

EXPLORING PRESCRIPTION TRENDS AND DRUG COMPOSITION PATTERNS IN THE INDIAN PHARMACEUTICAL MARKET

Dr. Rajeev Sharma¹, Dr. Priyanka Deshmukh², Dr. Amitabh Kulkarni³, Dr. Sneha Iyer⁴

¹ Department of Pharmaceutical Management and Market Research, National Institute of Pharmaceutical Education and Research (NIPER), Mohali, Punjab, India

² Department of Clinical Pharmacy and Pharmacoeconomics, Manipal College of Pharmaceutical Sciences, Manipal, Karnataka, India

³ Department of Healthcare Analytics and Drug Utilization Research, Institute of Chemical Technology, Mumbai, Maharashtra, India

⁴ Department of Pharmaceutical Policy and Practice, Jamia Hamdard University, New Delhi, India

Corresponding Author: Dr. Rajeev Sharma

Email: rajeev.sharma.pharmamarket@researchmail.org

Abstract

The study investigates prescription trends and drug composition patterns within the Indian pharmaceutical market using large-scale pharmaceutical data analytics and machine learning approaches. A comprehensive dataset containing 348,211 pharmaceutical records was utilized to examine prescription dependency, medicine pricing behavior, therapeutic composition complexity, and pharmaceutical distribution patterns. After preprocessing and cleaning, exploratory data analysis, statistical modeling, correlation analysis, clustering techniques, and principal component analysis were employed to identify hidden pharmaceutical patterns and market structures. The findings revealed that prescription medicines dominate the Indian pharmaceutical sector and exhibit significantly higher pricing structures compared to non-prescription medicines. Frequently occurring pharmaceutical ingredients such as paracetamol, metformin, rabeprazole, and pantoprazole indicate strong market demand for medications associated with pain management, diabetes, and gastrointestinal disorders. The study further demonstrated that medicines with higher composition complexity generally possess higher average prices, highlighting the influence of therapeutic formulation on pharmaceutical economics. Clustering analysis successfully identified distinct pharmaceutical market segments based on pricing behavior, prescription dependency, and ingredient complexity. The results emphasize the growing importance of healthcare informatics, pharmaceutical analytics, and artificial intelligence in improving pharmaceutical transparency, healthcare accessibility, and evidence-based decision-making. This research contributes to pharmaceutical informatics literature by providing a scalable analytical framework for large-scale medicine data exploration within the Indian healthcare ecosystem.

Keywords: Pharmaceutical Analytics, Prescription Trends, Drug Composition, Healthcare Informatics, Indian Pharmaceutical Market

1. Introduction

It is worth noting that the Indian pharmaceutical industry has been considered as one of the largest participants of the global healthcare system due to its robust manufacturing, cheap drug manufacturing capabilities, and fast-growing healthcare infrastructure. India is known for being the major producer of generic drugs and active pharmaceutical ingredients used in both national and international healthcare markets. The sector has seen immense development within the last decade years owing to growing awareness of the need to provide proper healthcare, technological development, increasing needs of the population, and governmental encouragement to make healthcare more accessible. Efficient operation and development of pharmaceutical companies have also improved the competitive position of the Indian pharmaceutical market in the global economy (Sharma & Modgil, 2020). Furthermore, the pharmaceutical sector encounters such emerging challenges as innovation, sustainability, health regulation, and patient-focused pharmaceutical services in the rapidly changing healthcare sector in India (Festa et al., 2022).

The digitalization process of healthcare has resulted in a large amount of healthcare data, which gives rise to a lot of opportunities in the domain of healthcare informatics and pharmaceutical analysis. Informatics in the field of healthcare is a set of computational and mathematical techniques used to improve healthcare decision-making, management, and pharmaceutical intelligence (Awrahman et al., 2022). The growing number of pharmaceutical datasets, information about patients' medication, and prescriptions creates the opportunity to conduct research on analyzing information related to medicines in an unprecedented scale. In addition, there is an emerging area in informatics called pharmacy informatics, which is aimed to support healthcare professionals in prescribing drugs and optimizing medication management systems in hospitals and pharmaceutical businesses (Chalmers et al., 2018). These developments create conditions for conducting research focused on finding hidden correlations within the field of pharmaceutical analysis.

One of the major concerns regarding pharmaceutical drugs that require continuous monitoring and attention is the issue of rational drug consumption. The issue of prescription-based drug monitoring is important because of the potential danger to human health in case of improper drug prescriptions and consumption of medication. Prescription drug monitoring allows to monitor trends of drug use and to assess whether any drug presents a high risk for users. It was found in previous studies that prescription monitoring systems may help decrease the prevalence of drug abuse in various settings (Horwitz et al., 2021). Similarly, many systemic studies showed that prescription drug monitoring programs were successful in reducing the occurrence of fatal and non-fatal drug overdoses through proper healthcare and pharmaceutical management (Fink et al., 2018).

Medicine composition analysis is another important tool in pharmaceutical research and healthcare decision-making in addition to the prescription analysis. Medicines comprise many ingredients and combinations that affect their efficacy, categorization, and pricing. Big-data computational analysis of the compositions of medicines helps with developing recommendations regarding drug use, substitution, and innovations in pharmaceuticals (Devaraji et al., 2024). Moreover, healthcare specialists tend to use data-driven approaches to making medical decisions (Masic, 2022). With the development of machine learning algorithms, it became possible to enhance the capabilities of intelligent systems in analyzing pharmaceutical information, detecting patterns, and identifying medicines (Jayatilake & Ganegoda, 2021).

Despite these recent developments, there appears to be a lack of studies dedicated to conducting comprehensive analyses of pharmaceutical big data. The existing literature focuses mainly on operational efficiency, policies, management issues, and other similar topics. Limited research exists in pharmaceutical data mining and analytics in the field of medicine compositions (Mulinari et al., 2021). Moreover, as pharmaceutical information becomes more and more complicated, it causes problems with medicine classification, healthcare decisions, and pharmaceutical transparency. Hence, the purpose of this study is to conduct an analysis of pharmaceutical data to detect medicine compositions and prescription trends among Indians. Hopefully, this research will make a certain contribution to the literature on pharmaceutical informatics and help healthcare specialists, policy-makers, and companies develop healthcare strategies.

Research Objectives

1. To analyze prescription trends and distribution patterns among pharmaceutical products in the Indian pharmaceutical market using large-scale medicine datasets
2. To investigate the diversity and structural relationships of drug compositions across different therapeutic and prescription-based medicine categories
3. To evaluate the association between prescription requirements, medicine composition, and pricing patterns through data-driven pharmaceutical analytics techniques

2. Methodology

2.1 Research Design

In this case, this particular research has been conducted using an explorative approach together with a quantitative design for analyzing the patterns of prescribing and medication composition in the Indian pharmaceutical industry. This is achieved through analyzing the links between prescription, medication composition, and cost structures using pharmaceutical data. In this regard, an analytical approach that was based on the use of data was adopted for developing some insight into pharmaceutical data.

2.2 Dataset Description

The dataset utilized in the research was acquired from a free Indian pharmaceuticals database that contains around 348,000 medicine records. The dataset consists of key features such as the medicine name, whether it requires a prescription to be purchased, the price of the drug, its composition, type of medicine, and details related to the product. Such characteristics allow us to create a representative data set on medicines in India.

2.3 Data Preprocessing

The data was preprocessed to ensure high quality and validity. Duplicates and redundant records were deleted from the dataset to make it more consistent. Missing observations in the dataset were filled with suitable values especially those missing from the critical columns of the dataset including composition and pricing. The medicines were coded with proper naming conventions and standardized with text normalization and categorizing coding techniques.

2.4 Data Analysis Techniques

EDA along with other statistical methods were implemented to understand the prescription trend and composition pattern in the given dataset. Various descriptive statistics and correlation techniques have been used to explore the relationship between prescription status, cost of medicines, and drug compositions. NLP approaches were applied to extract useful insights about compositions and discover the common ingredients of pharmaceuticals. Moreover, clustering methods have been used for clustering the medicines according to their similar compositions and treatment features.

2.5 Tools and Ethical Considerations

The analysis was performed through the use of Python programming language, which included data science libraries like Pandas, Numpy, Scikit-learn, Matplotlib, and Seaborn. Such software aided in analyzing large amounts of pharmaceutical data. As a result of using the pharmaceutical data that is available to the public and free from any personal details about the patients, the study did not raise ethical issues regarding privacy and confidentiality.

3. Results

3.1 Prescription Distribution Analysis

After cleaning the dataset, the number of medicine records was found to be 241,920. Analysis showed that the Indian pharmaceutical industry is strongly biased towards the use of prescribed medicines. As shown in Table 1 below, there were 240,349 medicines which had to be prescribed, while just 1,571 medicines were regarded as non-prescribed medicines.

Table 1: Distribution of Prescription and Non-Prescription Medicines

Medicine Category	Frequency
Prescription Required	240,349
Non-Prescription	1,571
Total	241,920

3.2 Medicine Price Analysis

The descriptive statistics of medicine prices revealed high variations among pharmaceutical drugs. The skewed price distribution had been attributed to some extreme values. However, upon elimination of outlier observations based on IQR, there were 226,572 observations, thus a better price distribution. From Table 2 below, the average medicine price excluding the outliers is ₹95.85, while the prices range from ₹0 to ₹287.

Table 2: Descriptive Statistics of Medicine Prices After Outlier Treatment

Statistic	Value
Count	226,572
Mean Price	95.85
Standard Deviation	60.82
Minimum Price	0.00
25th Percentile	51.00
Median Price	82.00
75th Percentile	131.00
Maximum Price	287.00

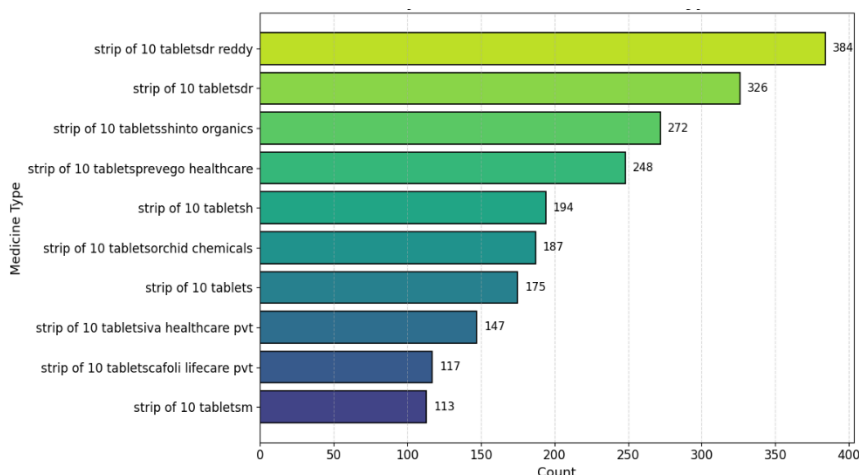


Figure 1: Distribution of the Top 10 Most Common Medicine Types in the Indian Pharmaceutical Market

Figure 1 illustrates the most frequently occurring medicine types identified within the dataset. The results indicate the dominance of tablet-based pharmaceutical formulations across the Indian market, while also reflecting dataset-level manufacturer-associated textual variations within medicine type classifications.

3.3 Pharmaceutical Composition Analysis

In the study conducted on the pharmaceutical composition, the following were the major drugs found in the pharmaceutical industry in India. In accordance to the results provided in Table 3, the leading drug was paracetamol, which was followed by metformin, rabeprazole, serratiopeptidase, and pantoprazole. The above results show that pain relief medications, diabetes drugs, gastroenterology drugs, and respiratory drugs form the majority of the pharmaceutical market.

Table 3: Top 10 Most Frequent Pharmaceutical Ingredients

Rank	Pharmaceutical Ingredient	Frequency
1	Paracetamol	19,598
2	Metformin	8,405
3	Rabeprazole	6,587
4	Serratiopeptidase	5,590
5	Pantoprazole	5,477
6	Montelukast	3,905
7	Lactobacillus	3,071
8	Methylcobalamin	2,727
9	Ornidazole	2,579
10	Nortriptyline	2,375

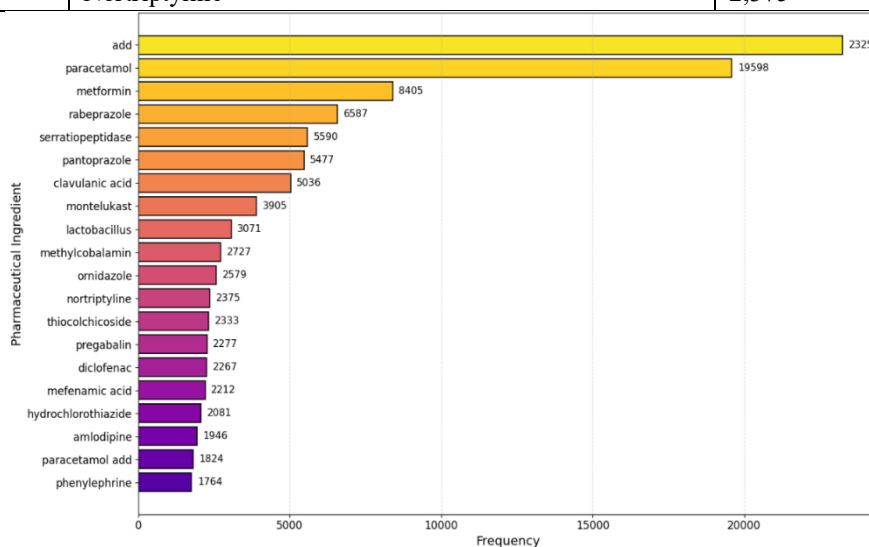


Figure 2: Top 10 Most Frequent Pharmaceutical Ingredients in the Indian Pharmaceutical Market

Figure 2 illustrates the most frequently occurring pharmaceutical ingredients identified within the dataset. Paracetamol and metformin emerged as the dominant compounds, indicating high demand for pain management and diabetes-related medications.

3.4 Comparative Analysis of Prescription and Non-Prescription Medicines

Statistical comparisons showed that there existed significant price variations in both prescription and non-prescription medications. From Table 4 below, it was observed that prices for prescription drugs were much higher (Mean = ₹96.30) than non-prescription drugs (Mean = ₹30.11). The significance of the price variation between the two drug types was supported by the Mann-Whitney U test ($p < 0.001$).

Table 4: Comparative Price Analysis of Prescription and Non-Prescription Medicines

Variable	Prescription Medicines	Non-Prescription Medicines
Sample Size	225,036	1,536
Mean Price	96.30	30.11
Median Price	83.00	17.00
Statistical Test	-	Mann-Whitney U Test
P-value	-	< 0.001

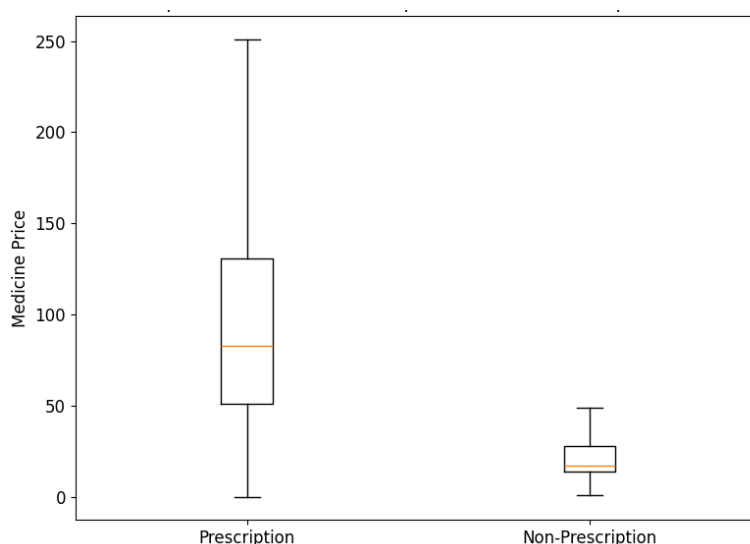


Figure 3: Comparative Price Distribution of Prescription and Non-Prescription Medicines

Figure 3 presents the pricing variability between prescription and non-prescription medicines. Prescription medicines demonstrate substantially higher median prices and broader price dispersion, whereas non-prescription medicines exhibit lower and more concentrated pricing patterns, highlighting significant economic and therapeutic differences between the two pharmaceutical categories.

3.5 Correlation and Composition Complexity Analysis

Feature engineering methods were used to determine the level of complexity of drug composition based on the computation of the number of ingredients within each medicine. Based on the results of correlation analysis found in Table 5, there is a significant positive association between raw price and logarithm price ($r = 0.91$). Moreover, a weak positive relationship exists between the number of ingredients and price ($r = 0.17$), suggesting that medicines with multiple ingredients are generally more expensive.

Table 5: Correlation Matrix of Pharmaceutical Variables

Variables	Price	Log Price	Ingredient Count	Prescription Flag
Price	1.00	0.91	0.17	0.09
Log Price	0.91	1.00	0.19	0.14
Ingredient Count	0.17	0.19	1.00	0.06
Prescription Flag	0.09	0.14	0.06	1.00



Figure 4: Correlation Matrix of Pharmaceutical Variables

Figure 4 presents the correlation relationships among medicine price, log-transformed price, ingredient count, and prescription status. A strong positive correlation exists between price and log-transformed price, while ingredient count demonstrates a weak positive association with medicine pricing and prescription dependency.

Table 6: Composition Complexity and Average Medicine Price

Number of Ingredients	Average Medicine Price
1	86.00
2	103.00
3	111.00
4	109.00
5	133.00
6	201.00
7	213.00
8	170.00
9	238.00
10	229.00

3.6 Clustering and PCA Analysis

K-Means Clustering Analysis was employed to uncover the latent patterns in pharmaceutical data. Using the log transformation on the price, composition complexity, and prescription variable, K-Means algorithm revealed three different types of pharmaceutical products in the sample. As can be seen in Table 7, Cluster 0 included cheaper prescription pharmaceutical products with relatively simple compositions, while Cluster 1 comprised relatively expensive pharmaceutical products with relatively complex compositions.

Table 7: Cluster Summary of Pharmaceutical Products

Cluster	Average Price	Average Ingredient Count	Prescription Flag
Cluster 0	82.13	1.07	1.00
Cluster 1	111.66	2.29	1.00
Cluster 2	30.11	1.10	0.00

Table 8: Distribution of Pharmaceutical Clusters

Cluster	Number of Medicines
Cluster 0	117,075
Cluster 1	107,961

Cluster 2	1,536
-----------	-------

Afterwards, Principal Component Analysis (PCA) was performed for reducing feature dimensions and creating clustering patterns. The first two principal components accounted for about 73.8% of the total variance present in the data set, reflecting significant representation of clusters.

Table 9: PCA Explained Variance Ratio

Principal Component	Explained Variance Ratio
PCA 1	0.423
PCA 2	0.314
Total Explained Variance	0.738

4. Discussion

The results obtained from this study are of great importance in providing information about prescription patterns, medicine price behaviors, and pharmaceutical compositions within the Indian pharmaceutical market. It was discovered that prescription medicines form the largest part of pharmaceutical products in this country's pharmaceutical sector. The outcome is consistent with other research which demonstrates a growing tendency toward the utilization of clinically-regulated medicines due to an increasing degree of intricacy of the pharmaceutical industry and healthcare system (Rani, 2020). Therefore, there is a need for enhanced pharmaceutical governance, effective regulation, and supervision within the healthcare system, which ensures safe practices and minimizes improper consumption of prescribed medicines (Dhiman et al., 2019).

Significant differences were also identified between prescription and non-prescription medicines with regard to the prices and distribution processes within the Indian pharmaceutical industry. More precisely, prescription medicines had higher mean prices and larger pricing ranges than their counterparts. Such patterns are confirmed by other studies which demonstrate that medicines requiring prescriptions are more complicated and involve advanced manufacturing procedures and technologies (Ozawa et al., 2022). Over-the-counter medicines usually target common conditions that are easy to diagnose, which implies cheaper and less diverse pricing strategies for such pharmaceuticals (Kim et al., 2018). Differences established using the Mann-Whitney U test prove a significant difference between the studied groups.

As per the findings of the composition analysis, pharmaceuticals such as paracetamol, metformin, rabeprazole, pantoprazole, and montelukast comprised some of the most common ingredients across the dataset (Luo et al., 2020). This is an indication of high demand for medicines used to treat pain, diabetes, stomach-related ailments, and respiratory problems. Global pharmaceutical market research studies have revealed the same consumption pattern whereby chronic diseases and universal illnesses have influenced pharmaceutical usage (Gonzalez Pena et al., 2021). In addition, the frequent use of multi-ingredient medicines points to the increasing use of pharmaceutical medicines within modern healthcare systems.

A key contribution of the study was the discovery of the correlation between the price and number of ingredients of medicines. Higher average medicine prices were reported in pharmaceutical products with a large number of active ingredients. However, there was only a moderate correlation between medicine ingredient counts and medicine price. The results are consistent with existing literature in which pharmaceutical composition and combination of treatments have influenced functionality, efficacy, and usage (Vich Vila et al., 2020). Furthermore, the composition and combination of drugs might involve a more complicated pharmaceutical production process hence influencing pharmaceutical pricing.

The results of clustering further provided information about hidden market segments in India's pharmaceutical industry. There were three primary clusters according to the clustering exercise. The first major grouping was prescription medicines with simpler ingredients (Kohli and Gill, 2020). The second cluster included pharmaceutical products that were expensive and complex in nature. The third cluster consisted of over-the-counter drugs with lower complexity and price points. The study findings indicate that pharmaceutical products can be classified into different groups by applying data-driven analysis models. Other researchers have noted that the role of machine learning and data analytics in optimizing the pharmaceutical industry is on the rise (Nguyen et al., 2022).

The use of machine learning techniques, clustering algorithms, and dimensionality reduction in this research shows the potential role of artificial intelligence in healthcare analytics and pharmaceutical informatics (Bhabad et al., 2023). Nowadays, artificial intelligence and healthcare informatics significantly influence the transformation of pharmaceutical research, including development of predictive analytics, automated medicines classification, and intelligent healthcare decision support systems (Arun, 2023). Recently, systematic reviews showed that modern AI-based systems were extremely important for healthcare systems because they help to achieve pharmaceutical intelligence, optimize treatments, and analyze huge amounts of healthcare data (Hasan et al., 2023). Machine learning approaches become very important for pharmaceutical industries, especially when it comes to drug design, development of recommendation systems and healthcare innovations (Selvaraj et al., 2022).

It is essential to note some implications that can affect sustainability of healthcare and pharmaceutical market in general. The growing popularity and demand of pharmaceutical products cause serious worries about environmental sustainability, pharmaceutical pollution, and proper medicine waste management. As it is proven by the previous researches, pharmaceutical products manufacture and consumption significantly contribute to environmental loading of active

pharmaceutical ingredients into water and wastewater streams (Kleywegt et al., 2019). Therefore, information on pharmaceutical market distribution and composition may help to develop more sustainable approach to pharmaceutical industry and healthcare in general.

In spite of the contribution made by the study, there are some limitations that should be mentioned. Firstly, there were problems with data formatting, which were associated with medicine type category that included manufacturers' data combined with medicine description. Secondly, it was impossible to analyze patients' health data, which included effectiveness of dosage, treatment results, and therapeutic efficiency of particular medicines. In order to conduct more complicated analysis, it is necessary to introduce information on electronic health records, prescriptions, and clinical efficacy of different medicine types.

Thus, this research shows the importance of pharmaceutical data analytics, statistical modeling, and machine learning techniques that help to detect prescription patterns and drug composition patterns within the Indian pharmaceutical market. The study contributes to the field of pharmaceutical informatics. Moreover, the research provides some practical implications that may interest healthcare professionals, pharmaceutical companies, regulators, and policymakers. The combination of healthcare analytics and artificial intelligence will be able to play an important role in future.

5. Conclusion

Pharmaceutical trends and composition of medicines were investigated in the Indian pharmaceutical market employing big data analytics and machine learning models. Results have demonstrated the dominating role of prescription medicines in the pharmaceutical sector, being characterized with notably higher prices and variability in comparison with other kinds of medicines. In addition, commonly used pharmaceutical ingredients have been detected which correspond to some health problems such as pain control, diabetes, gastroenterological disorders, and respiratory diseases. Moreover, it was found out that medicines composed of several active ingredients tend to be priced higher than the ones with a single ingredient. Correlation analysis, clustering methods, and PCA allowed identifying certain pharmaceutical segments that differ with the degree of prescription drugs usage, composition complexity, and price levels. It is apparent that the roles of healthcare informatics and artificial intelligence keep growing in order to develop and sustain data-oriented healthcare system and pharmaceutical intelligence. This study adds up to pharmaceutical informatics research by presenting a large-scale pharmaceutical analysis model. Furthermore, its practical value can be seen in facilitating data-driven pharmaceutical activities in India.

References

1. Arun, R. (2023). Impact of artificial intelligence on healthcare informatics: opportunities and challenges. *Healthcare informatics*, 3(2).
2. Awrahman, B. J., Aziz Fatah, C., & Hamaamin, M. Y. (2022). A review of the role and challenges of big data in healthcare informatics and analytics. *Computational intelligence and neuroscience*, 2022(1), 5317760.
3. Ayush, A. (2024). *India medicines and drug info dataset* [Data set]. <https://www.kaggle.com/datasets/apkaayush/india-medicines-and-drug-info-dataset>
4. Bhabad, S., Lamkhade, D., Koyate, S., Karanjkehele, K., Kale, V., & Doke, R. (2023). Transformative trends: A comprehensive review on role of artificial intelligence in healthcare and pharmaceutical research. *IP Int J Comprehensive Adv Pharmacol*, 8, 210-9.
5. Chalmers, J., Siska, M., Le, T., & Knoer, S. (2018). Pharmacy informatics in multihospital health systems: opportunities and challenges. *The Bulletin of the American Society of Hospital Pharmacists*, 75(7), 457-464.
6. Devaraji, V., Sivaraman, J., & Prabhu, S. (2024). Large-scale computational screening of Indian medicinal plants reveals *Cassia angustifolia* to be a potentially anti-diabetic. *Journal of Biomolecular Structure and Dynamics*, 42(1), 194-210.
7. Dhiman, S. K., Gummadi, V., & Dureja, H. (2019). Partnership efforts—Their potential to reduce the challenges that confront regulators and pharmaceutical industry. *Applied Clinical Research, Clinical Trials and Regulatory Affairs*, 6(1), 7-17.
8. Festa, G., Kolte, A., Carli, M. R., & Rossi, M. (2022). Envisioning the challenges of the pharmaceutical sector in the Indian health-care industry: a scenario analysis. *Journal of Business & Industrial Marketing*, 37(8), 1662-1674.
9. Fink, D. S., Schleimer, J. P., Sarvet, A., Grover, K. K., Delcher, C., Castillo-Carniglia, A., ... & Cerdá, M. (2018). Association between prescription drug monitoring programs and nonfatal and fatal drug overdoses: a systematic review. *Annals of internal medicine*, 168(11), 783-790.
10. Gonzalez Pena, O. I., López Zavala, M. A., & Cabral Ruelas, H. (2021). Pharmaceuticals market, consumption trends and disease incidence are not driving the pharmaceutical research on water and wastewater. *International journal of environmental research and public health*, 18(5), 2532.
11. Hasan, M. E., Islam, M. J., Islam, M. R., Chen, D., Sanin, C., & Xu, G. (2023). Applications of artificial intelligence for health informatics: A systematic review. *J Artif Intell Med Sci*, 4(2), 19-46.
12. Horwitz, J. R., Davis, C., McClelland, L., Fordon, R., & Meara, E. (2021). The importance of data source in prescription drug monitoring program research. *Health Services Research*, 56(2), 268-274.
13. Jayatilake, S. M. D. A. C., & Ganegoda, G. U. (2021). Involvement of machine learning tools in healthcare decision making. *Journal of healthcare engineering*, 2021(1), 6679512.

14. Kim, H. J., Yang, Y. M., & Choi, E. J. (2018). Use patterns of over-the-counter (OTC) medications and perspectives on OTC medications among Korean adult patients with chronic diseases: gender and age differences. *Patient preference and adherence*, 1597-1606.
15. Kleywegt, S., Payne, M., Ng, F., & Fletcher, T. (2019). Environmental loadings of active pharmaceutical ingredients from manufacturing facilities in Canada. *Science of the Total Environment*, 646, 257-264.
16. Kohli, M., & Gill, S. (2020). Impact of family involvement on strategy and CEO compensation: Evidence from the Indian pharmaceutical industry. *Journal of Family Business Management*, 10(3), 189-212.
17. Luo, Y., Kataoka, Y., Ostinelli, E. G., Cipriani, A., & Furukawa, T. A. (2020). National prescription patterns of antidepressants in the treatment of adults with major depression in the US between 1996 and 2015: a population representative survey based analysis. *Frontiers in psychiatry*, 11, 35.
18. Masic, I. (2022). Medical decision making-an overview. *Acta Informatica Medica*, 30(3), 230.
19. Mulinari, S., Martinon, L., Jachiet, P. A., & Ozieranski, P. (2021). Pharmaceutical industry self-regulation and non-transparency: country and company level analysis of payments to healthcare professionals in seven European countries. *Health Policy*, 125(7), 915-922.
20. Nguyen, A., Lamouri, S., Pellerin, R., Tamayo, S., & Lekens, B. (2022). Data analytics in pharmaceutical supply chains: state of the art, opportunities, and challenges. *International Journal of Production Research*, 60(22), 6888-6907.
21. Ozawa, S., Billings, J., Sun, Y., Yu, S., & Penley, B. (2022). COVID-19 treatments sold online without prescription requirements in the United States: cross-sectional study evaluating availability, safety and marketing of medications. *Journal of Medical Internet Research*, 24(2), e27704.
22. Rani, D. (2020). An Analysis of the trends in Indian Pharmaceutical Trade. *JAC: A Journal Of Composition Theory*, XIII, 724-734.
23. Ridgely, M. S., Buttorff, C., Wolf, L. J., Duffy, E. L., Tom, A. K., Damberg, C. L., ... & Vaiana, M. E. (2020). The importance of understanding and measuring health system structural, functional, and clinical integration. *Health Services Research*, 55, 1049-1061.
24. Selvaraj, C., Chandra, I., & Singh, S. K. (2022). Artificial intelligence and machine learning approaches for drug design: challenges and opportunities for the pharmaceutical industries. *Molecular diversity*, 26(3), 1893-1913.
25. Sharma, S., & Modgil, S. (2020). TQM, SCM and operational performance: an empirical study of Indian pharmaceutical industry. *Business Process Management Journal*, 26(1), 331-370.
26. Vich Vila, A., Collij, V., Sanna, S., Sinha, T., Imhann, F., Bourgonje, A. R., ... & Weersma, R. K. (2020). Impact of commonly used drugs on the composition and metabolic function of the gut microbiota. *Nature communications*, 11(1), 362.