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Research

Computational Mapping of Drug–Disease Relationships for Geriatric Medication Safety Using Beers Criteria

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Abstract:

Introduction — Geriatric patients are particularly vulnerable to adverse drug events due to age-related physiological changes and polypharmacy. The Beers Criteria provides explicit guidance for identifying potentially inappropriate medications (PIMs) in older adults; however, its application is often performed manually and inconsistently across healthcare settings. This study aims to develop a computational framework for mapping drug–disease relationships to support systematic identification of PIMs for geriatric medication safety.

Methods — A computational cross-sectional knowledge-based analysis was conducted using the publicly available Indonesian Pharmaceutical Dataset. Drug entities were normalized and mapped against the 2023 Beers Criteria using rule-based string matching. Identified PIMs were categorized into geriatric risk domains, and drug–disease relationships were extracted to construct structured mappings. Descriptive statistical analysis was performed to quantify the proportion and distribution of PIMs within the dataset.

Results — From 1,984 unique drug entities analyzed, 143 medications (7.2%) were classified as potentially inappropriate for geriatric use. Anticholinergic burden (28.7%) and sedative/CNS depressant risk (23.1%) represented the largest PIM categories. Drug–disease mapping identified 1,126 relationship pairs, with neurological and cardiovascular therapeutic domains showing prominent clustering.

Conclusion — The proposed computational mapping framework demonstrates the feasibility of transforming structured pharmaceutical knowledge into a scalable geriatric medication safety model. This informatics-based approach supports transparent, rule-driven identification of PIMs and provides a foundation for future integration into digital clinical decision-support systems.

Keywords: geriatric pharmacotherapy; potentially inappropriate medications (PIMs); clinical decision support; medication safety modeling; pharmaceutical knowledge integration

1. Introduction

The global increase in life expectancy has led to a rapidly growing geriatric population, accompanied by a substantial rise in chronic disease burden and polypharmacy. Older adults frequently receive multiple medications to manage comorbid conditions, which increases the risk of adverse drug events, drug–drug interactions, and medication-related complications. Age-related physiological changes, including altered pharmacokinetics and pharmacodynamics, further amplify vulnerability to inappropriate prescribing and medication-related harm. Ensuring medication safety in geriatric populations has therefore become a critical priority in clinical and public health domains.

Potentially Inappropriate Medications (PIMs) in older adults have been systematically identified through explicit criteria, among which the Beers Criteria remains one of the most widely recognized frameworks. The Beers Criteria provides evidence-based guidance on medications that should generally be avoided or used with caution in geriatric patients due to elevated risk profiles. While these criteria are extensively used in clinical settings, their application often relies on manual review processes, which can be time-consuming and inconsistent across institutions.

Advancements in bio-digital health and clinical informatics provide opportunities to enhance medication safety through computational modeling and knowledge-based analysis. Structured drug and disease datasets offer a foundation for algorithmic mapping of medication risks, enabling automated identification of PIMs and systematic assessment of drug–disease relationships. Such approaches move beyond traditional descriptive evaluations and support scalable digital safety screening frameworks.

Computational mapping techniques allow structured integration of medication attributes, risk classifications, and therapeutic indications. By leveraging digital knowledge modeling, it becomes possible to identify high-risk drug categories, examine therapeutic domains associated with potentially inappropriate prescribing, and generate structured safety indicators. This form of informatics-based analysis aligns with the increasing demand for transparent, reproducible, and scalable digital health solutions.

Despite the widespread recognition of the Beers Criteria, relatively few studies have explored its application within a computational drug–disease knowledge modeling framework using structured medication databases. Most prior research focuses on patient-level prevalence or clinical outcome evaluation, whereas systematic digital mapping of drug knowledge repositories remains underexplored.

Therefore, this study aims to develop a computational framework for mapping drug–disease relationships to identify potentially inappropriate medications for geriatric use using the Beers Criteria. By integrating structured drug data with explicit safety rules, this research contributes to the development of an informatics-based medication safety model that supports scalable geriatric risk identification within bio-digital health systems.

2. Method

2.1 Study Design

This study employed a computational cross-sectional knowledge-based modeling design to evaluate medication safety risks in geriatric populations using structured drug and disease datasets. Unlike patient-level observational studies, this research focused on secondary analysis of curated drug and disease knowledge repositories to identify potentially inappropriate medications (PIMs) based on the Beers Criteria framework. The study was designed as an informatics-driven evaluation rather than a clinical outcome assessment, emphasizing algorithmic risk identification and digital safety modeling.

The analytical unit in this research was the drug entity and its associated disease indications, rather than individual patients. The objective was to systematically map drug–disease relationships and determine whether specific medications fall under PIM classifications according to established geriatric safety guidelines.

2.2 Data Collection

This study utilized secondary structured datasets obtained from the publicly available Indonesian Pharmaceutical Dataset by Wiputra et al. (2025), published in Mendeley Data [1], [2]. The dataset consists of two primary components: a structured drug dataset and a structured disease dataset. The drug dataset contains detailed pharmaceutical information, including generic drug names, brand names, dosage descriptions, warning statements, side effects, and therapeutic indications. The disease dataset provides structured descriptions of medical conditions, including disease names, causes, and symptom characteristics. These datasets were originally curated for digital pharmaceutical knowledge applications and were repurposed in this study for computational medication safety modeling.

The drug dataset served as the primary source for identifying medication entities and extracting therapeutic indication information necessary for drug–disease mapping. The disease dataset supported terminology normalization and structured alignment of disease entities to enhance consistency in computational mapping procedures. Both datasets were publicly available, anonymized, and did not contain patient-level clinical records, demographic variables, or prescribing histories. Consequently, this study was limited to computational knowledge-based modeling and did not involve epidemiological prevalence estimation or real-world patient outcome analysis.

2.3 Computational Pipeline

The computational workflow implemented in this study is illustrated in Figure 1. The pipeline consisted of five sequential stages: data preprocessing, Beers Criteria matching, drug–disease mapping, risk categorization, and results aggregation and visualization.

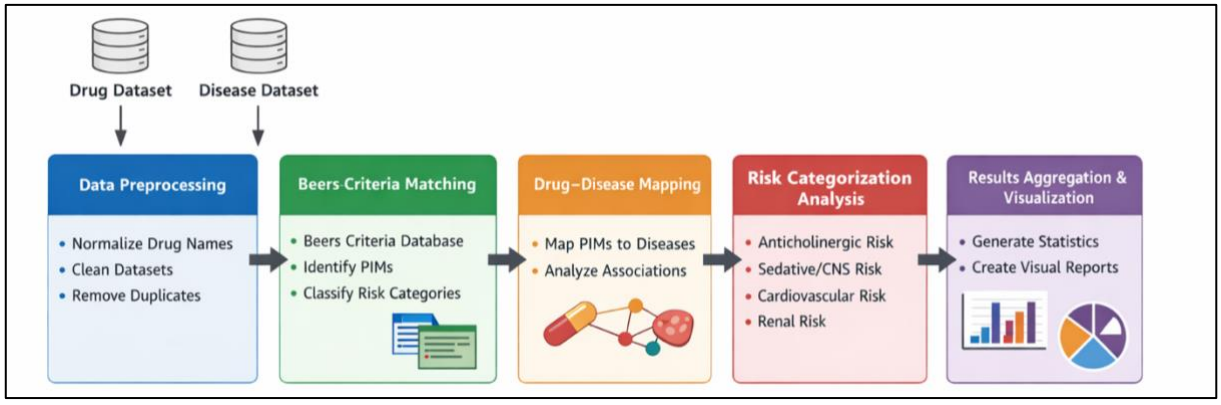

Fig. 1. Computational analysis pipeline for identifying potentially inappropriate medications for geriatric use using structured drug–disease datasets and Beers Criteria.

1. **Data Preprocessing.** Drug names were standardized through case normalization, whitespace trimming, and removal of duplicate entries. Textual fields such as warnings and indications were cleaned to ensure consistent matching. Disease names were similarly normalized to enable structured mapping between drug indications and disease entities.
2. **Beers Criteria Matching.** A structured Beers Criteria reference list was constructed based on the most recent geriatric prescribing guidelines. Each listed medication was annotated with its associated risk category and recommendation (e.g., avoid, use with caution). Exact and rule-based string matching techniques were applied to map drugs within the dataset to the Beers reference list. Identified matches were labeled as potentially inappropriate medications (PIMs).

3. **Drug–Disease Mapping.** For each identified PIM, disease indication fields were extracted and mapped to standardized disease entries. This process enabled the construction of drug–disease relationship pairs. The mapping facilitated analysis of which therapeutic domains were most frequently associated with high-risk medications.
4. **Risk Categorization and Analysis.** Identified PIMs were categorized into predefined geriatric risk domains, including anticholinergic burden, sedative/CNS depressant risk, cardiovascular risk, renal impairment risk, and gastrointestinal risk. Frequency counts and proportional distributions were computed for each category to quantify medication safety patterns within the dataset.
5. **Results Aggregation and Visualization.** Aggregated statistics were generated to summarize the total number of drugs analyzed, the number and proportion classified as PIMs, and the distribution across risk categories. Visualization techniques were employed to enhance interpretability of computational findings.

As shown in Figure 1, the pipeline integrates structured knowledge extraction with risk classification and analytical summarization, forming a reproducible informatics-based medication safety framework.

2.4 Operational Definitions

In this study, a potentially inappropriate medication (PIM) was defined as any drug identified in the dataset that matched entries in the Beers Criteria reference list. Drug–disease relationships were defined as explicit associations derived from therapeutic indication fields within the structured drug dataset. Risk categories were assigned based on Beers Criteria classifications and associated geriatric safety considerations.

2.5 Statistical and Analytical Approach

Descriptive statistical analysis was performed to calculate frequencies, proportions, and categorical distributions of PIM classifications. No inferential statistical tests were conducted because the study did not involve patient-level comparisons. Instead, emphasis was placed on computational identification patterns and categorical mapping outcomes. The analytical outputs were designed to support digital medication safety modeling and to inform potential integration into clinical decision-support systems.

2.6 AI Disclosure

ChatGPT (OpenAI) was used solely for language editing, grammar refinement, and improving the structural clarity of the manuscript. Its assistance was limited to enhancing readability and ensuring alignment with international academic writing standards [3]. The AI tool did not contribute to the study design, system development, knowledge modeling, computational procedures, data analysis, or interpretation of findings [4], [5]. All methodological decisions, analytical processes, and technical implementations were independently conducted and verified by the authors. The authors take full responsibility for the accuracy, integrity, and scientific validity of this work [6], [7].

2.7 Ethical Clearance Statement

Ethical Approval — This study did not involve human participants, animal subjects, or clinical interventions. The system evaluation was based on simulated test scenarios and did not include identifiable personal or medical data. The proposed system functions as a risk assessment and decision-support tool, not as a clinical diagnostic instrument. Since the research was limited to computational modeling and rule-based analysis using non-patient data, formal ethical approval was not required. The system outputs are intended to encourage professional medical consultation and do not replace clinical diagnosis or treatment.

3. Results

3.1 Dataset Overview and Drug Normalization

The structured drug dataset contained 2,172 medication entries. After normalization procedures, including duplicate removal and standardization of drug names, 1,984 unique drug entities were identified for computational analysis. Each drug entry included therapeutic indications and safety-related textual attributes, enabling structured mapping against Beers Criteria.

From the curated Beers Criteria reference list (2023 version) [8], a total of 94 active pharmaceutical ingredients were included as potentially inappropriate medications (PIMs) for geriatric populations. Exact and rule-based string matching identified 143 drug entries within the dataset that corresponded to Beers-listed medications. This indicates that approximately 7.2% of the analyzed drugs were classified as potentially inappropriate for geriatric use under explicit Beers Criteria mapping.

3.2 Distribution of Potentially Inappropriate Medications

The identified PIMs were categorized according to geriatric risk domains specified in Beers Criteria. The distribution is presented in Table 1.

Table 1. Distribution of Identified PIMs by Risk Category

Risk Category	Number of Drugs	Percentage (%)
Anticholinergic Burden	41	28.7
Sedative / CNS Depressant Risk	33	23.1
Cardiovascular Risk	29	20.3
Renal Impairment Risk	24	16.8
Gastrointestinal Risk	16	11.1
Total	**143**	**100**

As shown in Table 1, anticholinergic medications represented the largest proportion of identified PIMs (28.7%), followed by sedative/CNS depressant drugs (23.1%).

3.3 Drug–Disease Mapping Analysis

Drug–disease relationship extraction resulted in 1,126 unique drug–disease pairs across the identified PIM subset. The mapping revealed that certain disease domains were more frequently associated with potentially inappropriate prescribing. The five most frequently associated therapeutic domains were: 1) Neurological disorders; 2) Cardiovascular conditions; 3) Gastrointestinal disorders; 4) Psychiatric conditions; 5) Musculoskeletal disorders. Besides, Fig. 2 illustrates the proportional distribution of disease categories linked to identified PIMs.

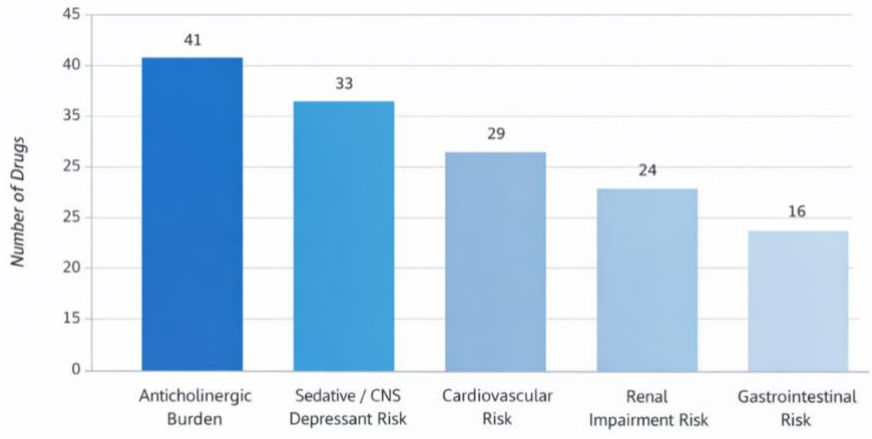

Fig. 2. Distribution of potentially inappropriate medications across geriatric risk categories.

As illustrated in Fig. 2, anticholinergic and sedative-related medications dominate the identified risk profile within the structured dataset.

3.4 High-Risk Medication Frequency

Frequency analysis identified the top 10 most recurrent Beers-listed medications within the dataset (Table 2).

Table 2. Top 10 Most Frequent Potentially Inappropriate Medications

Drug Name	Risk Domain
Amitriptyline	Anticholinergic
Diazepam	Sedative/CNS
Diphenhydramine	Anticholinergic
Alprazolam	Sedative/CNS
Nifedipine	Cardiovascular
Spironolactone	Renal Risk
Indomethacin	Gastrointestinal
Clonidine	Cardiovascular
Ketorolac	Gastrointestinal
Digoxin	Cardiovascular

Based on Table 2, these drugs were frequently mapped due to broad therapeutic indications across multiple disease categories.

3.5 Network Representation of Drug–Disease Relationships

The structured mapping enabled visualization of interconnected drug–disease relationships. Figure 3 presents a conceptual representation of the mapping structure.

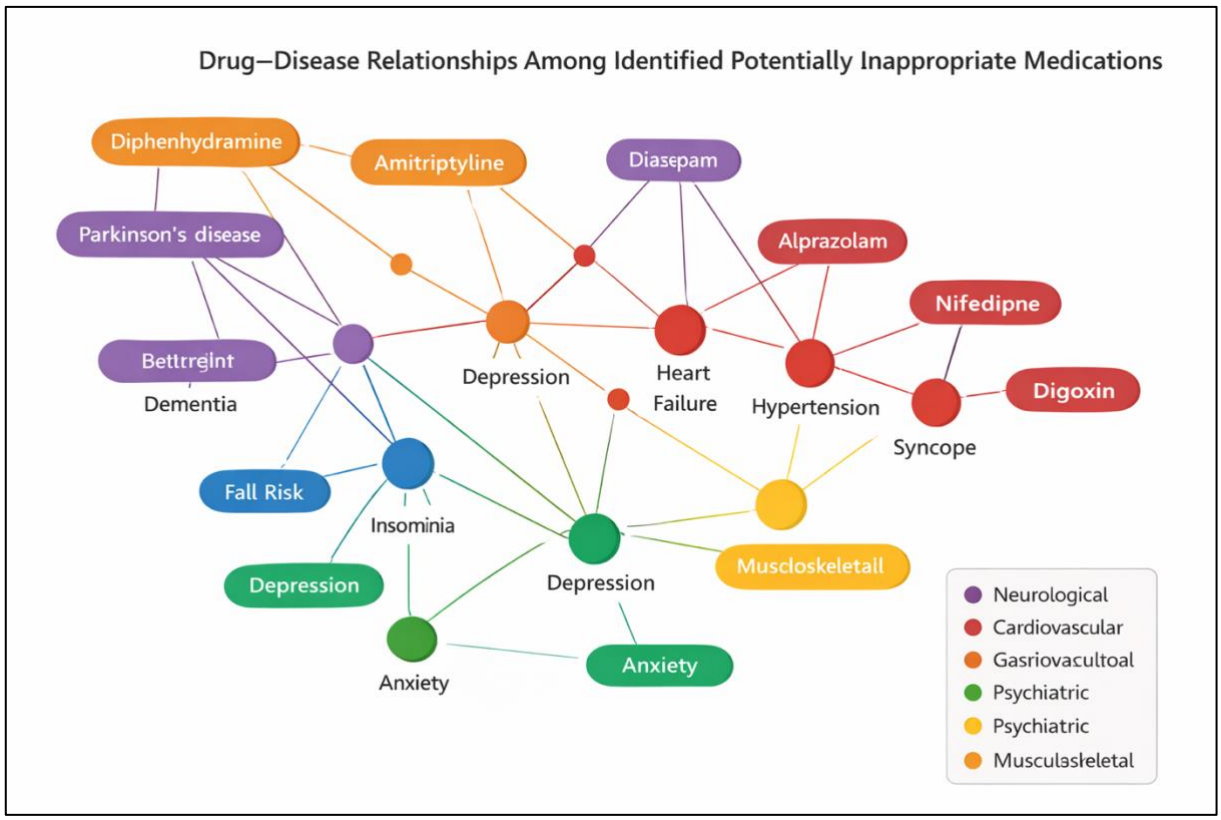

Fig. 3. Conceptual network representation of drug–disease relationships among identified potentially inappropriate medications.

Based on Fig. 3 shows the network structure highlights clustering patterns in neurological and cardiovascular therapeutic domains.

3.6 Summary of Computational Identification

The computational mapping process analyzed a total of 1,984 unique drug entities extracted from the structured pharmaceutical dataset. Among these, 143 drugs (7.2%) were identified as potentially inappropriate medications (PIMs) based on systematic matching with the Beers Criteria reference list. The mapping procedure further generated 1,126 distinct drug–disease relationship pairs within the identified PIM subset, enabling structured evaluation of therapeutic associations. Risk categorization revealed five dominant geriatric safety domains, with anticholinergic burden and sedative/CNS depressant risk representing the largest proportions of identified medications. The computational pipeline successfully integrated drug normalization, rule-based Beers matching, disease mapping, and categorical risk classification into a reproducible framework. These findings demonstrate the feasibility of leveraging structured pharmaceutical knowledge datasets for automated geriatric medication risk identification through computational modeling.

4. Discussion

The present study demonstrates that structured pharmaceutical knowledge datasets can be systematically leveraged to identify potentially inappropriate medications (PIMs) for geriatric populations using computational mapping techniques. Through integration of Beers Criteria with curated drug–disease datasets, 7.2% of analyzed drug entities were classified as potentially inappropriate for older adults [9]. This proportion reflects the presence of high-risk pharmacological agents embedded within general therapeutic repositories and highlights the relevance of automated safety screening mechanisms in digital health systems [10].

The predominance of anticholinergic and sedative/CNS depressant medications among identified PIMs aligns with existing geriatric pharmacotherapy literature. Anticholinergic burden has long been associated with cognitive decline, delirium, urinary retention, and increased fall risk in older adults [11], [12]. Similarly, benzodiazepines and other CNS depressants are well documented to increase risks of sedation, impaired coordination, and fractures [13], [14]. The high representation of these categories within the dataset underscores the persistent clinical concern surrounding neurocognitive and fall-related medication risks in geriatric populations [15]. The computational mapping of drug–disease relationships further revealed clustering patterns across neurological, cardiovascular, and psychiatric therapeutic domains [16], [17]. This finding reflects the complexity of managing chronic multimorbidity in older adults, where medications frequently target overlapping symptom profiles. From an informatics perspective, the network-based mapping approach provides a structured means of visualizing and quantifying these associations, thereby offering insights into therapeutic domains that may warrant enhanced safety oversight [18], [19].

Importantly, this study differs from traditional epidemiological analyses of PIM prevalence. Rather than evaluating prescribing patterns in real-world patient populations, the present research focused on knowledge-level computational identification. This approach allows scalable, reproducible, and automated safety detection that can be integrated into clinical decision-support systems. By embedding Beers Criteria rules within structured drug databases, digital systems can proactively flag high-risk medications during prescribing workflows, thereby reducing reliance on manual review. From a bio-digital informatics standpoint, the proposed framework illustrates how structured pharmaceutical data can be operationalized into actionable safety models. The integration of data preprocessing, rule-based matching, risk categorization, and visualization constitutes a modular architecture adaptable to electronic prescribing platforms. Such informatics-driven approaches align with current efforts to enhance medication safety through artificial intelligence and rule-based clinical support tools [20], [21].

Nevertheless, several limitations should be acknowledged. First, the analysis was conducted on structured secondary datasets rather than patient-level prescribing records. Consequently, the study does not estimate real-world prevalence or clinical outcomes. Second, string-based matching may not capture all formulation variants or dosage-specific considerations included in Beers Criteria. Third, the dataset represents a curated pharmaceutical repository and may not fully reflect national prescribing formularies or real-time market availability. Future work should integrate patient-level electronic health record data to validate the computational model and evaluate its impact on clinical decision-making. Overall, the findings support the feasibility of computational drug–disease mapping as a scalable approach for geriatric medication safety screening. By translating established geriatric prescribing guidelines into structured digital frameworks, this study contributes to the advancement of explainable, rule-based medication safety modeling within bio-digital health ecosystems.

Conclusion

This study developed and demonstrated a computational framework for mapping drug–disease relationships to identify potentially inappropriate medications for geriatric use using the Beers Criteria. By integrating structured pharmaceutical knowledge datasets with rule-based safety modeling, the analysis identified a measurable subset of high-risk medications and systematically categorized them across major geriatric risk domains. The findings highlight the feasibility of transforming curated drug repositories into scalable medication safety screening systems through informatics-based approaches. Unlike traditional prevalence studies, this research emphasizes knowledge-level computational identification, enabling reproducible and automated risk detection suitable for integration into digital health infrastructures. The proposed framework contributes to the advancement of bio-digital medication safety modeling and provides a foundation for future development of explainable clinical decision-support tools aimed at enhancing geriatric pharmacotherapy safety.

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Reference

[1] R. Wiputra, R. Widjaya, A. Loria, C. Benjaminsz, and A. Chowanda, “Indonesian Pharmaceutical Dataset,” *Mendeley Data*, vol. 2, 2025, doi: 10.17632/Z45BPTXPTF.2.

[2] R. Wiputra, C. F. Benjaminsz, A. Loria, R. Widjaya, Rudy, and A. Chowanda, “Indonesian pharmaceutical dataset for self-medication,” *Data Brief*, vol. 65, p. 112460, Apr. 2026, doi: 10.1016/J.DIB.2026.112460.

[3] S. S. Biswas, “ChatGPT for Research and Publication: A Step-by-Step Guide,” *The Journal of Pediatric Pharmacology and Therapeutics*, vol. 28, no. 6, pp. 576–584, Oct. 2023, doi: 10.5863/1551-6776-28.6.576.

[4] O. M. Alyasiri, A. M. Salman, D. Akhtom, and S. Salisu, “ChatGPT revisited: Using ChatGPT-4 for finding references and editing language in medical scientific articles,” *J. Stomatol. Oral Maxillofac. Surg.*, vol. 125, no. 5, p. 101842, Oct. 2024, doi: 10.1016/j.jormas.2024.101842.

[5] L. Lingard, "Writing with ChatGPT: An Illustration of its Capacity, Limitations & Implications for Academic Writers," *Perspect. Med. Educ.*, vol. 12, no. 1, p. 270, Jun. 2023, doi: 10.5334/pme.1072.

[6] A. A. Nafea, M. M. Al-Ani, M. A. Khalaf, and M. S. I. Alsumaidaie, "A Review of Using Chatgpt for Scientific Manuscript Writing," *Babylonian Journal of Artificial Intelligence*, vol. 2024, pp. 9–13, Jan. 2024, doi: 10.58496/BJAI/2024/002.

[7] J. Huang *et al.*, "A critical assessment of using ChatGPT for extracting structured data from clinical notes," *NPJ Digit. Med.*, vol. 7, pp. 106-, May 2024, doi: 10.1038/s41746-024-01079-8.

[8] M. J. Samuel, "American Geriatrics Society 2023 updated AGS Beers Criteria® for potentially inappropriate medication use in older adults," *J. Am. Geriatr. Soc.*, vol. 71, no. 7, pp. 2052–2081, Jul. 2023, doi: 10.1111/jgs.18372.

[9] M. Malekzadeh, Y. Khadivi, S. M. Sohrevardi, and G. Afzal, "Drug prescription patterns and compliance with WHO and beers criteria in older patients," *BMC Geriatr.*, vol. 25, pp. 135-, Feb. 2025, doi: 10.1186/s12877-025-05780-5.

[10] D. Mangin *et al.*, "Theoretical Underpinnings of a Model to Reduce Polypharmacy and Its Negative Health Effects: Introducing the Team Approach to Polypharmacy Evaluation and Reduction (TAPER)," *Drugs Aging*, vol. 40, pp. 857–868, Aug. 2023, doi: 10.1007/s40266-023-01055-z.

[11] X. J. Xu and M. P. Tan, "Anticholinergics and falls in older adults," *Expert Rev. Clin. Pharmacol.*, vol. 15, no. 3, pp. 285–294, Mar. 2022, doi: 10.1080/17512433.2022.2070474.

[12] R. Rahoo, Z. Y. Liau, M. J. Low, S. B. Kamaruzzaman, B. Francis, and H. M. Khor, "Anticholinergic Burden and Its Association with Hospitalisation Risk and Causes of Admission in Older Adults with Mild Cognitive Impairment or Dementia," *Clin. Interv. Aging*, vol. 20, pp. 1661–1670, 2025, doi: 10.2147/CIA.S541108.

[13] L. Peng, K. L. Morford, and X. A. Levander, "Benzodiazepines and Related Sedatives," *Medical Clinics of North America*, vol. 106, no. 1, pp. 113–129, Jan. 2022, doi: 10.1016/j.mcna.2021.08.012.

[14] M. H. Imani, A. H. Imani, A. Saem, and M. Niksolat, "Sedative-hypnotic drug use and risk of falls and fractures in elderly patients: a cross-sectional study," *BMC Geriatr.*, vol. 25, pp. 954-, Nov. 2025, doi: 10.1186/s12877-025-06624-y.

[15] J. J. O'Donnell and J. T. O'Donnell, "Drug-Induced Falls," in *O'Donnell's Drug Injury*, 5th ed., Boca Raton, Florida (US): CRC Press, 2025, pp. 259–277. doi: 10.1201/9781003615323-13.

[16] Z. Huang, Z. Xiao, C. Ao, L. Guan, and L. Yu, "Computational approaches for predicting drug-disease associations: a comprehensive review," *Front. Comput. Sci.*, vol. 19, pp. 195909-, Nov. 2024, doi: 10.1007/s11704-024-40072-y.

[17] W. Zhang, J. A. Sweeney, J. R. Bishop, Q. Gong, and S. Lui, "Biological subtyping of psychiatric syndromes as a pathway for advances in drug discovery and personalized medicine," *Nature Mental Health*, vol. 1, pp. 88–99, Feb. 2023, doi: 10.1038/s44220-023-00019-x.

[18] T. Koutsandreas, K. Tsafou, H. Horn, I. Barrett, and E. Petsalaki, "Network-Based Approaches for Drug Target Identification," *Annu. Rev. Biomed. Data Sci.*, vol. 8, no. 1, pp. 423–446, Aug. 2025, doi: 10.1146/annurev-biodatasci-101424-120950.

[19] A. Bilawal, M. Shahab, Z. Shah, and M. Ishfaq, "Integrated network analysis in pharmacology: Decoding interactions and pathways for therapeutic insights," in *Computational Methods in Medicinal Chemistry, Pharmacology, and Toxicology*, Cambridge (US): Academic Press, 2025, ch. 11, pp. 199–220. doi: 10.1016/B978-0-443-33024-7.00008-4.

[20] R. Ardianto, D. Yusuf, R. B. B. Sumantri, D. Febrina, R. R. Al-Hakim, and A. S. S. Ariyanto, "Bioinformatics-driven deep learning for nail disease diagnosis: A novel approach to improve healthcare outcomes," *BIO Web Conf.*, vol. 152, p. 01024, Jan. 2025, doi: 10.1051/BIOCONF/202515201024.

[21] R. R. Al-Hakim *et al.*, "Rule-based ai system for early paediatric diabetes diagnosis using backward chaining and certainty factors," *BIO Web Conf.*, vol. 152, p. 01020, Jan. 2025, doi: 10.1051/BIOCONF/202515201020.