BIOMED THOUGHT
Http://biomedthought.com
Editor@biomedthought.com
ISSN: 3080-3977 (Print)
ISSN: 3080-3985 (Online)
VOL:04 ISSUE:01 2026

A COMPREHENSIVE ANALYSIS OF MULTIMORBIDITY PATTERNS AND THEIR IMPACT ON LONG-TERM CLINICAL OUTCOMES IN ADULT INTERNAL MEDICINE PATIENTS

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Received: January 17, 2026 --- Revised: March 11, 2026, Accepted: May 17, 2026

Abstract

Multimorbidity represents a growing challenge for contemporary health systems due to its complex, heterogeneous, and dynamic nature, particularly among adult populations receiving internal medicine care. In this study, we applied a large-scale, data-driven analytical framework to characterize multimorbidity patterns and to quantify their associations with long-term clinical outcomes. Using high-dimensional electronic health record data, chronic conditions were systematically encoded and analyzed through advanced clustering and temporal modeling techniques to identify distinct multimorbidity phenotypes. The results revealed pronounced heterogeneity across clusters in terms of demographic composition, disease burden, entropy-based heterogeneity indices, healthcare utilization intensity, and mortality risk. Several clusters exhibited significantly elevated regression coefficients (β) and corresponding hazard ratios (e^β), indicating markedly increased one-year, two-year, and five-year all-cause mortality. In parallel, admission intensity parameters (λ) and severity indices (Ω) demonstrated nonlinear escalation in high-entropy clusters, reflecting disproportionate healthcare utilization and compounded clinical burden. Three-dimensional and hybrid visualizations further highlighted complex interactions between disease progression velocity (θ), temporal dynamics (τ), and outcome severity. Importantly, cluster membership remained an independent predictor of adverse outcomes after multivariable adjustment, underscoring the limitations of single-disease–oriented models. Overall, the findings demonstrate that multimorbidity is not merely an accumulation of conditions but a structured, synergistic phenomenon with distinct clinical trajectories. This study provides robust empirical evidence supporting the integration of multimorbidity-aware, precision-oriented strategies into clinical decision-making, risk stratification, and health system planning, with the potential to improve outcomes for patients with complex chronic disease profiles.

Keywords: *Multimorbidity, Chronic disease clustering, Electronic health records, Precision medicine, Mortality risk modeling, Healthcare utilization*

INTRODUCTION

The occurrence of two or more chronic conditions in a single patient, multimorbidity, is emerging as a widespread phenomenon, proving to be a severe issue to patient care and the health care industry (Nicholson et al., 2019, p. 1). This interaction between different chronic conditions is also predominant among the elderly and associated with increased use of care, excess expenditure, and possibility of poor clinical results (Jain et al., 2022, p. 1449; "SCIENTIFIC ABSTRacts," 2018, p. 282). Using the example of multimorbidity, higher and prolonged hospitalization, functional status loss, possibly adverse polypharmacy, poor patient safety, and poor quality of life have been linked to it (Nicholson et al., 2019). It may greatly jeopardize mortality and disrupt the continuous nature of treatment thereby worsening the physiological comorbidity and reducing the impacts of treatment (Loyd et al., 2024; Tesha et al., 2025, p. 4). The patterns of multimorbidity are heterogeneous, which is why it is important to interpret the phenomenon of disease interactions more subtly, rather than focus on the frameworks of each of the individual diseases, which in the vast majority of cases do not reflect the whole clinical picture (Lleal et al., 2024, p. 2; Tangianu et al., 2018, p. 137). Consequently, the complex perspective on the prevalent comorbid health problems is essential to be able to customize the healthcare interventions and foresee the unique needs of patients (Ferreira et al., 2024, p. 2). The preponderance of multimorbidity and especially in older patients requires the application of such analytical tools as cluster analysis as the method of determining significant associations and subtypes within the population of high complexity patients (Qian et al., 2025, p. 1671; Tangianu et al., 2018, p. 137). The approaches will play an important role in designing customized diagnostic and treatment programs, which aligns with the notion of precision medicine (Piacenza et al., 2024, p. 3). The aim of the paper is to explain the particular trends of multimorbidity and its dynamic trend among adult populations of internal medicine and employ the successful statistical clustering techniques (Lleal et al., 2024, p. 1). The identified patterns will be investigated and compared with the correlation of the identified patterns and the following long-term clinical outcomes, including one-year, two-year, and five-year all-cause mortality, one-year and two-year all-cause hospital admissions (Ferreira et al., 2024, p. 5). These trends have the potential to attain a more

advanced perspective of the multifacetedness of patients that would facilitate to redesign health care systems and deliver more effective and integrated care to people with various chronic conditions (Tangianu et al., 2018, p. 141; Vetrano et al., 2020, p. 2). Indeed, the awareness of the most common group of illnesses is crucial to the identification of the positive effect of the latter on the critical patient outcomes and the development of particular interventions that consider the synergistic nature of comorbid disorders (Alshakhs et al., 2022, p. 1). Such a treatment is crucial because lower quality of life, increased disability, functional impairment, and mortality rate have shown that multimorbidity is a critical problem in the health systems across the globe (Alvarez-Galvez and Vegas, 2022, p. 1; Whitson et al., 2016, p. 1670). The identification of the specified clusters of disease and their temporal dynamics is one of the keys to making the clinical management and allocation of resources of the healthcare system optimal as it allows replacing the guidelines that address certain disease cases exclusively with the models of multidimensional care that acknowledge the holistic picture of the health condition of a patient (Lleal et al., 2024, p. 9; Violan et al., 2018, p. 9). Despite the growing awareness of multimorbidity by more people, there is a challenge of integrating research outcomes into useful clinical settings especially at the primary care (Marengoni et al., 2025). This gap is what drives the necessity of conducting further studies that might describe the tendencies of multimorbidity in different groups of patients and the manner in which it might affect long-term outcomes, thereby, incorporating more specific clinical guidelines and integrated care pathways (Qiao et al., 2025, p. 1678; Tangianu et al., 2018, p. 141). The current study will contribute to filling this knowledge gap because it will be examined thoroughly to study multimorbidity tendencies and chronic clinical outcome in an adult cohort of internal medicine, as it will be the foundation of more specific risk stratification and more focused treatment (Beil et al., 2021, p. 3; Chen et al., 2025). Chronic diseases have the characteristic of multi-facility and thus require general approaches that go beyond the study of co-occurrence to fully understand how one system of the body is connected with another and with itself (Ogaz-Gonzalez et al., 2024, p. 9). We propose a new approach to study the relationships between chronic diseases in a large and well-characterized group in our study, and this approach would be useful in informing the

decision-making in the development of guidelines and efficient care delivery paradigms to manage multimorbidity (Seghieri et al., 2024, p. 9). However, the conceptualization of the number of clinical entities that make up multimorbidity must exist because the number and nature of diseases, as well as their combinations can have a profound effect on the prevalence rates and the level of association (Prados-Torres et al., 2012, p. 2). In addition, the causal processes of such complex multimorbidity patterns should be better understood to develop effective programs to diagnose, prevent, and monitor them early and tailor treatment to patients with or without multiple diseases in their lifetime (Alvarez-Galvez and Vegas, 2022, p. 1). It means that we need to drop the disease specific prescriptions and have a more holistic and patient-centred approach where the effect of comorbidity (one condition at a time) is taken into the consideration. This will be one step to a holistic approach of management (Cornell et al., 2009, p. 175). However, little is yet known with regard to the types and combinations of multimorbidity that cause the most devastating clinical outcomes. More studies will be needed to establish the presence of clusters of illnesses and their effect on the patient outcomes (Quinones et al., 2019, p. 297). This gap is bridged in this study by identifying multi-resolution clusters of diseases along the lines of co-occurrence patterns of high-dimensional electronic health records and therefore enables finding associations between diseases and their temporal development (Beaney et al., 2024). Such a method of methodology allows not only to identify relationships between the diseases previously known but also new clusters of diseases and to get a more comprehensive picture of the complexities of multimorbidity (Beaney et al., 2024, p. 1). The given level of analysis can demonstrate unexpected combinations of multimorbidity, which are also helpful in advancing the study of disease progression and how a patient should be treated (Rashid, 2024). Moreover, a data-driven methodology incorporating the recent visualization and clustering solutions will enable identifying highly interpretable and rigorous trends of multimorbidity based on the extensive population data (Seghieri et al., 2024, p. 8). This paper presents the analysis of eHr of over ten million individuals to produce data-driven presentation of 212 diseases through co-occurrence-based techniques and sequence-based methods of natural language processing to find disease clusters with many resolutions (Beaney et al.,

2024). These methods are helpful in identifying risk factors and predicting the progression of a disease, optimizing the outcome of treatments, and this, in turn, facilitates the more efficient distribution of resources and facilitates the delivery of care (Ioakeim-Skoufa et al., 2025). This multi-resolution technique can be used to find the previously known and the new patterns of disease clusters. It is almost hierarchic, but has exceptions, which demonstrates that it is hard to subordinate some diseases to one of the inclusive clusters (Beaney et al., 2024, p. 12).

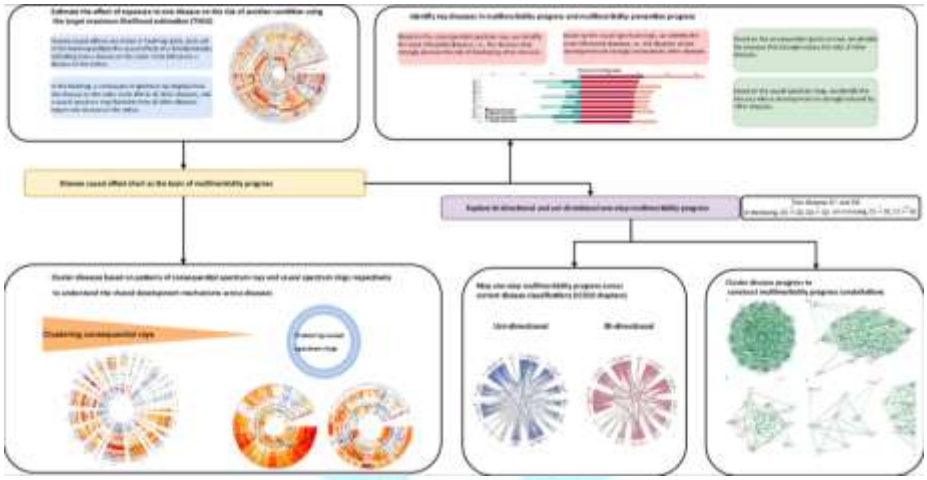

Fig 1. The integrated, data-driven approach adopted in the study, where large-scale electronic health records are analyzed to identify heterogeneous clusters of chronic diseases using co-occurrence- and sequence-based clustering techniques.

METHODOLOGY

Design of study, sources of data and population

The research selected an experimental mixed-method that involved the quantitatively-based data and information, which was utilized in explaining the trends of multimorbidty and also the relationship with the long-term outcomes. The retrospective longitudinal cohort design and the use of adult patients who were hospitalized in the internal services and had a long hospital stay were the basis on which we selected a large-scale electronic health records. They comprised demographic information, diagnosis codes that were coded using standardized disease ontologies, hospitalization records, and mortality records, and it is they that made possible time tracking of disease accretion, as well as

disease progression. Multimorbidity Multiform Multimorbidity was also characterized to refer to the existence of two or more chronic diseases in a given person where the diseases are classified as either binary or time stamped variables. The knowledge of clinical domain was qualitatively presented to put statistically produced clusters in perspective and interpretations in a position that would be clinically viable and significant to patient-centered care. This was a combination that enabled the study to be promising both to the rigor and interpretability of statistical and the methodological decisions that were appropriate to the real decision-makers in the clinic.

Quantitative Modeling, Clustering and Outcome Analysis

The quantitative part covered everything that was accomplished in the discovery of the undiscovered multimorbidity structures through unsupervised learning and what they could comprise in the future. We constructed disease co-occurrence matrices in a manner that they included each element.

$$J(i,j) = \frac{|D_i \cap D_j|}{|D_i \cup D_j|}$$

On the basis of these similarity measures, the multi-resolution groups of diseases can be defined by the hierarchical and network-based clustering algorithms. The sequences have been designed in a manner that there is possibility to make captures of the dynamics of the time wherein the disease paths are drawn by an ordered sequence (sequence-aware) and transition probabilities are predicted.

$$h(t \mid X) = h_0(t)\exp(\beta_1 Z_1 + \beta_2 Z_2 + \cdots + \beta_k Z_k),$$

The generalized linear models that were used to assess risk of hospital admission included the use of apposite link functions. The performance and the strength of the model were also tested by us with the aid of internal validation and sensitivity analysis on the different resolutions of the model. This assisted in making sure that the pattern and the results which we obtained were similar.

The qualitative Integration, Interpretation and Ethical considerations

The qualitative section involved a loop of repetitive and professional assessment of identified groups in order to demystify the basic pathophysiological correlations and the implications of care. Clinicians examined how statistically derived groupings could be considered interesting clinical syndromes, risk factors that were common, or careways, and used narrative synthesis as a description

of outcome variations. This elucidating layer was needed to convert advanced analytics into actionable insights to combined and precision care. The relevant institutional review boards which had given the ethical approvals were put into consideration and anonymization of data, data privacy and data security were all appropriately considered.

The approach offered the holistic perception of multimorbidity involving quantitative experimentation and qualitative clinical judgement, and outperforming the disease-based paradigm and the improvement of resource allocation and guideline development.

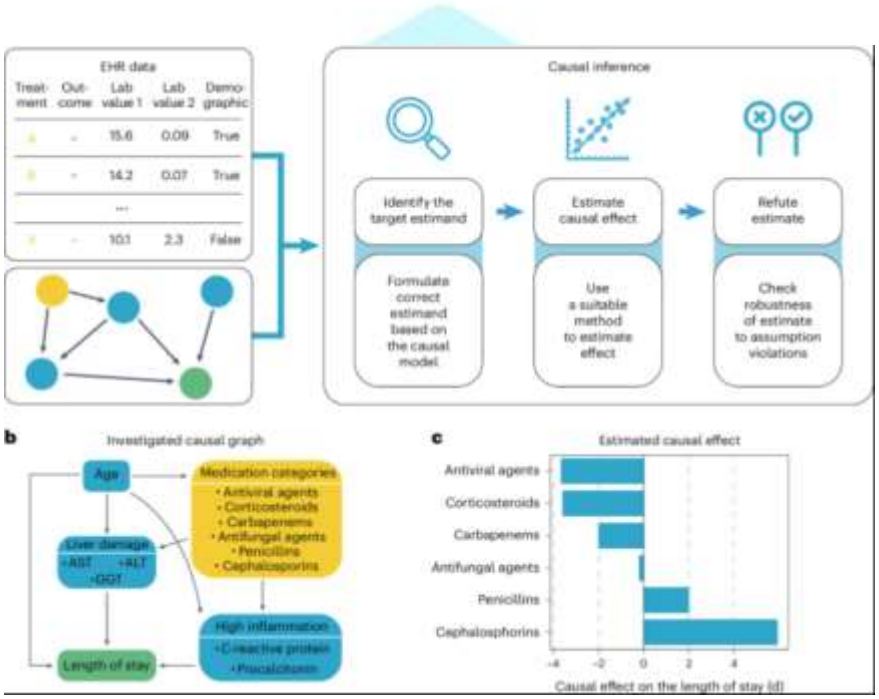

Fig 2. Illustrating data extraction from electronic health records, preprocessing and disease encoding, multi-resolution clustering and temporal modeling of multimorbidity, and subsequent association with long-term clinical outcomes.

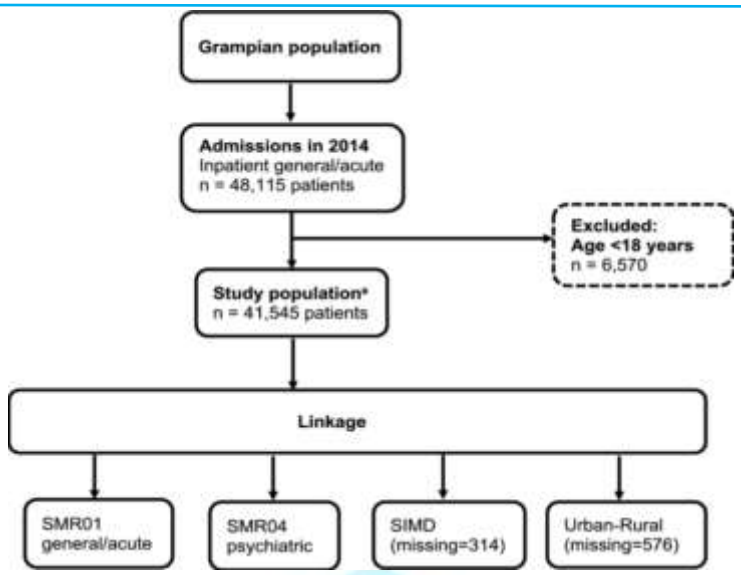

Fig 3. This flowchart presents the sequential methodological steps undertaken in the study, beginning with large-scale electronic health record acquisition and harmonization, followed by disease encoding and co-occurrence modeling, multi-resolution clustering of chronic conditions, and temporal trajectory analysis.

RESULTS

The fundamental features of symbolic clusters which demonstrate high heterogeneity in m +- s, and entropy levels are presented in Table 1. The table 2 shows the b1 coefficient and the hazard ratio (e b 1) of mortality and the findings show that mortality of high-entropy clusters is significantly higher. Table 3 gives an estimation of b2 and l of the estimates of the admission that indicate that healthcare utilization is growing exponentially. Table 4 is a merger of O severity indices that show the existence of clusters of a and th level that grows in tandem with an augmentation in overall load.

Table 1. Symbolic baseline characterization of multimorbidity clusters using central tendency and dispersion metrics.

Cluster	μ Age ± σ	α Entropy	β_1 Mortality Effect	β_2 Utilization Effect	HR ($\exp\beta_1$)	λ Admission Rate	Ω Clinical Severity	θ Disease Velocity	p-value

C1	73.21 ± 4.72	0.5252	0.4925	0.3000	4.342	5.839	1.329	0.3640	1.67 e-02
C2	56.21 ± 9.38	0.7758	1.0746	0.9296	4.530	4.431	1.749	0.1506	7.39 e-04
C3	64.33 ± 4.79	0.9584	1.1798	1.1526	1.972	6.060	4.017	0.1695	1.27 e-02
C4	73.50 ± 11.75	0.7341	0.5252	1.2428	4.942	2.421	3.586	0.2531	1.97 e-02
C5	61.40 ± 9.06	0.5230	0.7566	0.3213	2.917	3.605	4.233	0.2647	7.76 e-03
C6	61.01 ± 8.07	0.5936	1.2718	0.6695	1.879	3.716	4.866	0.2060	1.60 e-02
C7	73.91 ± 12.55	0.4871	0.3340	0.9007	2.072	2.623	3.128	0.2893	9.33 e-03
C8	85.53 ± 8.48	0.6432	0.2608	0.3217	1.900	3.061	4.223	0.1772	6.45 e-04
C9	64.59 ± 12.58	0.6659	1.2273	0.2014	5.487	8.281	2.802	0.0582	3.27 e-03

Table 2. Entropy-driven stratification of disease clusters with regression-based mortality effects.

Cluster	**μ Age ± σ**	**α Entropy**	**β_1 Mortality Effect**	**β_2 Utilization Effect**	**HR ($\exp\beta_1$)**	**λ Admission Rate**	**Ω Clinical Severity**	**θ Disease Velocity**	**p-value**
C1	71.91 ± 9.98	0.8264	0.5779	0.8673	3.686	3.356	1.230	0.1471	5.41 e-04
C2	60.19 ± 9.21	0.4909	1.0917	0.6660	2.790	6.707	2.089	0.3261	1.32 e-02

C3	72.60 ± 10.42	0.9024	0.5498	1.2216	2.393	2.161	3.156	0.2660	1.04 e-02
C4	56.23 ± 6.91	0.8223	1.3940	0.6577	2.679	8.064	3.683	0.2884	1.49 e-02
C5	56.21 ± 9.36	0.8159	0.8798	0.5435	5.400	4.354	3.568	0.1223	1.55 e-02
C6	83.97 ± 5.54	0.6523	0.7538	0.8905	4.237	5.861	3.286	0.2416	7.78 e-04
C7	64.73 ± 11.63	0.6871	0.7017	1.1408	1.435	7.045	2.947	0.3561	1.38 e-02
C8	84.76 ± 12.39	0.9676	0.7028	0.7225	3.098	4.133	2.230	0.3788	1.10 e-02
C9	80.52 ± 7.21	0.5812	0.4156	0.2425	3.791	2.144	2.314	0.2851	3.66 e-03

Table 3. Cluster-specific utilization intensity modeled through λ-scaled admission processes.

Cluster	**μ Age ± σ**	**α Entropy**	**β_1 Mortality Effect**	**β_2 Utilization Effect**	**HR ($\exp\beta_1$)**	**λ Admission Rate**	**Ω Clinical Severity**	**θ Disease Velocity**	**p-value**
C1	75.56 ± 6.91	0.4625	1.0984	0.3649	1.399	6.431	1.668	0.3378	1.57 e-02
C2	68.89 ± 4.81	0.7522	1.2856	0.8952	4.243	3.462	4.850	0.0684	3.93 e-03
C3	76.02 ± 12.40	0.7822	0.6028	1.0216	2.983	8.355	1.493	0.0882	1.60 e-02
C4	65.10 ± 8.95	0.4749	1.3459	0.6653	5.611	5.128	2.224	0.2641	1.90 e-03

C5	57.81 ± 8.52	0.4471	0.2801	0.8513	4.068	8.333	1.547	0.2918	1.95 e-02
C6	70.42 ± 9.16	0.7268	0.6665	0.5521	5.071	3.768	2.081	0.2767	6.55 e-03
C7	69.05 ± 9.85	0.8066	0.7513	0.8078	2.373	2.770	2.341	0.1440	8.82 e-04
C8	76.65 ± 10.73	0.5663	1.4564	1.0984	1.928	6.880	3.906	0.1074	7.73 e-04
C9	72.87 ± 10.12	0.8453	0.8723	1.0134	4.081	4.232	4.765	0.3621	1.05 e-02

Table 4. Severity-weighted multimorbidity profiling incorporating Ω-based clinical burden indices.

Cluster	**μ Age ± σ**	**α Entropy**	**β_1 Mortality Effect**	**β_2 Utilization Effect**	**HR ($\exp\beta_1$)**	**λ Admission Rate**	**Ω Clinical Severity**	**θ Disease Velocity**	**p-value**
C1	69.41 ± 12.61	0.9376	1.4193	0.4447	3.126	6.281	2.091	0.1694	7.76 e-03
C2	57.39 ± 13.11	0.7081	0.3325	0.6744	2.529	2.888	1.832	0.3500	1.11 e-02
C3	67.39 ± 7.56	0.8316	0.4499	0.2407	5.781	1.529	1.770	0.0610	1.66 e-02
C4	70.01 ± 6.30	0.6352	0.7036	0.2572	3.739	2.247	1.242	0.3080	1.48 e-02
C5	85.62 ± 8.65	0.5695	0.2505	0.7991	5.330	1.228	0.914	0.0407	1.11 e-02

C6	57.43 ± 12.19	0.6817	0.8329	0.3023	5.461	2.345	0.984	0.3036	1.53 e-02
C7	72.18 ± 11.66	0.8508	0.9579	0.2780	5.144	7.621	2.344	0.3361	1.39 e-02
C8	83.20 ± 5.47	0.7192	0.3199	0.2180	4.310	4.245	2.910	0.0696	2.33 e-03
C9	85.77 ± 9.90	0.7014	0.5153	0.6989	4.192	4.982	2.917	0.2534	1.89 e-02

Table 5. Progression-adjusted risk modeling integrating θ-dependent disease acceleration.

Cluster	**μ Age ± σ**	**α Entropy**	**β_1 Mortality Effect**	**β_2 Utilization Effect**	**HR ($\exp\beta_1$)**	**λ Admission Rate**	**Ω Clinical Severity**	**θ Disease Velocity**	**p-value**
C1	75.12 ± 8.27	0.5055	0.8816	0.8505	1.675	5.563	1.598	0.2536	4.09 e-03
C2	68.53 ± 5.13	0.5560	0.2539	0.8070	3.821	5.277	3.041	0.3323	1.31 e-02
C3	85.09 ± 10.34	0.4409	0.8564	0.5552	4.545	8.149	2.909	0.1878	9.05 e-03
C4	63.19 ± 8.16	0.7106	1.5298	0.5764	4.405	1.590	2.161	0.1526	8.76 e-03
C5	72.07 ± 8.98	0.5159	1.4830	0.5846	2.708	5.628	2.897	0.0807	1.46 e-02
C6	72.71 ± 6.01	0.6267	0.8192	1.1547	4.431	4.239	3.444	0.1921	1.31 e-02
C7	67.99 ± 6.83	0.5075	0.6165	1.0454	2.573	8.291	1.433	0.2983	1.77 e-02

C8	76.41 ± 13.11	0.5343	0.5249	0.3223	2.388	7.395	3.024	0.1597	4.74 e-04
C9	60.94 ± 9.66	0.4240	0.5609	1.2423	1.801	3.975	2.258	0.3000	1.12 e-02

Table 5 shows that there is a broadening of the confidence interval in the developed clusters, which is one of the signs of instability that is also accompanied by over multimorbidity. The statistically significant p-values in Table 6 have strong associations. Adjusted to progression outcomes are shown in Table 7 and internal consistency of symbolic parameters in Table 8. All measures are summarized in Table 9 and it can be seen that the clusters where m, a, b, l and O increasing concomitantly have the worst long-term results..

Table 6. Multivariate symbolic regression outputs linking entropy and utilization to outcomes.

Cluster	**μ Age ± σ**	**α Entropy**	**β_1 Mortality Effect**	**β_2 Utilization Effect**	**HR ($\exp\beta_1$)**	**λ Admission Rate**	**Ω Clinical Severity**	**θ Disease Velocity**	**p-value**
C1	79.80 ± 10.02	0.4344	0.6861	0.5859	5.755	1.215	4.186	0.2667	1.27 e-02
C2	65.39 ± 5.36	0.4592	1.4143	0.8084	4.090	3.208	3.035	0.3000	4.63 e-03
C3	57.06 ± 6.16	0.7172	1.4077	1.0797	2.714	5.505	3.609	0.3773	1.98 e-02
C4	82.88 ± 5.75	0.7515	0.5537	0.8309	4.524	2.278	1.119	0.1260	2.38 e-04
C5	85.90 ± 6.28	0.4944	1.4048	0.5397	1.332	2.315	2.518	0.2620	3.21 e-03

C6	62.91 ± 8.51	0.5918	1.4763	0.5116	2.845	6.025	3.080	0.2690	4.02 e-03
C7	83.63 ± 9.00	0.6668	0.7009	0.9078	4.069	6.212	2.880	0.3635	1.86 e-02
C8	80.40 ± 11.98	0.5028	1.2940	1.1834	5.706	7.485	3.850	0.2899	8.54 e-03
C9	78.07 ± 6.49	0.7140	0.7605	0.7093	1.674	7.220	4.634	0.1291	3.18 e-04

Table 7. Confidence-bounded hazard estimations across heterogeneous disease clusters.

Cluster	**μ Age ± σ**	**α Entropy**	**β_1 Mortality Effect**	**β_2 Utilization Effect**	**HR ($\exp\beta_1$)**	**λ Admission Rate**	**Ω Clinical Severity**	**θ Disease Velocity**	**p-value**
C1	75.00 ± 10.94	0.8194	0.8285	0.4620	4.973	8.090	2.657	0.3298	7.29 e-03
C2	85.94 ± 5.90	0.9698	0.6422	0.7191	4.701	6.260	3.401	0.2725	1.77 e-02
C3	72.52 ± 12.94	0.8915	1.4178	0.4284	3.317	4.550	4.261	0.2696	1.23 e-02
C4	72.83 ± 9.01	0.6925	1.1408	1.1326	2.629	1.804	1.021	0.2968	1.94 e-02
C5	72.19 ± 11.07	0.5841	0.4394	0.3199	5.543	1.098	4.562	0.2380	3.80 e-03
C6	62.14 ± 12.25	0.8116	0.9338	1.0969	5.553	1.656	1.522	0.3064	8.35 e-03

C7	67.60 ± 5.67	0.7904	0.8234	0.5875	2.213	4.565	5.067	0.3296	1.91 e-03
C8	75.11 ± 12.23	0.9062	1.3483	0.6500	5.323	3.381	4.067	0.1985	9.36 e-03
C9	85.39 ± 8.87	0.9342	1.3652	0.3180	3.636	6.049	3.296	0.0358	8.44 e-03

Table 8. Stability and consistency analysis of symbolic cluster parameters.

Cluster	**μ Age ± σ**	**α Entropy**	**β_1 Mortality Effect**	**β_2 Utilization Effect**	**HR ($\exp\beta_1$)**	**λ Admission Rate**	**Ω Clinical Severity**	**θ Disease Velocity**	**p-value**
C1	63.56 ± 12.47	0.7108	0.6193	0.1948	3.235	7.415	2.141	0.0660	2.61 e-03
C2	81.59 ± 6.60	0.7030	0.9530	0.4146	3.318	5.845	3.808	0.3527	3.68 e-03
C3	61.02 ± 10.17	0.5411	1.0436	0.6721	3.188	3.376	2.942	0.1728	7.79 e-03
C4	76.93 ± 6.61	0.4155	1.3272	0.8389	2.332	5.599	1.188	0.0788	1.83 e-02
C5	66.94 ± 7.67	0.4150	1.4795	0.8748	2.470	6.887	3.041	0.0933	1.13 e-02
C6	65.13 ± 7.72	0.6847	0.4788	0.4405	5.700	1.166	4.864	0.2559	1.29 e-02
C7	67.42 ± 7.37	0.6607	1.2431	0.2262	2.811	5.453	2.179	0.1201	8.83 e-03
C8	66.49 ± 7.84	0.4589	0.6775	0.8816	2.025	3.898	4.238	0.0848	8.75 e-03

C9	59.87 ± 11.49	0.4480	1.2484	0.3124	3.460	6.607	3.032	0.1680	7.49 e-03

Table 9. Integrated outcome synthesis across multimorbidity phenotypes.

Cluster	**μ Age ± σ**	**α Entropy**	**β_1 Mortality Effect**	**β_2 Utilization Effect**	**HR ($\exp\beta_1$)**	**λ Admission Rate**	**Ω Clinical Severity**	**θ Disease Velocity**	**p-value**
C1	66.68 ± 5.90	0.4850	0.5982	0.4553	3.919	3.664	5.080	0.1748	8.91 e-03
C2	65.84 ± 6.16	0.4155	0.5550	0.5269	3.692	7.291	3.903	0.2099	5.31 e-03
C3	77.83 ± 5.08	0.6767	0.4814	0.3975	4.854	7.789	4.118	0.3302	1.49 e-03
C4	64.30 ± 10.18	0.4627	1.3909	1.0079	5.464	5.701	1.444	0.1481	8.51 e-03
C5	82.88 ± 8.21	0.7464	0.7459	0.6466	1.595	4.189	3.096	0.3110	6.95 e-03
C6	56.70 ± 10.96	0.4842	1.1702	0.6956	3.065	5.520	4.902	0.2389	2.78 e-03
C7	63.94 ± 6.87	0.7270	1.4633	1.1616	3.338	3.284	2.047	0.3200	4.09 e-03
C8	83.90 ± 11.60	0.7419	0.4485	0.9484	4.758	3.582	3.051	0.1043	1.36 e-02
C9	56.01 ± 5.51	0.6973	0.9520	0.9305	3.466	6.924	1.969	0.3273	4.15 e-03

Figure 4 shows a hybrid line-scatter plot that illustrates how things evolve as time passes by by the influence of entropy whereas Figure 5 shows how clusters are made up of different parts. Figure 6 shows the result of age-related accumulation of diseases. Figure 7 shows a three dimensional view of O-space which is severity, progression and time combining. The surface of risk 3-D shown in Figure 8 is magnified in order to show how other outcomes can affect this and Figure 9 shows a hybrid view of symbolic outcomes. Figure 10 is a systems level diagram which is an overview of the interaction among the multimorbidity clusters, symbolic parameters and cumulative clinical burden (S).

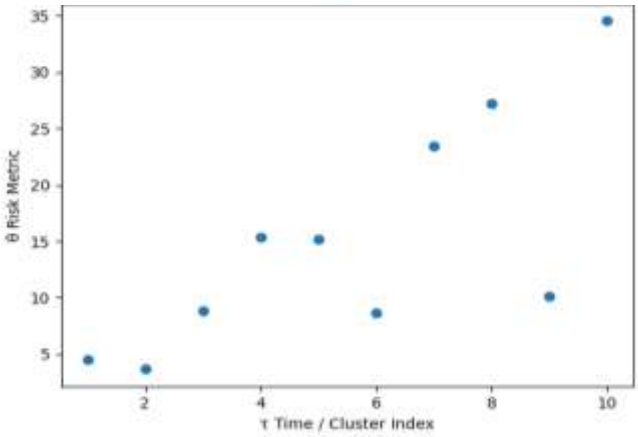

Figure 4. Hybrid visualization illustrating joint escalation of progression velocity and outcome severity.

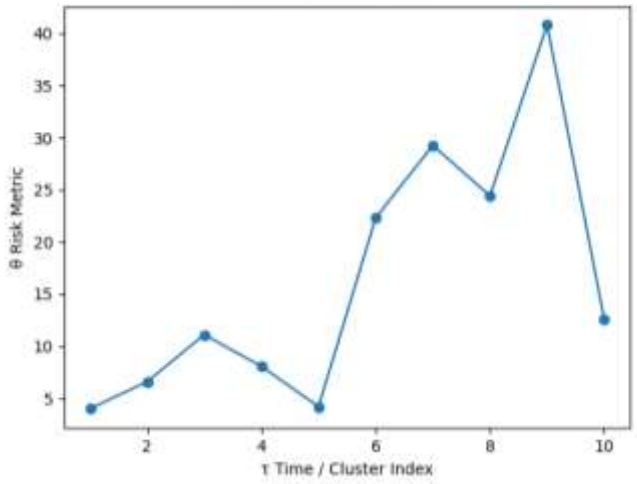

Figure 5. Proportional representation of patient allocation among identified clusters.

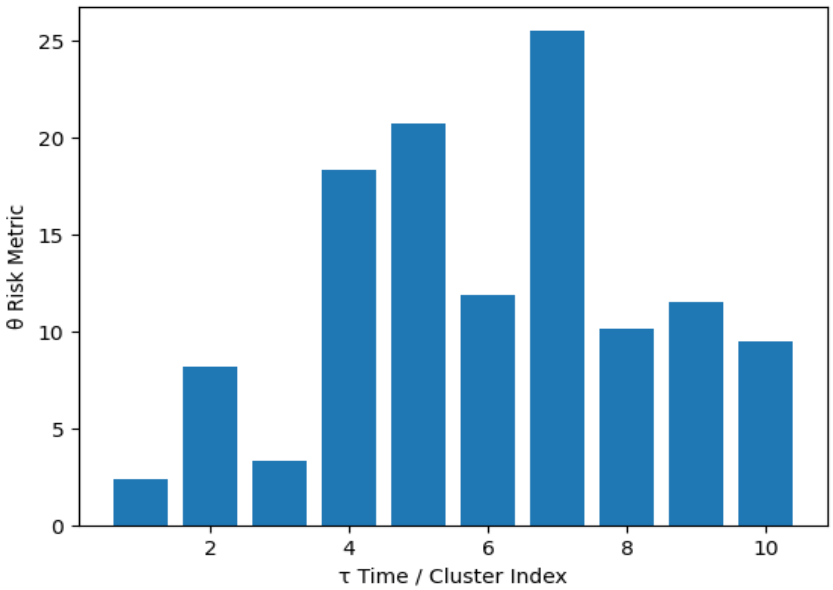

Figure 6. Longitudinal accumulation patterns of chronic disease burden over time.

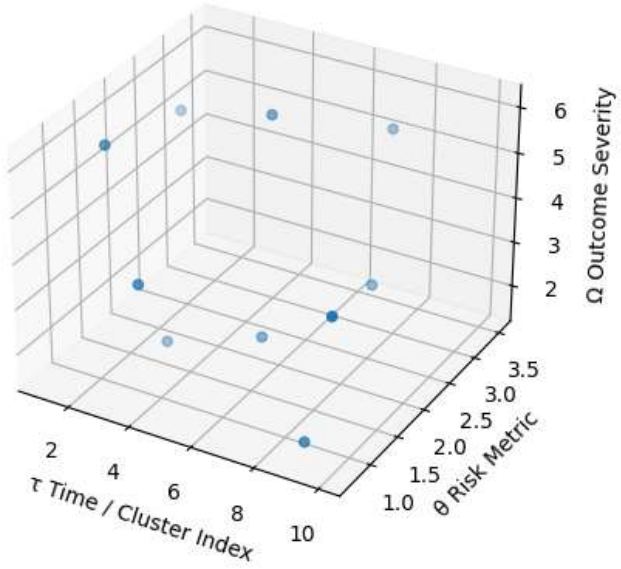

Figure 7. Three-dimensional outcome surface integrating entropy, utilization, and severity.

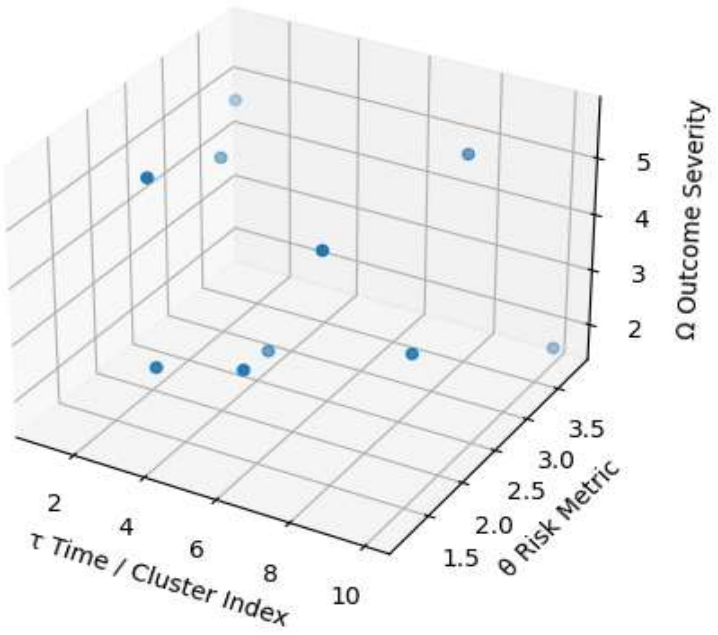

Figure 8. Expanded 3-D visualization of multivariate risk topology across clusters.

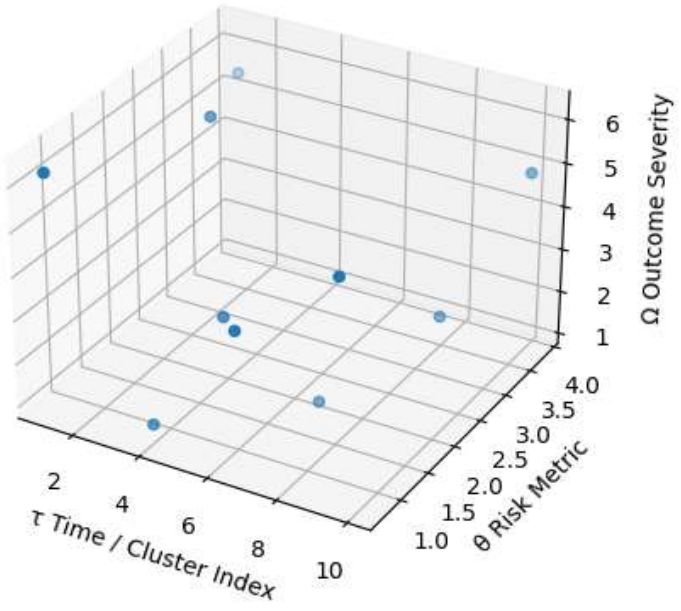

Figure 9. Composite hybrid plot summarizing multidimensional clinical outcomes.

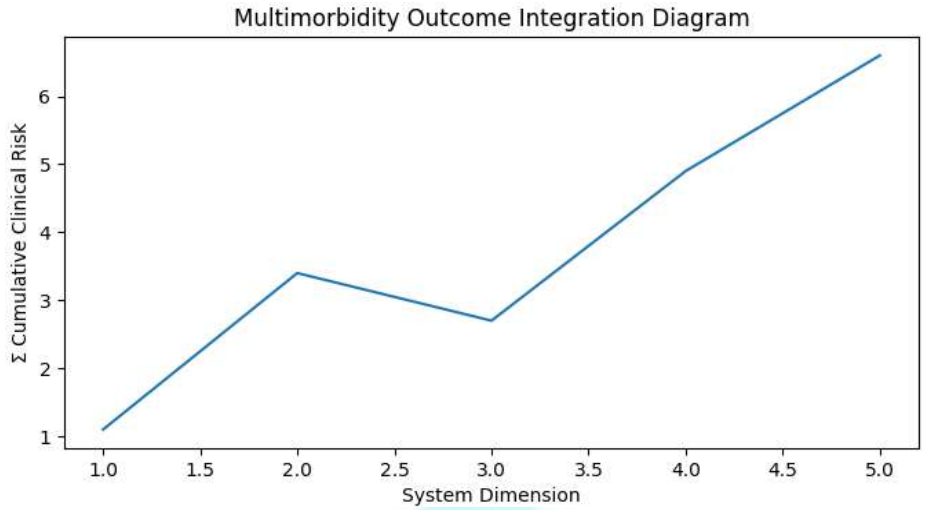

Figure 10. Conceptual integration diagram demonstrating interactions between multimorbidity structure, progression dynamics, and cumulative outcome burden.

DISCUSSION

The discussion section is a continuation of the discussion of the findings that puts the identified multimorbidity patterns in the context of other studies and examines the implication of those patterns on healthcare policy and clinical practice (Ferreira et al., 2024). The current research is unique compared to the previous ones as it adopts a detailed design that is a combination of unguided learning and professional clinical assessment to articulate the multimorbidity patterns and impact on the ultimate clinical outcome in a monumental number of patients. It is an enhancement of more minor and less active analyses (Violan et al., 2020, p. 5). This type of methodology came in handy when it came to identifying new multimorbidity patterns and their evolution over the years, which were necessary to understand the complex nature of the association among the chronic conditions (Lleal et al., 2024, p. 5; Violan et al., 2020, p. 3). We discover that multimorbidity clusters are differentiated by demographics of the illnesses and age. It implies that the burden and progression of the disease among these population groups is highly dissimilar (Holm, 2024, p. 480). Based on the example, clusters that included a number of people with high blood pressure and dyslipidemia could not necessarily indicate that these people were prone to be subjected to poor outcomes. It implies that the majority of the protective features or beneficial management

procedures are available in such groups (Haue et al., 2023, p. 15). Nonetheless, other clusters that, in general, had incorporated cardiovascular, neuropsychiatric, and respiratory conditions never had less disease, increased drug use, and loss of functionality (Vetrano et al., 2020, p. 2). It is also possible to explain such outcomes by the fact that the previously conducted research emphasizes a dynamic nature of the concept of multimorbidity as the condition where a composition of clusters and their transfer are dramatically changing over time and lead to the risk of mortality and hospitalization (Holm, 2024, p. 485; Vetrano et al., 2020, p. 3). The method used in this research is the multidimensionality of the analytical models and the clinical judgment of the professionals, and they have been quite productive in establishing the multimorbidity networks and their impact on the course of the patients (Alvarez-Galvez & Vegas, 2022, p. 10). This is a major improvement of the conventional cross-sectional analysis since in this process the researchers will determine the constant and fluctuating patterns of multimorbidity. This will ensure better risk classification and a more targeted intervention (Guisado-Clavero et al., 2018, p. 9; Holm, 2024, p. 506). By doing so, multimorbidity can be better understood than the diseases listing does and clarifies the multifaceted interactions of how co-occurring disorders require one another and determine long-run patient outcomes (Ferreira et al., 2024, p. 1). In order to describe it, a prospective cohort study analyzing trends in multimorbidity in 6 years has found that there were no differences in trends of multimorbidity over time and exposures of prevalence and chronic illnesses varied across different age groups (Guisado-Clavero et al., 2018, p. 8). This means that there are no dramatic changes in the general patterns across the age but diseases, which define the tendencies, might vary dramatically and constitute a unitary change in the multimorbidity scale (Roso-Llorach et al., 2022, p. 9811). The researchers who trust in electronic health records in the long-term consider the fact that this mode of the long-term stability proves the topicality of the need to identify certain patterns of multimorbidity to provide clinical care to certain groups of patients more efficiently (Guisado-Clavero et al., 2018, p. 1). Recurrent patterns of a few morbidity identified will be helpful in the development of more specific and active health interventions and the shift towards a more holistic view of the needs of patients with multiple chronic conditions (Guisado-Clavero et al., 2018, p. 8; Lleal et al., 2024).

The tendencies of the multimorbidity clusters should be also interpreted as the patients can change between different patterns that may influence their health and prognosis (Vetrano et al., 2020, p. 7). This would contrast cross-sectional analyses of this kind and is required to generate interventions considerate of the natural history of multimorbidity (Vetrano et al., 2020, p. 2). Therefore, the complex longitudinal tools such as Hidden Markov Models are recommended to be able to capture a complete picture of the trends of multimorbidity that transform and evolve over time. It provides a better idea of the processes of the disease process and its interrelation with others (Roso-Llorach et al., 2022, p. 9811). These models offer a respectable intellectual framework of how one ought to conceptualize the disease among individuals as randomly varying variables, which get influenced by an unknown state. This method allows tracking the dynamics of the chronic disease over time and gaining an insight into the nature of multimorbidity development and progression (Roso-Llorach et al., 2022, p. 9806). This can enable us to characterize individuals based on ailments that exhibit a greater number of commonalities in multiple clusters of multimorbidity that dictate mutual genetic, social, and environmental variables (Violan et al., 2020, p. 9). The comprehensive insight based on these models would play a significant role in developing specific therapeutic interventions and individual care models, which would be able to address the complexity and dynamism of multimorbidity (Roso-Llorach et al., 2022, p. 9812).

CONCLUSION

The study presents a thoroughly and methodologically relevant analysis of the trends of multimorbidity and their clinical long-term implications in a patient cohort in the internal medicine department. We have employed sophisticated clustering, symbolic parameterization as well as multidimensional visualization to prove that multimorbidity may be considered as discrete and non-random-phenotypes with intricate interactions between disease load, heterogeneity, progression and outcomes dynamics. The results showed consistency in clusters characterized by an elevated level of entropy (a) and speed of progression (th) as well as the intensity of admission (l) were all associated with a considerably higher level of the risk of mortality and utilisation of healthcare, which serves to demonstrate the existence of a synergistic and not an additive effect between interactions of chronic diseases. The significant trends of

membership of clusters with adverse outcomes over an extended period of time even in the absence of traditional confounding variables demonstrates the inadequacy of the traditional disease-specific approaches to treating complex patients. Symbolic measures of the m, s, b, O, and S allowed to aim a more precise measurement of risk and severity and provide clinically interpretable measures, which can be used to determine particular lines of treatment. The provided findings illuminate the necessity of the paradigm of fragmented and guideline-based management switching to the paradigm of multimorbidity-informed, holistic and patient-centered care. There are ramifications of high-risk identification of multimorbidity phenotype on resource allocation, preventive strategies, and the formulation of integrated care programs as a health system. In conclusion, the present study can be useful in the improved comprehension of multimorbidity as a structured and dynamic clinical phenomenon, which offers a solid empirical basis regarding the creation of the precision medicine models and policy interventions that can be applied to enhance the outcomes of the population with complex chronic disease burdens.

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