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INTERACTIVE ICD-10-BASED MORBIDITY DASHBOARD USING BPJS CENTRAL DATA: A CASE STUDY OF KARANGANYAR REGENCY

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Abstrak

Peningkatan kompleksitas tren penyakit pada era pascapandemi menuntut tersedianya alat bantu pengambilan keputusan yang berbasis data dan mudah diakses, khususnya di layanan kesehatan primer. Penelitian ini bertujuan mengembangkan dashboard morbiditas interaktif berbasis klasifikasi ICD-10 yang dibangun dari data sekunder BPJS Kesehatan. Fokus penelitian terletak pada kunjungan rawat jalan di Kabupaten Karanganyar selama periode 2020–2024. Metode yang digunakan adalah pendekatan kuantitatif deskriptif dengan pengembangan sistem berbasis Python. Proses pra-pemrosesan data mencakup standarisasi kode ICD-10, penanganan data kosong, serta pengelompokan berdasarkan tahun, jenis kelamin, dan kelompok usia. Hasilnya berupa dashboard visual yang memungkinkan pengguna menyaring data berdasarkan variabel demografi dan kategori penyakit. Sepuluh kelompok penyakit dengan prevalensi tertinggi meliputi gangguan pernapasan, pencernaan, endokrin, dan sirkulasi. Dashboard ini mendukung pemantauan tren morbiditas serta pengambilan keputusan berbasis data untuk intervensi promotif dan preventif di fasilitas kesehatan tingkat pertama.

Kata Kunci: *Dashboard; Morbiditas; ICD-10; BPJS; Layanan Primer*.

Abstract

The increasing complexity of disease trends in the post-pandemic era necessitates more accessible and data-driven decision-making tools, particularly in primary healthcare services. This study aims to develop an interactive morbidity dashboard based on ICD-10 classifications using secondary data from BPJS Kesehatan. The research focuses on outpatient visit records in Karanganyar Regency from 2020 to 2024. A descriptive quantitative approach was applied, accompanied by system development using Python. Data preprocessing involved standardizing ICD-10 codes, handling missing values, and grouping by year, gender, and age category. The resulting dashboard allows users to filter morbidity trends based on demographic variables and disease categories. The ten most prevalent disease groups include respiratory, digestive, endocrine, and circulatory disorders. This dashboard facilitates data-based decision-making and enables targeted promotive and preventive interventions in primary healthcare facilities.

Keywords**:** *Dashboard; Morbidity; ICD-10; BPJS; Primary Care*.

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INTRODUCTION

In the aftermath of the COVID-19 pandemic, health systems globally are facing increased complexity in managing diseases. This has accelerated the need for data-driven public health strategies. Reliable morbidity data is vital for healthcare policy, service optimization, and targeted interventions (Schulze et al. 2023). Indonesia's BPJS Kesehatan holds vast healthcare utilization data. Yet, its use in informatics-driven decisions remains limited. ICD-10 enables standardized classification and international comparisons. Integrated with dashboard technology, it offers powerful tools for regional health governance. However, digital dashboards utilizing ICD-10 coded BPJS data are rare in Indonesia. This study fills that gap by building a web-based morbidity dashboard focused on Karanganyar Regency (2020–2024), offering stakeholders tools to analyze disease trends by demographics and time (Batko and Ślęzak 2022; Queen-Mary Akudo Ebugosi and Janet Aderonke Olaboye 2024).

Indonesia, through its national health insurance system (BPJS Kesehatan), collects an extensive volume of healthcare utilization data. However, the use of this data—especially in the form of structured, visual, and actionable outputs—is still limited. Secondary administrative datasets like those from BPJS contain rich epidemiological insights but are underutilized in informatics-based decision-making, particularly when structured using international standards like the International Classification of Diseases, 10th Revision (ICD-10) (Costich et al. 2022; Ng et al. 2019; Perera et al. 2011).

The ICD-10 standard allows for consistent disease classification and facilitates both national and international comparisons. When integrated with visualization technologies—such as interactive dashboards—it offers significant potential to transform static datasets into real-time, decision-support tools for regional health management (Forsman et al. 2013; Huang et al. 2025; Huber et al. 2018; Matheus, Janssen, and Maheshwari 2020; Muskan, Kumari, and Ranjan 2022).

Recent studies confirm the growing importance of data visualization in public health governance (Karami and Safdari 2016; Manuela V. Ferro 2023; Muskan, Kumari, and Ranjan 2022; Pei et al. 2024). Schulze et al. demonstrated how dashboards can improve interpretation of complex indicators and institutional responsiveness (Schulze et al. 2023). Jing et al. showed that visual analytics significantly enhance the usability of large-scale health datasets (Jing et al. 2023). Dixon and Grannis, through their work on COVID-19 response systems, illustrated the real-world applicability of visual health data platforms (Dixon and Holmes 2021).

Yet, within Indonesia, the application of ICD-10-coded BPJS data in localized digital dashboards remains scarce. Fuad noted the availability of sample datasets but emphasized the lack of innovation in translating this data into user-friendly tools for public health stakeholders [8]. Furthermore, the '2023 Indonesian Mortality and Morbidity Table Book' released by BPJS Kesehatan still lacks an interface that supports interactivity or drill-down analysis (Manuela V. Ferro 2023).

This research addresses that gap by developing a web-based morbidity dashboard that integrates ICD-10 classifications using BPJS Central data focused on Karanganyar Regency (2020–2024). The purpose of this dashboard is to empower local health stakeholders with tools to monitor disease trends by gender, age group, ICD-10 categories, and time.

The main objective of this study is to design and prototype an interactive dashboard system that translates BPJS secondary data into visual insights. This tool aims to enhance data transparency, support regional health planning, and showcase how structured modeling can strengthen public health informatics in Indonesia.

Table 1. Summary of Relevant Research on Morbidity Data Visualization and ICD-10

Author	Issues Raised	Method Used	Research Results
Putra et al.	Dashboard for disease surveillance	Web-based dashboard with SQL	Improved early detection of outbreaks
Handayani & Nugroho	Visualization of service utilization	Data mining and visual analytics	Improved hospital resource efficiency
Sari et al.	Use of ICD-10 in hospital records	Qualitative case study	Highlighted coding inconsistencies

Despite the growing interest in public health informatics, most morbidity dashboards in Indonesia remain confined to internal hospital systems or national surveillance portals. This research addresses a critical gap by transforming BPJS secondary data from Karanganyar Regency (2020–2024) into a web-based, ICD-10-classified morbidity dashboard.

The objective of this study is to design and prototype an interactive visualization platform that enables local health stakeholders to analyze morbidity patterns by ICD-10 code, age group, gender, and time. By converting raw health insurance data into intuitive insights, this system aims to support evidence-based policy formulation, enhance data transparency, and strengthen the role of digital health governance at the regional level.

METHOD

This study employed a descriptive quantitative research design combined with a system development approach to construct an interactive, ICD-10-based morbidity dashboard. The primary objective was to transform aggregated administrative health data into a dynamic tool to support public health planning at the regional level, in line with established digital health informatics practices (Borges do Nascimento et al. 2023; Javaid, Haleem, and Singh 2024; Marwaha et al. 2022).

Data Sources

The dataset used in this study was obtained from BPJS Kesehatan Central Office, filtered specifically for outpatient records from Karanganyar Regency. It comprises five years of secondary outpatient visit records (2020–2024), including ICD-10 diagnostic codes, year of visit, patient age group, and gender. The dataset was anonymized prior to access, formatted in Microsoft Excel, and conformed with research ethics and data protection principles (EDPB 2021).

Data Collection and Preprocessing

Data were collected through document analysis, focusing entirely on secondary sources without direct patient involvement. Preprocessing was performed using Python. The steps included:

- Standardizing column labels and data types
- Handling null values and correcting misformatted records
- Grouping cases by ICD-10 code, year, gender, and age group
- Restructuring the dataset for visual analysis using pivot tables and normalized formats

These procedures ensured a high level of data integrity and analytical consistency (Guo et al. 2023; Mathôt and Vilotijević 2023; Roy et al. 2019).

System Development Procedure

The dashboard system was developed using open-source tools within a Python-based data science stack:

- Pandas: For data manipulation and aggregation
- Matplotlib and Seaborn: For static and comparative visualizations
- Streamlit: To build the dashboard's interactive interface

Streamlit was selected for its low-code architecture and suitability for rapid deployment in web environments (Vesjolijs 2025). The development process followed an ETL-like pipeline (Extract, Transform, Load), as illustrated in Figure 1, to ensure traceability and maintainability of system components.

Figure 1: Dashboard Development Workflow

Data Analysis Techniques

Descriptive statistics were applied to explore morbidity trends across the dataset. The analysis included:

- Identifying the top 10 most common disease categories by ICD-10 code
- Analyzing temporal patterns in disease distribution (2020–2024)
- Evaluating disease burden based on gender and age group
- Assessing the relative share of each ICD group in total outpatient visits

The final result was an interactive dashboard capable of real-time filtering by user-selected variables. This platform provides evidence-based insights to support localized health interventions, service prioritization, and resource distribution (Almadani et al. 2025; Fraser-Hurt et al. 2021; Oluwafunmilayo Ogundeko-Olugbami et al. 2025; Rong, Ristevski, and Carroll 2023).

RESULTS AND DISCUSSIONS

This section presents the key findings of the research and provides comprehensive interpretations aligned with the research objectives. The outcomes are organized into three main subsections: identification of disease prevalence, dashboard development results, and analysis of trends with implications for public health.

Top 10 ICD-10 Morbidity Groups

The analysis of BPJS secondary data from Karanganyar Regency for the period 2020–2024 revealed ten major ICD-10 disease groups that consistently appeared with high prevalence. These include both communicable and non-communicable diseases such as infectious diseases, respiratory disorders, digestive system conditions, metabolic syndromes, and cardiovascular illnesses.

The breakdown of the top ten morbidity groups, based on cumulative patient numbers, is presented in Table 1. These findings align with broader national and international health reports, particularly those highlighting Indonesia's dual burden of disease—where communicable diseases remain prevalent while chronic, lifestyle-related illnesses are on the rise (Arifin et al. 2022; Mboi et al. 2022).

Table 1. Top 10 ICD-10 Disease Groups Based on Total Patients (2020–2024)

No	ICD-10 Disease Group	Total Patients
1	Certain Infectious and Parasitic Diseases (A00–B99)	38,724
2	Diseases of the Respiratory System (J00–J99)	33,101
3	Diseases of the Digestive System (K00–K93)	30,562
4	Endocrine, Nutritional, and Metabolic Diseases (E00–E90)	27,842
5	Diseases of the Circulatory System (I00–I99)	25,110
6	Mental and Behavioural Disorders (F00–F99)	22,908
7	Diseases of the Nervous System (G00–G99)	19,504
8	Diseases of the Musculoskeletal System (M00–M99)	17,619
9	Neoplasms (C00–D48)	15,033
10	Diseases of the Genitourinary System (N00–N99)	13,478

Visual Dashboard Output

A key output of this research is the development of a dynamic morbidity dashboard, which enables users to interactively explore disease patterns across ICD-10 groups, filtered by year, gender, and age category. The dashboard prototype was developed using Streamlit, a modern Python-based web framework, which allowed for rapid interface building and seamless integration of visual analytics. Figure 1 illustrates an example visualization generated by the dashboard, showing a comparative bar chart of the top 10 ICD-10 disease categories.

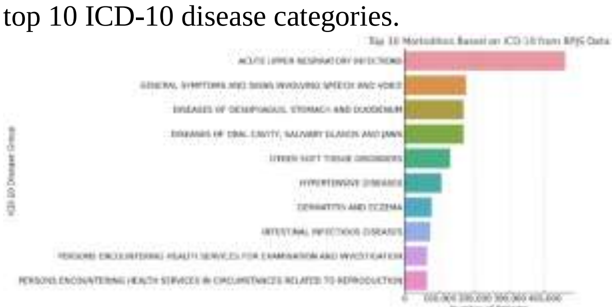

Figure 2: Bar Chart of Top 10 Morbidity ICD-10 Groups from BPJS Data

Unlike traditional static reports, this dashboard offers real-time filtering, enabling health officers to quickly identify shifting trends and allocate resources more efficiently. Its interactivity supports the transition from data reporting to actionable insights—a critical shift in the field of public health informatics (Ahmed Murtaza et al. 2024; Dash et al. 2019; Kobi 2024).

Discussion of Analytical Results

The results of this study strengthen the argument for the practical integration of digital tools in public health monitoring. As noted in Thorseth et al. (Thorseth et al. 2024), dashboards enhance surveillance systems by translating large datasets into clear, visual narratives. Khorram-Manesh et al (Khorram-Manesh, Goniewicz, and Burkle 2024). further demonstrated that health dashboards can accelerate response during outbreaks and streamline service delivery.

The use of ICD-10 as a classification backbone played a pivotal role in this study. Its standardized structure allowed for consistency, interoperability, and international comparability (Clark and Marshall 2022). The dashboard's ability to filter by demographic attributes such as age and gender also revealed important insights. For instance, respiratory infections were significantly higher in children under 11, while endocrine and cardiovascular diseases were more prominent among adults over 45. These patterns are consistent with global non-communicable disease trends reported by WHO (Hamad et al. 2021) and national health surveillance data [30].

Most importantly, this study introduces a novel application of underutilized secondary data from BPJS Central, filtered to reflect outpatient morbidity patterns in Karanganyar Regency. While many digital dashboards focus on hospital-based or aggregated national-level statistics, this research emphasizes the value of regional disaggregation for subnational health planning. The approach presented here offers a cost-effective and scalable solution that local health offices can adopt to improve strategic health governance (Torab-Miandoab et al. 2024).

CONCLUSION

This study has successfully designed and prototyped an interactive morbidity dashboard that utilizes ICD-10 classifications and secondary data from BPJS Central focused on Karanganyar Regency (2020–2024). The dashboard visualizes disease trends by age, gender, and year, addressing the core research objective of transforming administrative health data into actionable insights for regional health planning.

Main Findings:

The results indicate that the ten most prevalent disease groups in Karanganyar Regency align with national health concerns, including respiratory, digestive, endocrine, and circulatory conditions. The dashboard enables stakeholders to filter this data by key demographic variables, supporting evidence-based decisions in disease monitoring and intervention design.

Research Contribution:

This work contributes to the growing field of digital health informatics by offering a novel, region-specific use of BPJS data, bridging the gap between static health records and dynamic decision-making tools. It introduces a replicable model for local governments to convert underused administrative datasets into visual health intelligence systems.

Research Implications:

By providing a modular and scalable visualization platform, the dashboard promotes transparency and data literacy among health authorities. It demonstrates how data visualization tools can drive better policy alignment, resource allocation, and service delivery in decentralized healthcare settings.

Research Limitations:

This study was limited by its reliance on aggregated, anonymized data without direct integration with live clinical systems. The absence of real-time updates and granular clinical details restricts predictive capabilities and detailed case tracking.

Future Research Directions:

In addition to real-time data integration and predictive analytics, future studies are encouraged to explore the interoperability of the dashboard with existing national health information systems, such as SIRANAP, P-Care, and SIMRS. Further development may also focus on designing mobile-based or offline-compatible versions of the dashboard to enhance accessibility in remote or underserved regions. Moreover, qualitative studies involving local healthcare professionals and policy makers are recommended to gain deeper insights into user experience, adoption challenges, and organizational readiness for data-driven decision-making at the district level.

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