Indonesia.
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for publication status, which allows users to distinguish between fully published records and those still in press. Only records labeled as “final” were included to ensure the inclusion of peer-reviewed and fully edited articles with complete bibliographic data.

These exclusion criteria were applied to enhance the internal consistency, methodological clarity, and thematic relevance of the dataset. The ten-year window (2015–2025) was selected to capture the period of rapid growth in digital health and NLP innovation, particularly following the global acceleration of healthcare digitization post-2015. Focusing on selected subject areas avoids thematic dilution and ensures alignment with interdisciplinary domains relevant to NLP and patient-centered care. Limiting to peer-reviewed journal articles and conference papers preserves analytical quality, as these publication types usually provide structured methodologies and undergo scholarly scrutiny. Final-stage publications were retained to avoid inclusion of incomplete or preprint materials. Restricting to English-language articles helps maintain consistency in keyword processing and metadata standardization, which is especially critical for text-mining and bibliometric tools.

However, we acknowledge that such decisions may introduce potential biases, particularly language and database biases, which may limit the visibility of valuable research from non-English-speaking countries. These limitations are common in bibliometric studies and should be transparently reported to support reproducibility and critical interpretation [36,37]. This resulted in 283 records eligible for manual screening. A further assessment based on titles, keywords, and abstracts was conducted to ensure relevance to the application of NLP in patient-centered care. Documents that did not meet this criterion, such as those focused solely on NLP algorithm development without patient-centered context, were excluded, leaving 254 publications identified as relevant, which were then analyzed to investigate trends and intersections between NLP and PCC.

Table 1. Data search keywords

Data Search Keywords
TITLE-ABS-KEY (("natural language processing" OR "NLP" OR "computational linguistics" OR "language model" OR "text mining" OR "clinical NLP" OR "machine learning in text") AND ("patient-centered care" OR "person-centered care" OR "patient centric" OR "patient engagement" OR "patient experience" OR "shared decision making" OR "patient empowerment" OR "individualized care" OR "personalized care") AND ("healthcare" OR "healthcare" OR "medical" OR "clinical")) AND PUB YEAR > 2014 AND PUBYEAR < 2026 AND (LIMIT-TO (SUBJAREA , "MEDI") OR LIMIT-TO (SUBJAREA , "COMP") OR LIMIT-TO (SUBJAREA , "ENGI") OR LIMIT-TO (SUBJAREA , "HEAL") OR LIMIT-TO (SUBJAREA , "NURS") OR LIMIT-TO (SUBJAREA , "PHAR") OR LIMIT-TO (SUBJAREA , "IMMU") OR LIMIT-TO (SUBJAREA , "PSYC") OR LIMIT-TO (SUBJAREA , "DENT")) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp")) AND (LIMIT-TO (PUBSTAGE , "final")) AND (LIMIT-TO (SRCTYPE , "j")) AND (LIMIT-TO (LANGUAGE , "English"))

This manual screening was independently conducted by two reviewers using predefined inclusion criteria. Disagreements regarding eligibility were resolved through discussion, and if necessary, adjudicated by a third reviewer. Although formal inter-rater reliability measures were not applied, calibration was conducted prior to screening to align interpretation and maintain consistency.

The dataset, originally downloaded from the Scopus database in CSV format, was first cleaned using OpenRefine through clustering techniques to standardize keyword variations and ensure consistency. This involved unifying different spellings, capitalizations, and hyphenations of similar terms, for example, “Patient centered care”, “patient-centered care”, and “Patient-Centered Care” were merged into a single standardized term. Furthermore, semantically related keywords such as “patient satisfaction”, “patient engagement”, and “patient experience” were grouped under “patient experience” based on thematic similarity. This preprocessing step was crucial to reducing duplication and improving the accuracy of co-occurrence mapping. Descriptive statistics such as annual publication trends, author frequencies, and keyword counts were analyzed using Microsoft Excel. Subsequent analysis in MS Excel enabled the extraction of key metrics, while VOSviewer was utilized to visualize co-authorship, co-citation, and keyword co-occurrence networks. This included generating density and overlay maps to explore thematic structures and identify potential research gaps. For the keyword co-occurrence analysis, a minimum threshold of four occurrences was set to focus on the most relevant terms. VOSviewer’s modularity-based algorithm then grouped these terms into clusters, each reflecting a distinct thematic area within the research landscape. Mapping and clustering of bibliometric networks, including co-authorship, co-citation, and keyword co-occurrence, were performed using VOSviewer version 1.6.20. The full counting method was applied consistently across all analyses. For keyword co-occurrence mapping, a

Corresponding author: Bima Ananta Putra, bimaap052@gmail.com, Master of Hospital Administration, Postgraduate Program, Universitas Muhammadiyah Yogyakarta, Jl. Brawijaya, Geblagan, Tamantirto, Kec. Kasihan, Kabupaten Bantul, Yogyakarta 55183, Indonesia.
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minimum threshold of four occurrences was set to ensure thematic relevance. VOSviewer's modularity-based clustering algorithm was used to identify thematic clusters based on link strength.

For the co-citation analysis, we produced visualizations of co-cited references, co-cited journals, and co-cited authors. In the co-authorship analysis, we generated three types of networks: author-level co-authorship, institutional partnership maps, and international collaboration networks between countries. The co-occurrence analysis included network visualization (for structural linkage), density visualization (to highlight concentration of terms), and overlay visualization (to show temporal development). These steps provided a multidimensional view of collaboration structures and thematic cohesion within the research landscape of NLP in patient-centered care.

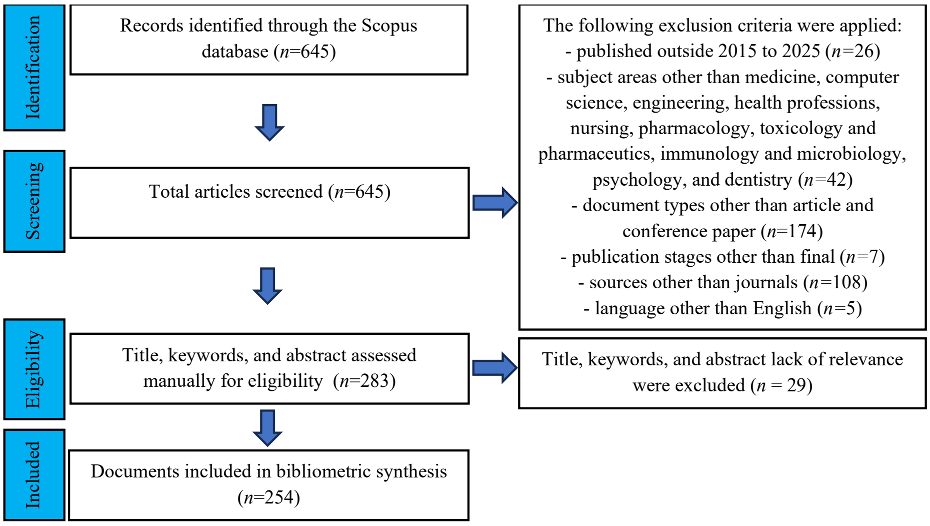

Fig. 1. The PRISMA flow diagram used to identify, screen, and include papers for our bibliometric review

III. Results

Over the past decade, research into the application of NLP in PCC has increased substantially. As shown in Fig. 2, the number of publications progressively rose from 5 in 2015 to 81 in 2024, reflecting a steady upward trend and growing academic interest. This surge can be attributed to several factors. First, the emergence of large pre-trained transformer models, such as BERT (Bidirectional Encoder Representations from Transformers) (2018) and GPT (Generative Pre-trained Transformer) (2018 onward), significantly advanced the ability of NLP systems to interpret clinical language nuances, including abbreviation resolution, negation detection, and contextual disambiguation, tasks that were previously limited by traditional rule-based or shallow ML methods [38]. Second, the increased availability of annotated clinical corpora, alongside improved computational infrastructure, has made it more feasible to train domain-specific models at scale [39]. This shift towards digital records is more than a logistical improvement; it represents a paradigm change, offering healthcare providers and researchers an unprecedented level of data accessibility, continuity, and accuracy, which can directly impact the quality of care and medical insights [40]**.** The resulting volume of unstructured clinical text has created both a need and an opportunity for NLP tools that can extract actionable information to support PCC.

Supporting this, Wu et al. (2022) reported that the clinical NLP research budget in the UK increased 80-fold between the periods 2007–2010 and 2019–2022, accompanied by the formation of an international research community spanning 23 countries [41]. However, this expansion has not been without challenges. Researchers frequently confront issues such as limited access to high-quality, anonymized data, heterogeneity in clinical terminologies, and ethical concerns related to algorithmic bias and patient privacy [30-32]. Moreover, regulatory uncertainty around AI in healthcare often slows down implementation, especially in cross-border projects.

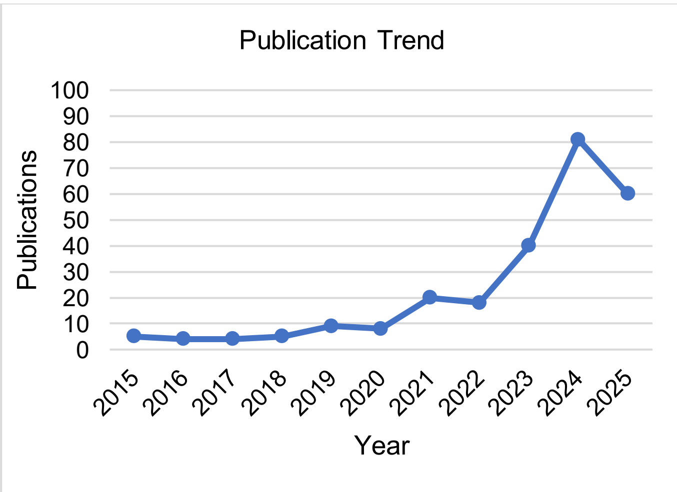

Fig. 2. Publication trend

Corresponding author: Bima Ananta Putra, bimaap052@gmail.com, Master of Hospital Administration, Postgraduate Program, Universitas Muhammadiyah Yogyakarta, Jl. Brawijaya, Geblagan, Tamantirto, Kec. Kasihan, Kabupaten Bantul, Yogyakarta 55183, Indonesia.
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This trajectory highlights sustained global investment and engagement with NLP in healthcare, especially in addressing the complexities of unstructured clinical data. Despite these hurdles, interdisciplinary collaboration, such as between NHS Digital, academic institutions, and AI labs, has facilitated the development of robust frameworks for applying NLP to electronic health records. These collaborations aim to balance innovation with safety, addressing concerns related to data governance, model transparency, and scalability. For example, recent work has focused on building modular NLP pipelines that can be adapted to different healthcare contexts, supporting a range of applications from automated documentation and patient feedback analysis to clinical trial recruitment and early warning systems. As this field continues to translate NLP innovations into real-world clinical impact.

Significant advances in data science and machine learning (ML), such as transformer-based models like BERT and GPT, have enhanced the accuracy and responsiveness of NLP in clinical settings [42,43]. For instance, these technologies are now applied not only to automated clinical documentation but also to patient feedback analysis, clinical trial recruitment, and early warning systems for patient deterioration [44]. These developments are often the result of interdisciplinary collaboration, such as joint efforts between NHS Digital, academic institutions, and AI research labs, which have produced frameworks for applying NLP to electronic health records while tackling challenges related to data privacy, standardization, and scalability [45–48]. Continued cross-sector partnerships remain critical to advancing safe and effective clinical NLP applications.

Table 2. Documents by year

Year	Documents	Total cited papers	Total citation	Citation impact	Cited paper impact
2015	5	5	92	18.4	18.4
2016	4	4	351	87.75	87.75
2017	4	4	190	47.5	47.5
2018	5	5	201	40.2	40.2
2019	9	9	195	21.67	21.67
2020	8	7	92	11.5	13.14
2021	20	20	259	12.95	12.95
2022	18	18	216	12	12
2023	40	39	278	6.95	7.13
2024	81	56	416	5.13	7.43
2025	60	14	27	0.45	1.93

Table 2 presents the publication and citation trends in studies on NLP applications in patient-centred care between 2015 and 2025. A total of 254 publications were identified, with 2,317 citations accumulated across the decade. Although the early years (2015-2017) produced only 13 documents, they accounted for 633 citations, over 27% of the total, highlighting a disproportionate influence relative to output. In particular, 2016 saw only four publications, yet had the highest citation impact (87.75), suggesting that the limited research published at the time addressed foundational or highly novel aspects of NLP in PCC that were widely cited by subsequent work. From 2018 onward, there was a gradual rise in publication volume, followed by a sharp increase in 2021 and peaking in 2024 with 81 documents. However, this surge in quantity has not been mirrored by citation impact: both 2023 and 2024 show significantly lower citation metrics (impact scores of 6.93 and 5.13, respectively). This is likely due to the recency of the publications, which have had limited time to accumulate citations [49,50]. It may also reflect a diversification in research focus or a shift towards more incremental, exploratory work rather than landmark studies [51]. These kinds of temporal citation patterns are common in bibliometric analysis, whereby publications published later tend to experience a time-lag before demonstrating their scholarly impact [52,53].

The decline in average citation impact despite increased output suggests a potential dilution in the quality or influence of individual publications, or a delay in recognition due to the rapid expansion of the field [54]. High citation impact in earlier years is often associated with seminal or agenda-setting research, while newer studies may take time to demonstrate comparable influence (H). These patterns underscore the importance of distinguishing between publication volume and research impact when evaluating the maturity and direction of emerging interdisciplinary fields such as NLP in PCC.

In comparison with the earlier years, particularly 2016, the years had fewer frequent but higher impact publications. The findings suggest that despite the exponential growth in research interest in NLP for PCC over the past few years, its citation influence is still not

Corresponding author: Bima Ananta Putra, bimaap052@gmail.com, Master of Hospital Administration, Postgraduate Program, Universitas Muhammadiyah Yogyakarta, Jl. Brawijaya, Geblagan, Tamantirto, Kec. Kasihan, Kabupaten Bantul, Yogyakarta 55183, Indonesia.
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mature. The COVID-19 pandemic has demonstrated the vast potential of natural language processing (NLP) in leveraging large-scale text-based health data; however, real-world deployment remains limited due to challenges in application, integration, and system readiness [55].This examination is valuable for high-impact early years and recent publication activity identification in this new research area.

Table 3 highlights the top-performing countries in NLP research for PCC. The United States ranks first with 131 publications and 1,844 citations, achieving the highest h-index (46), citation impact (14.08), and cited paper impact (22.76), underscoring both its research volume and influence. China follows in second with 11 publications and 73 citations; despite only 3 cited papers, it maintains a strong cited paper impact of 24.33. India ranks third with 10 publications, 109 citations, and a notable h-index of 10, reflecting consistent impact. In contrast, Italy, ranked tenth, contributed 6 publications, half of which were cited with a total of 44 citations, marking the lowest output and influence among the top ten. Generally, although the United States is ahead in quantity and impact, some countries, such as Switzerland and the Netherlands, mirror satisfactory performance regarding citation quality over their production, demonstrating the growing worldwide interest and impact in the application of NLP in patient-oriented medicine. These findings imply that global leadership in NLP for PCC remains concentrated in high-income countries with greater research capacity, but emerging contributions from countries like China and India suggest a shifting landscape and the growing democratization of NLP research in healthcare.

Table 3. Leading contributing countries

Country	Total papers	Total cited papers	Total citation	Citation impact	Cited paper impact	h-index
United States	131	81	1844	14.08	22.76	46
China	11	3	73	6.64	24.33	5
India	10	5	109	10.9	21.8	10
Germany	10	4	93	9.3	23.25	9
Switzerland	10	4	126	12.6	31.5	11
Australia	10	4	81	8.1	20.25	8
United Kingdom	9	4	83	9.22	20.75	12
Canada	8	4	63	7.87	15.75	8
Netherlands	7	3	66	9.43	22	6
Italy	6	3	44	7.33	14.67	5

Research on NLP applications in PCC is more prevalent in developed countries due to better access to computational resources, strong funding support, and established legal-ethical frameworks that facilitate healthcare innovation [56]. Their research is often more specialized, targeting tasks like clinical predictions and information extraction [43]. In contrast, developing countries face challenges such as limited infrastructure, lack of digital records, language exclusion, minimal real-world implementation, and absence of reporting standards, which hinder progress [41,57]. Despite not being high-income countries, China and India have also produced significant research on NLP in PCC. In China, this is driven by strong government support for digital health and talent recruitment [58]. And also by large-scale access to medical data under relatively flexible privacy regulations, as well as national initiatives in health information standardization and interoperability that provide a strong foundation for AI-driven clinical applications [59,60]. In India, this is driven by the imperative to bridge rural healthcare gaps with locally adapted, multilingual NLP solutions and improve clinical usability via bias reduction and model interpretability [61,62]. Table 4 shows the top 10 most cited articles. The article "Yelp reviews of hospital care can supplement and inform traditional surveys of the patient experience of care" is a key reference in NLP for PCC, as it shows that patient reviews on Yelp not only reflect existing survey domains (like HCAHPS) but also reveal additional dimensions such as staff empathy and cost. Using NLP, the study converts free-text reviews into measurable quality indicators, demonstrating the value of low-cost, real-time data to complement traditional surveys and inform more targeted PCC interventions [63]. A growing body of research highlights the vast potential of NLP to enhance PCC by leveraging data from social media and patient narratives. Several studies have demonstrated how platforms like Twitter, Reddit, and others can be utilized to capture patient perceptions, needs, and experiences in real time and at scale [64–69]. These analyses enable the identification of issues most important to patients, such as satisfaction with care or responses to treatments that are often omitted from formal surveys. On the other hand, NLP is also applied to simplify complex medical information for patients, such as generating patient-friendly radiology reports [70]. Additionally, processing narrative text from medical records or online healthcare workers' reviews helps

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uncover individual patient preferences and contextual needs [71,72]. Overall, the integration of NLP in analyzing patient experience and communication strengthens the implementation of PCC that is more informative, inclusive, and grounded in real-world needs.

Table 4. Most cited articles

No	Title	Author	Year	Journal	Cited by
1	Yelp reviews of hospital care can supplement and inform traditional surveys of the patient experience of care	B. L. Ranard, R. M. Werner, T. Antanavicius, et al. [63]	2016	Health Affairs HHS Public Access	185
2	ChatGPT makes medicine easy to swallow: an exploratory case study on simplified radiology reports	K. Jeblick, B. Schachtner, J. Dexl, et al. [70]	2024	European Radiology	135
3	Measuring patient-perceived quality of care in US hospitals using Twitter	J. B. Hawkins, J. S. Brownstein, G. Tuli, et al. [64]	2016	BMJ Quality and Safety	114
4	A clinician friendly data warehouse oriented toward narrative reports: Dr. Warehouse	N. Garcelon, A. Neurazb, R. Salomona, et al. [71]	2018	Journal of Biomedical Informatics	109
5	A tale of two countries: International comparison of online doctor reviews between China and the United States	H. Hao, K. Zhang, W. Wang, et al. [72]	2017	International Journal of Medical Informatics	93
6	Patient Understanding of the Risks and Benefits of Biologic Therapies in Inflammatory Bowel Disease: Insights from a Large-scale Analysis of Social Media Platforms	B. Martinez, F. Dailey, C. V. Almario, et al. [65]	2017	Inflammatory Bowel Disesases	53
7	Mining of textual health information from Reddit: Analysis of chronic diseases with extracted entities and their relations	V. Foufi, T. Timakum, C. G. Blavignac, et al. [66]	2019	Journal of Medical Internet Research	53
8	Utilizing Twitter data for analysis of chemotherapy	L. Zhang, M. Hall, D. Bastola [67]	2018	International Journal of Medical Informatics	51
9	Collecting and analyzing patient experiences of health care from social media	M. R. Mojarad, Z. Ye, D. Wall, et al. [68]	2015	Journal of Medical Internet Research	48
10	Evaluating Patient Experiences in Dry Eye Disease Through Social Media Listening Research	N. Cook, A. Mullins, R. Gautam, et al. [69]	2019	Ophthalmology and Therapy	44

IV. Discussion

A. Co-citation analysis

Co-citation analysis is conducted to identify relationships among articles, authors, and journals by measuring how often they are cited together. This method relies on co-citation counts to determine the degree of similarity between documents, authors, or journals. The core assumption behind co-citation analysis is that the more frequently two sources are cited together, the more likely they are to share related or complementary content. Co-citation analysis can be categorized into different types based on the unit of analysis, such as document co-citation, author co-citation, and journal co-citation [73].

1. Co-cited references

As a result, 26 co-cited references were identified from a total of 10793 journals that had received a minimum of three citations. The co-cited articles network is visualized in Fig. 3, which highlights the strongest collaborative clusters. Based on the co-cited references analysis, five major clusters were identified. The top-ranked article in the green cluster is titled "Performance of ChatGPT on USMLE: Potential for AI-assisted medical education using large language models" [74].

Corresponding author: Bima Ananta Putra, bimaap052@gmail.com, Master of Hospital Administration, Postgraduate Program, Universitas Muhammadiyah Yogyakarta, Jl. Brawijaya, Geblagan, Tamantirto, Kec. Kasihan, Kabupaten Bantul, Yogyakarta 55183, Indonesia.
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Fig. 3. Co-citation of cited literature on the application of NLP in PCC

This article, which discusses how ChatGPT shows potential to support medical education and clinical decision-making through consistent and insightful explanations, received the highest overall citations (11) and total link strength (10) [74]. In the yellow cluster, the highest-ranked article is "Use of Sentiment Analysis for Capturing Patient Experience From Free-Text Comments Posted Online" [75], with 10 citations and a total link strength of 9. The study demonstrates that sentiment analysis using ML can accurately capture patient experience from free-text comments and aligns with the results of conventional surveys [75]. Collectively, the highly cited papers highlight the interdisciplinarity of NLP and AI in all areas of health care, in education, patient experience, and social determinants, and demonstrate the diversity of applications positioned to facilitate research into patient-centred care [76,77]. The blue cluster is led by the article "The Intersections Between Social Determinants of Health, Health Literacy, and Health Disparities", which explores how low health literacy reinforces the impact of social disadvantage on health disparities [78]. This article ranks first in the cluster with 4 citations and a total link strength of 7. In the purple cluster, the highest-ranking article is "ChatGPT Utility in Healthcare Education, Research, and Practice: Systematic Review on the Promising Perspectives and Valid Concerns" [79]. It received 10 citations and a total link strength of 4, highlighting the benefits and risks of ChatGPT use in healthcare, and the urgent need for ethical guidelines to ensure responsible implementation [79]. Lastly, the red cluster is led by the article "The 1% Rule in Four Digital Health Social Networks: An Observational Study" [80], which confirms that a small group of Superusers generates the majority of content in digital health communities [80]. This article has 3 citations and a total link strength of 3, emphasizing the importance of engaging these users for long-term network sustainability and value.

2. Co-cited journals

Fig. 4 shows the network of co-citation of journals. Among a total of 5221 journals, 39 met the threshold of at least 20 citations. The co-citation network analysis revealed four clusters, represented by the colors yellow, blue, green, and red.

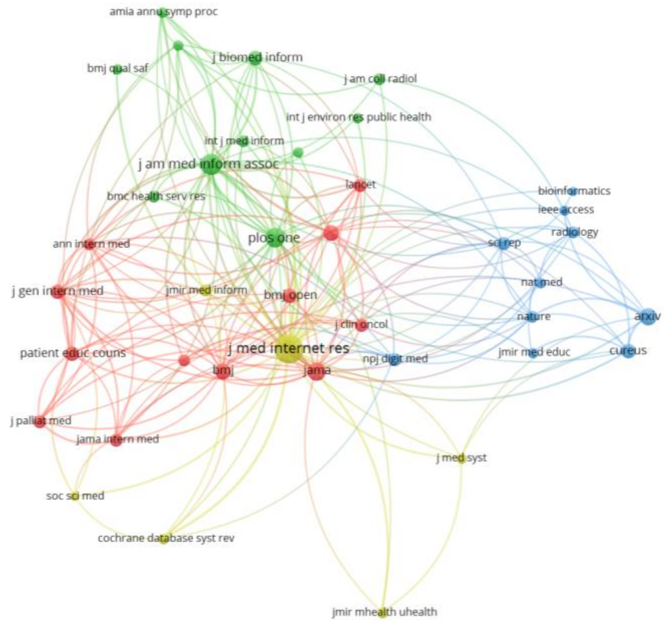

Fig. 4. Co-citation of cited journals on the application of NLP in PCC.

Journal of Medical Internet Research ranks first in the yellow cluster and overall, with 275 citations and a total link strength of 2526. The Journal of the American Medical Informatics Association is the second overall and the top in the green cluster, with 140 citations and 1637 total link strength. PLOS ONE ranks third overall and second in the green cluster, with 112 citations and a total link strength of 1084. JAMA is fourth overall and leads the red cluster with 93 citations and 1054 total link strength. In the blue cluster, arXiv holds the top position with 73 citations and a total link strength of 443. Although arXiv is a preprint repository rather than a peer-reviewed journal, its frequent co-citation reflects its crucial role in disseminating early-stage research, particularly in computer science and artificial intelligence domains. Meanwhile, the other top journals, Journal of Medical Internet Research, JAMA, and PLOS ONE are classified as Q1 journals, indicating their high impact and reputation in their respective fields. These co-cited journals in the bibliometric analysis of NLP applications in PCC indicate a multidisciplinary foundation, bridging medical informatics, clinical research, digital health, and computer science to support innovation in AI-driven healthcare solutions. The presence of high-impact journals in the co-citation network suggests that the knowledge base of NLP for PCC is grounded in credible, peer-reviewed sources, reinforcing the scientific quality and maturity of this emerging field. This trend indicates the cross-disciplinary nature of PCC research, where both clinical and technical disciplines have to work together, and confirms that co-

Corresponding author: Bima Ananta Putra, bimaap052@gmail.com, Master of Hospital Administration, Postgraduate Program, Universitas Muhammadiyah Yogyakarta, Jl. Brawijaya, Geblagan, Tamantirto, Kec. Kasihan, Kabupaten Bantul, Yogyakarta 55183, Indonesia.
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citation patterns and journal impact are useful indicators to track knowledge development and research maturity in digital health [81,82].

3. Co-cited authors

A total of 21 co-cited authors were identified from a dataset of 29518 authors who had received at least 20 citations. Fig. 5 illustrates the co-cited author network, highlighting the most significant collaborative patterns. The analysis revealed three primary clusters. The top-ranked co-cited author overall, as well as the leading figure in the green cluster, is Wang Y., with 44 citations and a total link strength of 810. Zhang J. ranks second overall and first in the red cluster, with 23 citations and a total link strength of 644. Wang J. holds third place overall and second in the green cluster, with 36 citations and 628 total link strength. In the blue cluster, Wang L. emerges as the most frequently co-cited author, with 24 citations and a total link strength of 485. These findings indicate a concentration of scholarly influence among a select group of authors predominantly from East Asia whose work forms the intellectual backbone of NLP-related research in PCC, underscoring the global but regionally clustered nature of academic collaboration in this field.

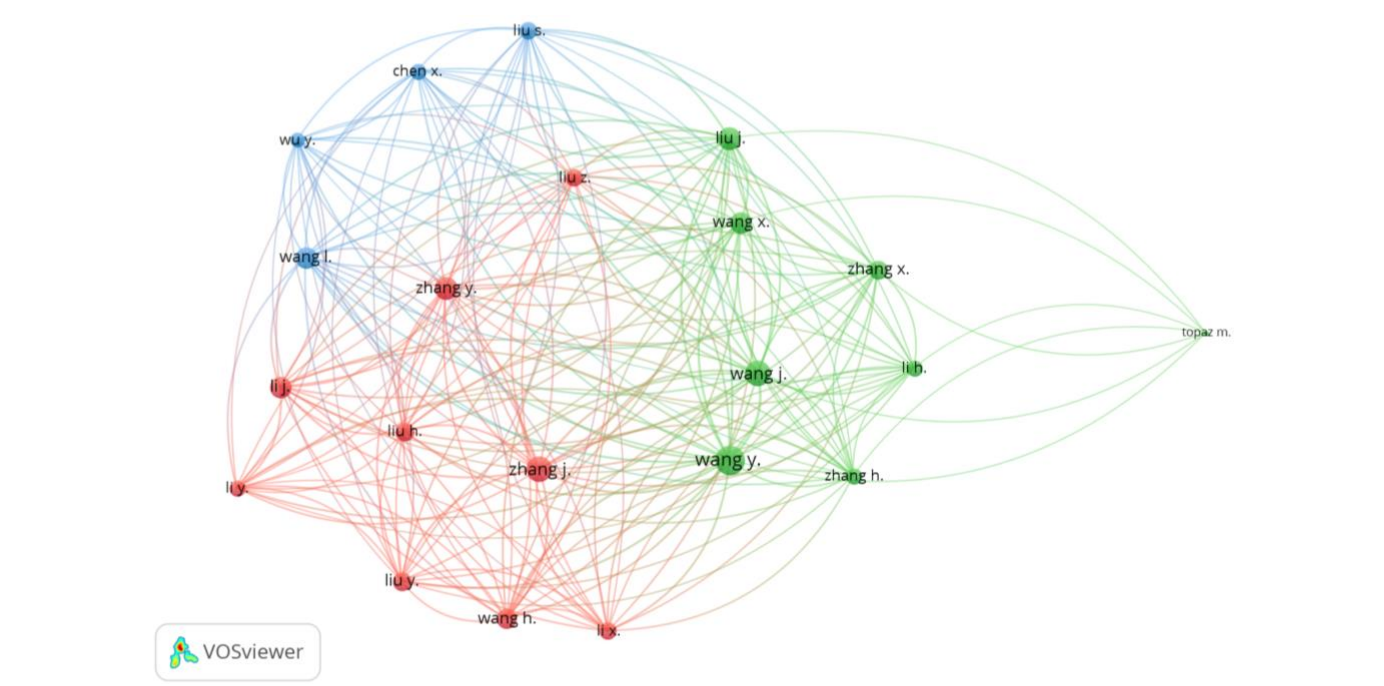

Fig. 5. Co-citation of cited authors on the application of NLP in PCC

B. Co-authorship analysis

Co-authorship in bibliometric analysis refers to the collaborative relationships between authors who publish together and is used to map scientific collaboration networks, identify key contributors in a field, and find potential partners for future research projects [83].

1. Co-authorship network

We conducted co-authorship analysis to determine the co-authors and countries in the area of study. Out of 1651 authors, we discovered 61 authors who have authored two or more papers, demonstrating regular participation and reiterated contribution to the area of research. Co-authorship analysis, as shown in Fig. 6, reveals that the author's team, led by Topaz and Maxim forms the most influential collaborative team in nursing informatics research on home health care, particularly in the unification of NLP and CDS systems. The majority of the authors in this group are at the Center for Home Care Policy & Research at VNS Health, New York, which is a hub for consolidating research in the field. Topaz, Maxim's two affiliations with Columbia University and the Data Science Institute further enhance cross-institutional collaboration. External partners such as Bowles, Kathryn H., and Song, Jiyoun of the University of Pennsylvania demonstrate significant interdisciplinary links between data science and nursing. Bibliometric metrics show topic coherence is high and collaboration for a span of 2022-2025, signifying maturity in research and strategic purpose in leveraging AI to support clinical decision-making for home care. The dominance of New York affiliations indicates a regional center of excellence that is leading the way in technology-based patient care innovation. In other words, this group is not only a representation of intensive collaboration, but also the main driving force in scientific development in the area of data-based nursing care digitalization. The structure of this network suggests strong internal collaboration within the dominant cluster, reflecting high thematic cohesion and research maturity. However, the limited presence of bridging authors between clusters highlights a relatively fragmented collaboration landscape overall. This implies opportunities for wider interdisciplinary and international collaboration to enhance knowledge integration across institutions and regions.

Collaborative networks, particularly those involving institutions from countries with strong research and

Corresponding author: Bima Ananta Putra, bimaap052@gmail.com, Master of Hospital Administration, Postgraduate Program, Universitas Muhammadiyah Yogyakarta, Jl. Brawijaya, Geblagan, Tamantirto, Kec. Kasihan, Kabupaten Bantul, Yogyakarta 55183, Indonesia.
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innovation systems (RIS), have been shown to positively influence citation impact and research quality [84]. However, international collaborations between countries with unequal RIS development may not always yield greater impact than domestic collaborations within high-performing systems.

Such interdisciplinary collaborations have also led to applied innovations, including the development of AI-based clinical decision support tools that integrate structured clinical data with NLP-derived insights. For instance, Topaz et al. proposed a CDS pipeline using time-series modeling and unstructured clinical text to predict hospitalizations in heart failure patients receiving home care, demonstrating real-world translational potential [85].

Notably, several highly cited studies, such as those ranked third and sixth in our analysis, were the result of international collaborations between institutions from high-income countries such as the United States and the United Kingdom. This suggests that cross-national partnerships within well-established research systems may contribute to greater visibility and citation impact, even if not always producing the absolute highest citation counts, aligns with previous bibliometric findings that international collaborations, particularly among high-income countries, tend to enhance research impact and accelerate knowledge diffusion in digital health domains [86].

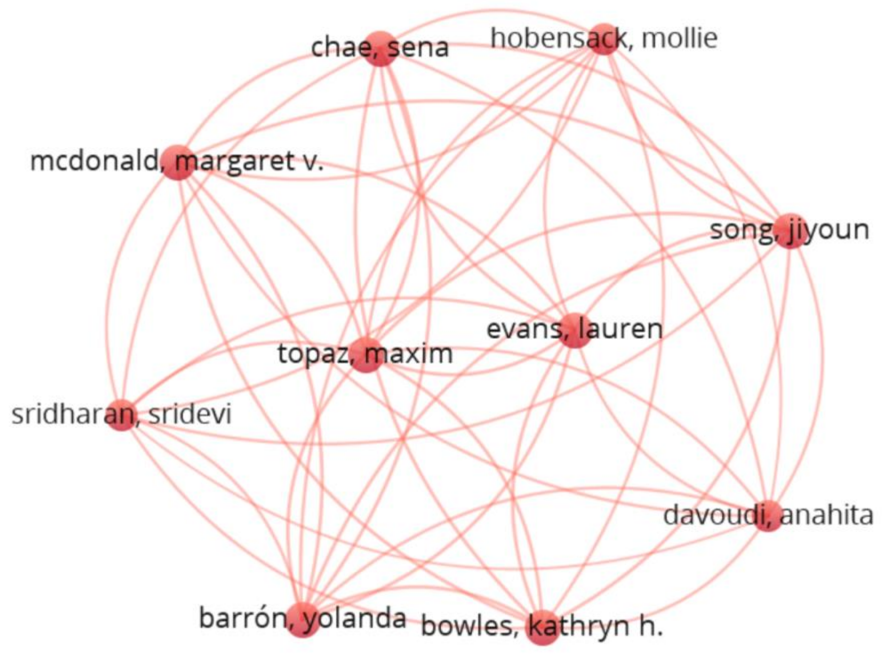

Fig. 6. **Co-authorship visualization**

2. Institutional partnership

Institutions with at least 2 publications in accordance with this theme were obtained from 1093 institutions; 19 met the threshold. Fig. 7 shows the most institutional partnership relationships. It was found that Anurag University has collaborated with Chitkara University in 2 different departments.

3. Country cooperation network

We identified 28 out of 58 countries with at least three publications, reflecting a broad international distribution of contributions in the field. The global collaboration network is visualized in Fig. 8, revealing seven major clusters based on research connectivity and intensity of collaboration in NLP for PCC. The United States holds the top position with 145 publications, 1,480 citations, and a total link strength of 64, underscoring its global leadership role in this area. The largest cluster (Cluster 1 – red) consists of Asian and Middle Eastern countries such as China, India, Japan, and Saudi Arabia, indicating a strong intra-regional research nexus. Cluster 2 (green) brings together Western and Central European nations like Germany, the Netherlands, and Spain, forming a well-connected regional network.

Cluster 3 (dark blue) includes the UK, France, Australia, and South Africa, suggesting active intercontinental collaborations. Cluster 4 (yellow), comprising Italy, South Korea, and Switzerland, displays more selective yet strategically valuable partnerships. Cluster 5 (purple) features Canada and Brazil, forming a bilateral research axis across the Americas. Cluster 6 (light blue) highlights collaborations between Ireland and Turkey, while Cluster 7 (orange) emphasizes the United States' central role in global research, particularly its strong connection with Israel. These findings underscore not only the global scope of research in NLP and PCC but also reveal the significance of regional and geopolitical patterns in shaping collaborative efforts.

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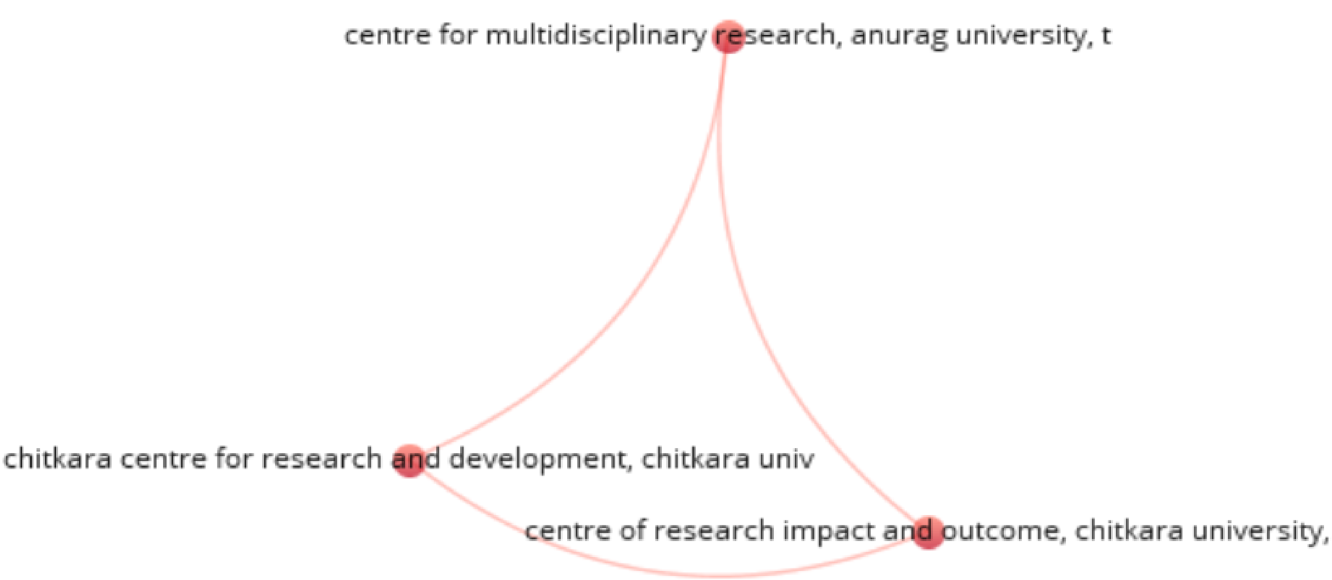

Fig. 7. Institutional partnership

These findings indicate that research on NLP in PCC has been on the rise globally, with diverse and systematic collaboration trends. The United States features multiple collaborations and high-citation and publication institutions, indicating that the United States is an important contributor to research and places the world first [87]. The existence of seven collaboration clusters indicates that geopolitical and geographical factors play a considerable role in building global scientific networks [88,89]. Not only does this collaboration pattern indicate interconnectivity between countries, but it also accelerates knowledge sharing between regions for the development of NLP technologies, driving PCC.

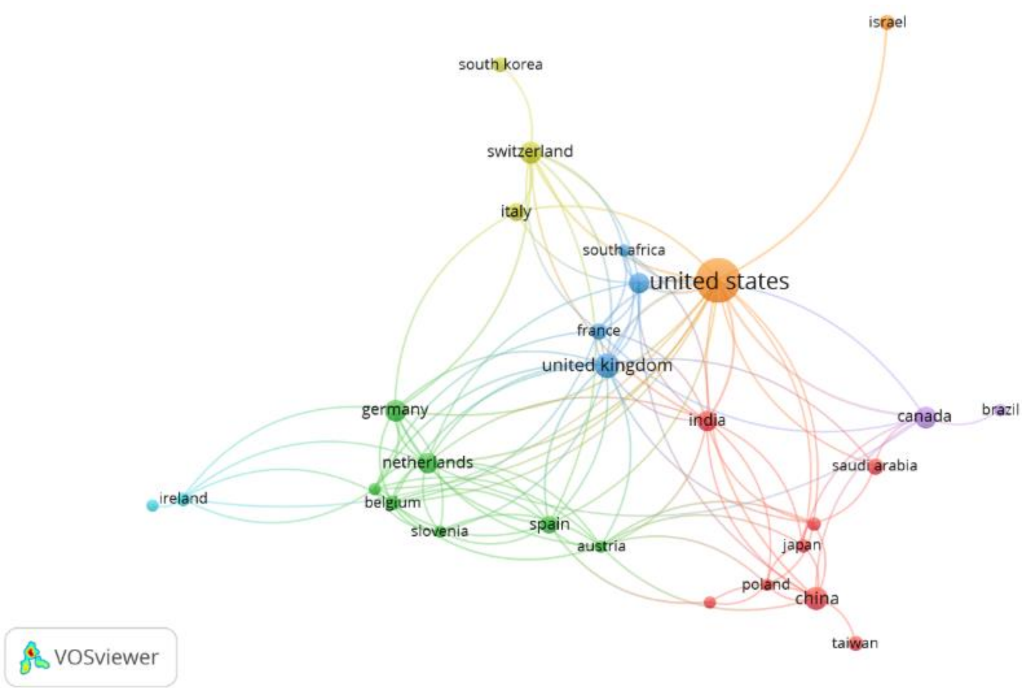

Fig. 8. Country cooperation network

While the findings highlight a broad international distribution and multiple regional collaboration clusters, there remains a notable disparity in research output between high-income countries (HICs) and low- and middle-income countries (LMICs). Most leading contributors, including the US, Western Europe, and parts of Asia, are countries with well-developed digital health infrastructures, advanced research ecosystems, and

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access to large-scale electronic health records. In contrast, many LMICs are either marginally represented or absent, which may reflect barriers such as limited funding, lack of NLP-capable data systems, and language or cultural mismatch with prevailing models. This imbalance raises important questions about the global equity of NLP innovations for PCC, particularly given the risk of developing models that fail to account for the linguistic, cultural, and healthcare system diversity found in underrepresented regions. Future bibliometric and implementation research should prioritize more inclusive, cross-regional collaborations to ensure that NLP tools are accessible, adaptable, and beneficial across a wider range of healthcare contexts.

C. Co-occurrence analysis

Co-occurrence analysis, which examines the simultaneous presence of terms within documents, is commonly used to identify effective search keywords and to evaluate the popularity, maturity, and impact of specific topics [83]. Among the 680 unique author keywords identified, 47 met the minimum occurrence threshold and were included in the co-occurrence network. These were grouped into five thematic clusters by VOSviewer based on the frequency and strength of co-occurrence among terms.

1. Keywords co-occurrence

The mapping reveals that NLP serves as a unifying thread that connects systemic, social, and patient perception-based approaches within the PCC ecosystem. Fig. 9 displays the keyword co-occurrence network derived from bibliometric analysis, revealing thematic clusters and relationships among frequently used terms. Table 5 provides a detailed interpretation of these clusters, outlining the main research themes and their interconnections.

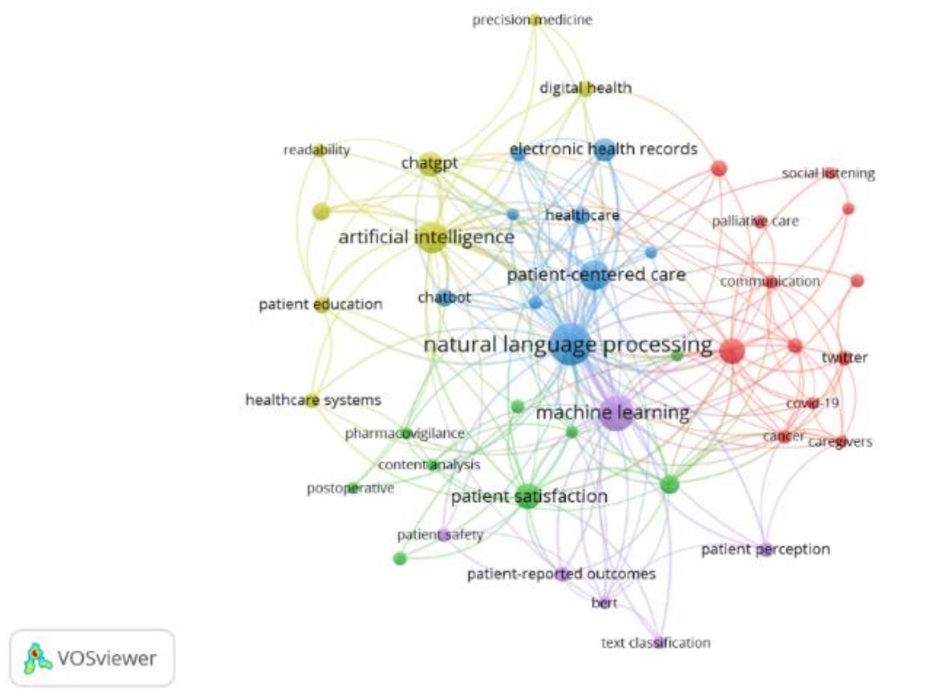

Fig. 9. Keywords co-occurrence network in the application of NLP for PCC

The co-occurrence keyword analysis reveals five thematic clusters illustrating how NLP supports PCC through a multidimensional integration. Clinical Systems & EHR (Cluster 3) serves as the central hub, embedding NLP into electronic health records and decision support systems (DSS). For example, studies have used NLP to extract smoking status, depression risk, or cancer symptoms from clinical notes to inform real-time decision-making (e.g., at Kaiser Permanente or the Veterans Health Administration). This supports personalized medicine by tailoring treatments based on longitudinal patient data [90]. Social Media & Communication (Clusters 1) and Patient Evaluation & Satisfaction (Cluster 2) represent patient-driven inputs. For instance, sentiment classification and topic modeling applied to patient tweets and online reviews help identify emotional tone, satisfaction levels, and emerging concerns, insights that can inform both organizational quality improvement and patient outreach strategies. Additionally, social media platforms provide unprompted, real-time feedback, which contrasts with more structured but delayed survey instruments. However, while NLP enhances these analyses, the reliability of social media content remains challenged by data sparsity, user anonymity, and lack of clinical context, underscoring the need for cautious interpretation and ethical safeguards. NLP has been applied to analyze health-related social media posts during crises like COVID-19 to track sentiment and misinformation, while in clinical settings, tools such as Qualtrics or IBM Watson mine patient feedback surveys to guide service improvement.

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AI-Powered Patient Empowerment (Cluster 4) reflects the rise of generative and conversational AI, such as ChatGPT and Woebot, being piloted for health coaching, behavior change encouragement, and self-management in chronic illness. While still experimental, such tools show promise in enhancing health literacy and adherence to care plans. Modeling Perceived Quality of Care highlights research using NLP to analyze subjective expressions in patient narratives, such as online reviews or clinical communication logs, to model perceptions of empathy, satisfaction, and trust. For instance, NLP has been used to detect emotional cues in oncology consultations to improve relational care. NLP enhances sentiment analysis in patient feedback, categorizing emotions and predicting patient outcomes based on textual information from clinical narratives and online health discussions [47,91]. Digitization & Adaptive AI (Cluster 4) acts as a digital enabler, with tools like ChatGPT enhancing and encouraging behavior change [92]. Finally, Deep Learning for Patient Perception (Cluster 5) utilizes advanced NLP techniques to model patient-reported outcomes and subjective evaluations by analyzing patient experiences [8,93]. These applications highlight the growing role of NLP in PCC, where analyzing unstructured data such as narratives and online discussions provides actionable insights for improving healthcare delivery and personalization [94–96]. The strength and interconnectivity of these clusters also reflect the thematic cohesion of the research field. The central position and high linkage of the blue cluster, comprising "natural language processing," "electronic health records," and "patient-centered care," illustrate a mature and well-integrated domain. In contrast, peripheral clusters such as those involving "social listening" and "BERT" show lower connectivity, pointing to areas where research is still evolving or fragmented.

Table 5. Thematic Clusters of Keyword Co-occurrence in NLP Applications for PCC

Cluster	Thematic Focus	Key Keywords	Relevance to PCC
Red – Social Media & Communication	Public Perception Analysis and Patient Communication through Social Media	twitter, communication, caregivers, social listening, COVID-19, palliative care	Amplifies real-time patient experiences to shape context-aware service responses
Green – Patient Evaluation & Satisfaction	Feedback Analysis and Patient–Healthcare workers Relationship	sentiment analysis, patient satisfaction, pharmacovigilance, content analysis, postoperative	Explores satisfaction and experiences to directly improve healthcare services
Blue – Clinical Systems & EHR	Integration of NLP with Clinical Information Systems and Decision Support Systems (DSS)	EHR, chatbot, clinical informatics, decision support system, patient-centered care	Enhances care personalization and system efficiency
Yellow – Digitization & Adaptive AI	AI Technologies for Patient Education and Empowerment	ChatGPT, AI, digital health, health literacy, patient education, readability	Improves health literacy and patient engagement in care decisions
Purple – Deep Learning for Patient Perception	Patient Perception Modeling from Textual Data	BERT, patient perception, patient-reported outcomes, text classification	Enables automated assessment of patient perceptions and outcomes

Despite growing interest, several critical research gaps remain. Few studies have integrated multimodal data, such as structured EHRs and unstructured social media, into unified analytical frameworks. The effectiveness of generative AI in patient engagement is largely anecdotal, with limited empirical validation. Real-time sentiment-informed decision tools at the point of care remain underdeveloped, and longitudinal NLP studies tracking patient perceptions across care episodes are rare. Additionally, the ethical challenges, particularly around bias, consent, and data privacy in social media mining, require more explicit attention.

There are several critical research gaps in the application of NLP for PCC that warrant further exploration. First, few studies have integrated multimodal data, such as structured EHR and unstructured social media content, into a single analytical framework. Second, the effectiveness of generative AI models like ChatGPT in enhancing health literacy and patient engagement remains largely unproven empirically. Third, innovations are needed to develop real-time feedback systems that combine sentiment analysis with clinical decision support at the point of care. Fourth, there is a scarcity of longitudinal NLP-based research mapping shifts in patient perceptions throughout the care cycle. Lastly, ethical and privacy concerns, especially regarding the use of social media data, require more rigorous attention. These include issues of data consent, representational bias, and the appropriate boundaries of surveillance in patient-facing NLP applications.

In addition to these technical gaps, current applications of NLP for PCC present unresolved ethical challenges. For example, studies that utilize social media data often overlook issues of user consent and privacy, despite the sensitive nature of publicly shared health information. Furthermore, the deployment of generative AI models like

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ChatGPT raises concerns around the accuracy of information, potential amplification of bias, and the lack of transparency in outputs. These concerns are particularly acute when AI is used to inform patient understanding or clinical decisions. Addressing such ethical dilemmas, especially regarding data provenance, algorithmic bias, and accountability, is critical to developing trustworthy and equitable NLP systems for PCC.

2. Density visualization

Based on the density visualization, as shown in Fig. 10, it can be concluded that research in the context of NLP and PCC is highly concentrated around core topics such as "natural language processing", "machine learning", "artificial intelligence", and "patient-centered care" itself. The density visualization reflects a close research focus on flagship technologies such as NLP, ML, and AI, along with the core concept of PCC. This reflects the current dominance of AI-driven approaches to revolutionizing healthcare provisioning, where AI might provide customized experiences depending on patients' individual needs [97]. The new centrality of "ChatGPT", "patient satisfaction", and "digital health" as high-density nodes is a result of the growing deployment of generative AI (GAI) models within healthcare. Use cases like ChatGPT and DALL-E are being used on a wide range of applications from personalized care to medical imaging, mental health support, and patient communication, signifying the transition towards more interactive, anticipatory, and patient-sensitive care systems [98]. This change reflects a move away from retrospective data analysis and toward proactive, dialogue-based models of healthcare with a focus on real-time interaction and personalized delivery of services in line with patient specifications.

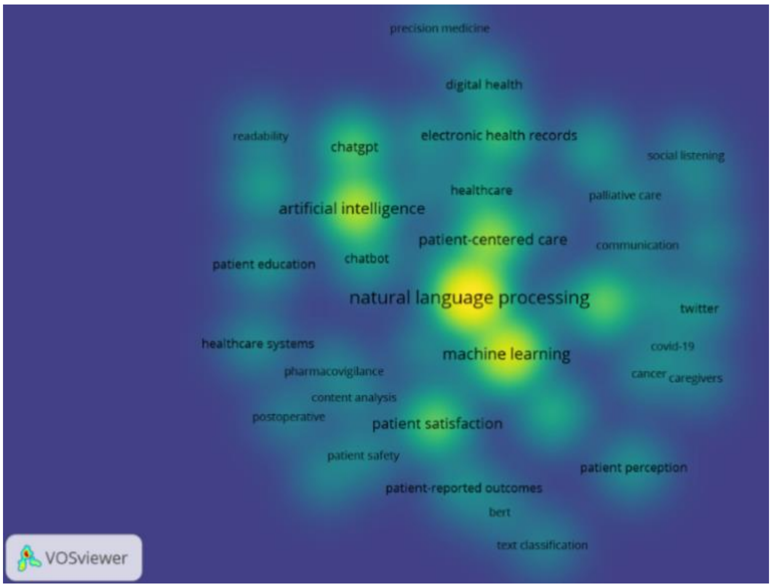

Fig. 10. Keywords density visualization in the application of NLP for PCC

Density in this context signifies the intensity of co-occurrence of keywords, indicating areas of sustained scholarly attention. High-density nodes such as "natural language processing" and "machine learning" suggest mature topics with significant academic output, while lower-density nodes such as "social listening" or "chatbot personalization" represent emerging themes with limited but growing exploration.

However, certain areas remain under-researched, though they possess high potential. For instance, content analysis and social listening are yet to be extensively studied as tools for comprehensively collecting patient voices via social media, though this tool can offer patient perception in real time and needs insight. Moreover, integrating models such as BERT and other transformer models into electronic health records (EHRs) is still limited, especially in adding contextual meaning and improving patient experience. The explainable AI dimension has similarly remained poorly explored in spite of its key responsibility of building user trust in AI systems. Further, applying NLP to detect and mitigate patient safety hazards is similarly not an intensively explored area. Lastly, patient-specific chatbot response is thinly studied in spite of being very relevant to enhancing good and empathetic communication.

Several low-density domains represent areas of study yet to be extensively investigated, such as the use of NLP to capture the patient voice through social media in the context of PCC and developing explainable AI that can be understood by patients as well as healthcare professionals. Additionally, the modification of transformer models like BERT and large language models to EHRs remains in its infancy, namely in quantifying trust and patient satisfaction. The connection between NLP and patient safety issues, such as predicting adverse events, is also unexplored. On the other hand, the personalization of chatbot responses based on cultural context and individual preferences is still rarely studied, indicating a substantial gap in the inclusive and responsive application of technology to meet patient needs.

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3. Overlay visualization

The research focus on the application of NLP to PCC experienced a significant shift from 2022 to 2024. Fig. 11 displays an overlay visualization of the shift in research focus according to the author's keywords. Meanwhile, this thematic shift is shown in Table 5 along with its relevance to PCC. Recent bibliometric data indicate a dramatic shift in the trend of studies relating to the usage of NLP for PCC. What used to be utilized solely as a retro-analytical tool is more and more utilized in more proactive and interventionistic roles. Some examples of such utilization include chatbots, clinical decision support systems, and AI-enabled platforms for patient education. There is also growing interest in generative AI technologies, such as ChatGPT, since they have the potential to simplify complicated medical information for patients. There is also greater usage of keywords such as "experience," "palliative care," and "mental health" as an indication of a broader movement towards more empathic, human-centered health technologies. Another significant advancement is the incorporation of NLP in precision medicine, with the goal of personalizing communication and interventions according to the literacy, preferences, and contextual demands of individual patients.

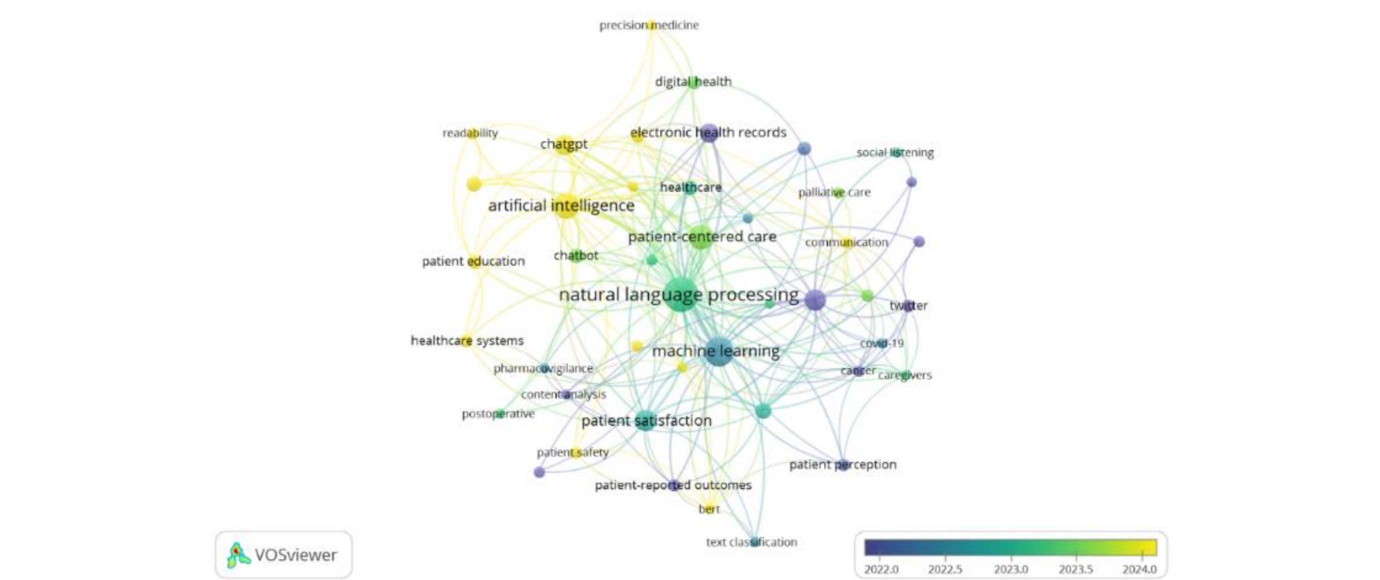

Fig. 11. Keywords overlay visualization in the application of NLP for PCC

This shift in research emphasis mirrors wider changes reported in recent literature. NLP technologies are being more and more integrated into clinical workflows to allow real-time engagement, assist in clinical decision-making, and contribute to the creation of high-quality and diverse datasets essential for training reliable AI systems for healthcare settings [99]. Generative AI models such as ChatGPT have proven to be extremely promising in simplifying intricate medical terminology into simplified language, thereby enhancing patient comprehension and allowing informed decision-making [100]. Moreover, growing focus on concerns like patient experience, palliative care, and mental health points to a technological shift towards more empathic, ethics-focused, and emotionally supportive healthcare models in which technology is applied to augment, not replace, human elements of care [101]. Finally, NLP adoption in precision medicine is indicative of moving towards more individualized, contextualized treatment that is sensitive to each patient's literacy level, values, and preferences, principles central to PCC [102]. This reflects the broader paradigm of human-centred AI in healthcare, which emphasizes aligning technological innovation with ethical principles, patient autonomy, and shared decision-making to strengthen PCC [103–105]

As the enriched literature on NLP application in PCC grows, the overlay visualization foresees a great research deficit that portends directions for future exploration. Such an evolving landscape is one of a shift from a passive era, where patients were largely seen through data, to an activist one, characterized by real-time participation and patient empowerment through AI-facilitated tools. For complete realization, researchers and digital health clinicians must move beyond retrospective analysis and begin to create adaptive, interactive, and tailored NLP interventions that support decision-making and patient empowerment. This development, however, will also necessitate the creation of considerable evaluation frameworks to conduct systematic assessments of the effectiveness, safety, and ethical implications of applying NLP/AI technologies directly in personalized care workflows. Closing these gaps is crucial to allow the contribution of NLP research to find a useful place in patient outcomes without losing trust and humanity in digital health spaces.

This study provides a focused bibliometric analysis of the application of NLP in PCC by systematically retrieving and evaluating literature indexed in the Scopus database between 2015 and 2025. The main strength of this research lies in its methodological rigor, using multiple analytic tools such as OpenRefine, MS Excel, and VOSviewer to comprehensively map publication trends,

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thematic clusters, co-authorship networks, and citation structures. This multifaceted approach successfully identifies major research themes, geographic contributions, and evolving directions in the field. Moreover, by highlighting underexplored areas, the study offers valuable guidance for future scholarly inquiry. However, limitations exist, primarily the reliance on a single database (Scopus), which may exclude relevant publications from other scholarly platforms. Additionally, while the keyword search strategy was broad, certain interdisciplinary or emerging terminologies may have been overlooked. The exclusion of non-English documents and the emphasis on final-stage journal articles might also narrow the scope of findings. These constraints may introduce language and database selection biases, which can affect the representativeness of the global research landscape. These limitations suggest the need for future research that incorporates broader data sources and mixed-method approaches for deeper thematic understanding.

Furthermore, the current literature often lacks critical engagement with ethical considerations, such as algorithmic bias, data privacy, and transparency, highlighting a need for future bibliometric and qualitative studies that explicitly examine these dimensions. In addition to these ethical gaps, there are notable methodological limitations within the current body of research. Many studies rely on small, institution-specific datasets, which limit the generalizability of findings. There is also a scarcity of longitudinal studies, making it difficult to assess the long-term impact of NLP applications on patient outcomes or care processes. Moreover, external validation of NLP models, particularly across diverse healthcare settings and populations, is often insufficient, raising concerns about their readiness for clinical integration. These limitations highlight the need for more robust study designs, including larger, multisite cohorts and cross-validation techniques, to better evaluate the real-world performance and equity implications of clinical NLP tools. Future research should also incorporate broader data sources and mixed-method approaches to enable deeper thematic, contextual, and ethical insights that can support the safe and effective translation of NLP into PCC practice.

V. Conclusion

This bibliometric study maps the development of NLP research in PCC between 2015 and 2025. The findings indicate a growing trend in publication output, especially from high-income countries with strong digital health ecosystems. Five main research themes emerged: public perception analysis and patient communication through social media, feedback analysis and patient–healthcare workers relationship, integration of NLP with Clinical DSS, AI technologies for patient education and empowerment, and patient perception modeling from textual data. Despite these advancements, critical research gaps persist. These include the limited integration of multimodal data, underdeveloped real-time feedback systems, and a lack of longitudinal studies on patient perceptions. Additionally, explainable AI, ethical considerations, personalized chatbot responses, and the application of advanced models like BERT in EHR systems remain underexplored. The field is shifting from passive data analysis to active, real-time patient engagement, but more adaptive and trustworthy interventions are needed. Future research should focus on integrating structured and unstructured data sources (e.g., EHRs and social media), developing real-time sentiment-based decision support systems, designing explainable and culturally adaptive NLP models, and conducting longitudinal evaluations of patient experience over time. However, current studies reveal several ethical challenges, such as algorithmic bias disproportionately affecting marginalized groups, a lack of transparency in model decision-making, and potential privacy breaches from unstructured data use. Addressing these dilemmas requires not only technical solutions but also robust interdisciplinary collaboration across clinical, computational, and ethical domains. This study provides a foundational roadmap to guide future research and innovation toward more inclusive, ethical, and effective NLP applications in patient-centered healthcare.

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Corresponding author: Bima Ananta Putra, bimaap052@gmail.com, Master of Hospital Administration, Postgraduate Program, Universitas Muhammadiyah Yogyakarta, Jl. Brawijaya, Geblagan, Tamantirto, Kec. Kasihan, Kabupaten Bantul, Yogyakarta 55183, Indonesia.
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Corresponding author: Bima Ananta Putra, bimaap052@gmail.com, Master of Hospital Administration, Postgraduate Program, Universitas Muhammadiyah Yogyakarta, Jl. Brawijaya, Geblagan, Tamantirto, Kec. Kasihan, Kabupaten Bantul, Yogyakarta 55183, Indonesia.
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AUTHOR BIOGRAPHY

dr. Bima Ananta Putra is a researcher from the Master of Hospital Administration, Postgraduate Program, Universitas Muhammadiyah Yogyakarta, Indonesia. His primary research interests are concentrated in the vital fields of Health and Hospital Administration, where he seeks to improve operational efficiency, patient care quality, and overall healthcare system management. His scholarly work contributes valuable insights to the evolving landscape of healthcare services in Indonesia and beyond. A proponent of academic transparency and collaboration, his detailed research profile and publication history are accessible through his ORCID ID 0009-0003-3085-7240. Dr. Putra is open to connecting with fellow researchers and professionals and can be reached for correspondence via email at bimaap052@gmail.com.

Dr. Merita Arini, MMR, earned her Bachelor of Medicine and Medical Profession from the Faculty of Medicine at the University of Muhammadiyah Yogyakarta. She received a full scholarship to pursue a Master’s in Hospital Administration while completing her medical studies at the same university. Dr. Merita finished her studies in the Doctoral Program in Medical and Health Sciences at the Faculty of Medicine, Public Health, and Nursing, Universitas Gadjah Mada, in 2021. Dr. Merita’s research focuses on public health and health administration, particularly quality healthcare and national health programs. She also served as a UMY Postgraduate

Corresponding author: Bima Ananta Putra, bimaap052@gmail.com, Master of Hospital Administration, Postgraduate Program, Universitas Muhammadiyah Yogyakarta, Jl. Brawijaya, Geblagan, Tamantirto, Kec. Kasihan, Kabupaten Bantul, Yogyakarta 55183, Indonesia.
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Program Quality Assurance Unit member during that time. She is a member of the National Tuberculosis Research Network and The Aisyiyah National Health Assembly. She has experience as a medical advisor for a national start-up telemedicine platform and is active as a health educator on multiple platforms. Furthermore, Dr. Merita is a national primary healthcare accreditation assessor. She is also active as a reviewer in national and international reputable journals. Her research profile can be found at ORCID ID 0000-0001-5193-6050. She can be reached for correspondence via email merita.arini@umy.ac.id

dr. Yoviena Kusuma Terichtia Tamaranny is a researcher from the Master of Women's Health, Postgraduate Program, University College London, United Kingdom.. Her academic focus and research interests are deeply rooted in the broader fields of Health and Medicine, with a specialized concentration on women's health issues. She established a strong foundation for her research career by obtaining her undergraduate degree from the Faculty of Medicine at Universitas Islam Indonesia. Her early scholarly work included an undergraduate thesis investigating "Hubungan Antara Tingkat Kecemasan Dengan Nyeri Dismenore Primer Pada Mahasiswi Fakultas Kedokteran Universitas Islam Indonesia Angkatan 2015." Dr. Tamaranny welcomes academic and professional correspondence and can be reached via email at yovienak.terichtia@gmail.com

Corresponding author: Bima Ananta Putra, bimaap052@gmail.com, Master of Hospital Administration, Postgraduate Program, Universitas Muhammadiyah Yogyakarta, Jl. Brawijaya, Geblagan, Tamantirto, Kec. Kasihan, Kabupaten Bantul, Yogyakarta 55183, Indonesia.
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