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Visualization in data-driven patient pathway analysis in healthcare: a systematic literature review

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Systematic Review

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Visualization in data-driven patient pathway analysis in healthcare: a systematic literature review

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Abstract

Rising healthcare costs, increasing treatment complexity, and the challenge of consistently implementing clinical guidelines place substantial pressure on healthcare providers. Patient pathway analysis has emerged as a structured approach for examining how diagnostic, therapeutic, and organizational processes unfold over the course of care. Visualization complements this approach by making complex pathway data interpretable, revealing recurring patterns, deviations, and relationships between care steps. This systematic review identifies and classifies the visualizations used in data-driven approaches that analyze or model patient pathways. It focuses on studies that explicitly depict the pathways or analytical results. Of 1 193 records retrieved from Web of Science, only 20 publications met the analytical and visualization criteria after title and abstract assessment, full-text review, and forward and backward citation tracking. This suggests that, although patient pathways are widely studied, explicit visualizations of pathways or results remain rare. The included publications were classified and analyzed according to four analytical categories: process characteristics, context and application, methods and modeling approaches and visualization techniques. The findings indicate that patient pathways are predominantly analyzed using electronic health record data, particularly in chronic somatic diseases and oncology. Process mining and probabilistic modeling are the most frequently applied methods, while graph-based representations dominate visualization techniques. Nevertheless, the integration of observed pathways with guideline-based reference processes, transitions between care settings, and scalable visualization of complex pathway remain insufficiently addressed. Future research should therefore prioritize interactive, clinically evaluated visualization approaches that combine cohort-level and individual-level perspectives and support comparisons between actual and recommended care pathways.

Keywords: Patient pathways; Clinical pathways; Visualization; Data-driven analysis; Healthcare informatics

1 Introduction

1.1 Motivation

Healthcare providers are required to manage an increasing volume of patients and medical costs while treatment processes become more resource-intensive and difficult to coordinate [1, 2]. This challenge is particularly relevant for hospitals and highly specialized fields such as oncology, where care often involves multiple disciplines and treatment stages [3–5]. Delivering consistent, high-quality care under these conditions requires both efficient use of resources and a clear understanding of how patients move through the healthcare system. However, the continuous development of new medical knowledge, technologies, and therapeutic options makes these processes increasingly difficult to oversee [6, 7].

To address these challenges, approaches such as patient journey mapping (PJM) and patient pathway analysis have gained traction. Although the two concepts are often used synonymously in practice, the literature highlights important distinctions. *Patient journeys* provide a patient-centered perspective by capturing experiences and touchpoints across the care continuum, whereas *patient*

pathways describe the structured sequence of diagnostic, treatment, and care processes from an organizational or institutional perspective [8–10]. In other words, patient pathways represent the formalized clinical process within which the patient journey unfolds. A further related concept is that of *clinical pathways*, described as structured, multidisciplinary care plans that translate clinical guidelines and evidence into local practice, outlining key steps in patient care [11]. Together, these concepts are crucial for understanding the quality, efficiency, and transparency of modern healthcare. However, the underlying processes are frequently complex and only partially documented, potentially concealing areas for improvement [12–14]. Visualization of patient pathways helps to reduce this complexity by making temporal sequences, recurring patterns, and relationships between clinical events more accessible and interpretable. Such representations can therefore enhance the quality of care, strengthen interdisciplinary communication, data-driven decision-making, and provide greater transparency for both patients and clinicians [15, 16].

1.2 Related research

PJM has emerged as a patient-centered approach for understanding, analyzing, and optimizing patient experiences, and is being adopted with increasing interest [17]. This approach places the individual and their lived experiences at the center of the analysis [18]. A foundational contribution to the conceptualization of clinical pathways was made by Kinsman et al. [11], who reviewed existing definitions of clinical pathways and developed five criteria for this concept in 2010.

Despite the growing interest in PJM, no specific reporting guidelines for this approach currently exist. Nevertheless, recommendations to improve reporting practices and guide future research have been discussed [19]. Research has also addressed the visualization of PJM. Bulto et al. [17] introduce six key steps for conducting PJM in the health sector, illustrated with cardiovascular examples, and describe its opportunities, benefits, and future implications. Two-dimensional graphing methods with color blocking and labeling provide additional detail and have been used to analyze common trajectories and patterns of care for people with opioid use disorder-associated endocarditis [18]. By contrast, Lee et al. [20] developed a user-friendly mobile application to deliver health information, such as disease treatment data, from the patient's perspective.

Another substantial body of research focuses on modeling patient pathways through hospitals, most commonly in emergency departments, using discrete-event simulation models to evaluate operational performance and improve resource planning, including capacity, scheduling, and staffing [21–24]. Such approaches aim to increase efficiency and reduce overcrowding [25].

Considerable research has also addressed the prediction of patient flow using statistical models, for example, to support real-time bed management or to identify risk factors associated with surgical delays [26, 27]. Beyond prediction, patient pathway analysis has been approached through mathematical modeling. Latent Dirichlet allocation has been applied to measure pairwise similarities of patient traces in clinical pathways based on behavioral topical features [28]. An adjusted Cox proportional hazards model has been used to evaluate length of stay in alcohol withdrawal treatment pathways [29]. Furthermore, Madsen and Kofoed-Enevoldsen [30] define five equations to simulate arrivals and capacity in the emergency department, modeling queuing processes using Poisson and exponential distributions.

1.3 Research objectives

Substantial research has been conducted on patient pathways and patient journeys; however, many existing studies focus primarily on statistical modeling for prediction, mathematical modeling for analysis, or discrete-event simulation for operational purposes. Even where visualization is the main topic, discussions often focus on conceptual considerations rather than actual implementations. When visual representations are provided, they tend to focus on touchpoints only and do not incorporate clinical data such as diagnoses, treatments, or systemic therapies.

Against this background, the aim of this review is to systematically examine how data-driven patient pathway analyses are visualized in healthcare. The review focuses on studies that analyze or model diagnostic, therapeutic, or organizational patient pathways based on healthcare data and provide an explicit visual representation of the underlying pathways or analytical results. In addition to the visualization techniques themselves, the review considers the process characteristics, application contexts, and analytical or modeling approaches underlying these representations.

1.4 Outline

The remainder of this paper is structured as follows. Section 2 describes the systematic review methodology, including the search strategy, eligibility criteria, screening procedure, and the analytical framework employed to classify the included publications. Section 3 presents the results organized into four analytical categories: process characteristics, context and application, methods and modeling approaches,

and visualization techniques. Section 4 examines the key findings, their implications, the limitations of the review, and opportunities for future research. Finally, Section 5 concludes the paper.

2 Research methodology

2.1 Review strategy

The structured literature review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines [31]. The search was performed using the Web of Science[1] database, which includes the U.S. National Library of Medicine's MEDLINE database and therefore covers a substantial proportion of articles indexed in PubMed.

Inclusion criteria were defined across four dimensions: language of publication, temporal scope, document type (restricted to peer-reviewed articles as classified by Web of Science), and thematic relevance. Thematic relevance was operationalized through topic-related keywords, synonyms, and conceptually related terms, developed on the basis of the PICo framework.[2] The search string was refined and validated iteratively by verifying a set of known relevant studies was retrieved. Given the heterogeneous terminology and large number of synonymous terms used for patient pathways, the search strategy was intentionally designed for high sensitivity to minimize the risk of missing relevant studies. Precision was subsequently achieved during title and abstract screening and full-text review through clearly defined inclusion and exclusion criteria.

The systematic review follows a six-step procedure, as depicted in Figure 1. Bibliographic records were retrieved from the Web of Science database using the search string reported in Footnote 3, on 1 December 2025. Predefined filters were applied to restrict the publication year (2010–2025) and language (English, German, French).

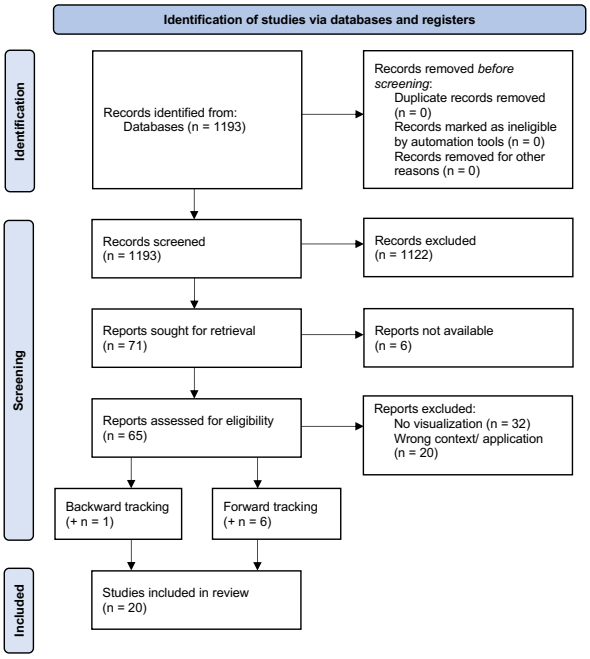


Figure 1: Study selection process based on the PRISMA 2020 flow diagram [31].

The 1 193 records retrieved from the search query were evaluated in three stages during initial screening. Following the assessment of the first 40 documents, it became evident that the search string retrieved a considerable number of publications with limited relevance to visualization. A more visualization-specific search formulation was additionally tested but showed substantially lower sensitivity and was therefore not retained.[4] To minimize potential bias, the initial 40 documents were independently screened by a second reviewer, and a consensus meeting was held to resolve discrepancies. Four discrepancies were identified and resolved through discussion; overall, inter-reviewer agreement was high. After screening the first 400 records, keyword frequency statistics were generated to assess the adequacy of the search strategy and identify potentially underrepresented terminology. The dominant terms remained closely aligned with patient pathways and related concepts, healthcare, and visualization, and no additional frequently occurring terms were identified that warranted modification of the search query.

[1] The Web of Science Core Collection is a curated bibliographic database of peer-reviewed journals, books, and proceedings across the sciences, social sciences, arts, and humanities. Web of Science is available at `https://www.webofscience.com/wos`.

[2] The PICo framework structures a research question into three components – population, phenomenon of interest, and context – and is commonly used to formulate search strategies for qualitative and mixed-methods systematic reviews [32].

[3] The final query was as follows: `("patient flow" OR "patient pathway" OR "care pathway" OR "clinical pathway" OR "patient journey") AND (model* OR "process mapping" OR "workflow analysis" OR "process modeling" OR simulation OR visualization) AND (diagnosis OR treatment OR "systemic therapy") AND (hospital OR clinical OR healthcare OR outpatient OR inpatient)`.

[4] Given that the visualization of patient pathways constitutes a central focus of this work, a targeted refinement was attempted by requiring visualization-related terms to appear in titles or abstracts via the following constraint: `(visualiz* OR graph* OR diagram OR dashboard OR app)`. This modified strategy yielded 50 records, all of which had already been identified through the original query. Moreover, of the 15 studies from the initial 40 documents that met the inclusion criteria, only one was captured by the refined string. It was therefore concluded that the refined search string lacked sufficient sensitivity, and the original, more broadly defined strategy was retained.

The central component of the systematic review is the screening process, which was conducted in three sequential phases: (1) title and abstract screening, (2) full-text review, and (3) backward and forward citation screening. To evaluate the identified publications for methodological quality and thematic relevance, a set of predefined inclusion and exclusion criteria was established and applied consistently across all screening stages:

- *Bibliographic metadata:* publication language English, German, or French; publication date 2010 or later; source type scientific or technical.
- *Availability:* abstract or full-text available and sufficiently detailed to permit a reliable assessment of relevance.
- *Domain:* study conducted within a healthcare context.
- *Thematic relevance:* study analyzes diagnostic, therapeutic, or organizational patient pathways, trajectories, clinical processes, or flow analysis.
- *Methodological relevance:* study conducts or proposes a data-driven analytical or modeling approach and provides an explicit visual representation of the pathway, underlying clinical events, or resulting analytical model.

Accordingly, studies focusing exclusively on patient experiences, or applying analytical, predictive, simulation, or modeling approaches without an explicit pathway visualization, were excluded.

Consistent with standard systematic review procedures, the initial screening phase was restricted to title and abstract assessment. However, for a small subset of records, the abstract did not provide sufficient information to evaluate eligibility with respect to the application of modeling or visualization methods. In these cases, papers were scanned for figures, which were assessed against the inclusion criteria. Publications whose eligibility could still not be determined were retained for full-text review. The initial screening yielded 71 articles, which were carried forward to full-text review. Keyword statistics were again generated to check for thematic gaps; the results confirmed strong alignment between the search strategy and the review's intended focus. Full-text screening yielded 13 articles, which were subsequently subjected to forward and backward citation tracking. Both tracking procedures were conducted systematically and analogously to the initial screening, beginning with title and abstract assessment. All selected papers subsequently underwent full-text review, adding seven studies to the final corpus.

The first author was responsible for selecting and screening the publications, extracting and coding relevant information, and subsequent analysis and visualizations. As described above, the second author supported the selection process by independently screening the first 40 publications and reassessing all subsequent publications the first author had flagged for further examination. In addition, all studies included in the final corpus were reassessed for eligibility by the second author. Any disagreements concerning inclusion decisions were discussed by the first and second authors until consensus was reached. The second author also reviewed the extracted information and the assigned codes. The categories and subcategories, as well as the inclusion and exclusion criteria, were developed and iteratively refined in joint meetings involving all authors. Any criteria or categories added during the review process were discussed and agreed upon at the subsequent joint meeting. Shared Excel files were used to document the screening and selection procedures, the extracted information, and the subsequent analysis. The involvement of multiple authors in these steps was considered essential to improving transparency and minimizing the risk of bias.

2.2 Synopsis of the results

The final corpus comprises 20 publications, an overview of which – including key contents and main findings – is provided in Table A1 in the Appendix.

During the screening and full-text assessment, four analytical categories were iteratively developed to structure the synthesis of the reviewed studies and provide the analytical framework for the subsequent analysis, as illustrated in Figure 2.

1. *Process characteristics: What is analyzed?* This category groups the included publications according to the type of process under consideration. As outlined in Section 1, various definitions and terminologies are used in the literature to describe patient processes, as reflected in the subcategory process type. The level of analysis is further captured by distinguishing whether a pathway is presented for an individual patient or as an aggregated cohort-level representation. In addition, it is documented whether care transfers are explicitly included in the process representation.
2. *Context and application: In which contexts are the methods applied?* This category characterizes the application setting in terms of data type and origin, clinical domain, and care context, differentiating in particular between outpatient and inpatient settings.
3. *Methods and modeling approaches: How are patient pathways analyzed, modeled, and processed?* This category differentiates between

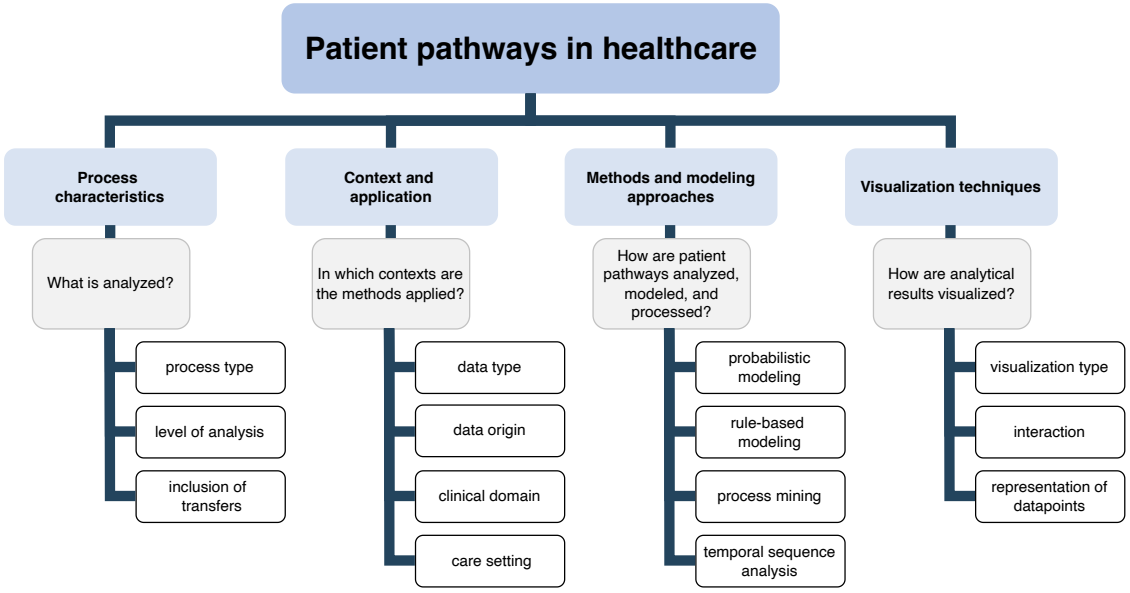


Figure 2: Analytical framework of the systematic review, illustrating the four derived analytical categories.

raw and preprocessed data and classifies the analytical methods and modeling approaches applied. Specifically, four methodological families are distinguished: probabilistic models, rule-based modeling approaches, process mining methods, and temporal sequence analysis techniques.

4. *Visualization techniques: How are analytical results visualized?* This category focuses on the visualization techniques employed to present data and derived analytical results, including the type of visualization, the degree and type of user interaction supported, and the manner in which data and analytical outcomes are encoded and represented.

An overview of the classification of all included publications is provided in Table A2 in the Appendix.

3 Classification of the literature

In this section, the publications included in this review are analyzed with respect to their general characteristics and the four analytical categories.

3.1 General characteristics

The temporal distribution of publications does not indicate a clear trend of increasing output. As shown in Figure 3, the period from 2015 to 2017 already reflects a substantial level of scholarly interest in the visualization and modeling of patient pathways, followed by a decline through 2021, after which interest appears to rise again. Notably, the only study identified through backward citation searching [33] is also the earliest publication in the dataset.

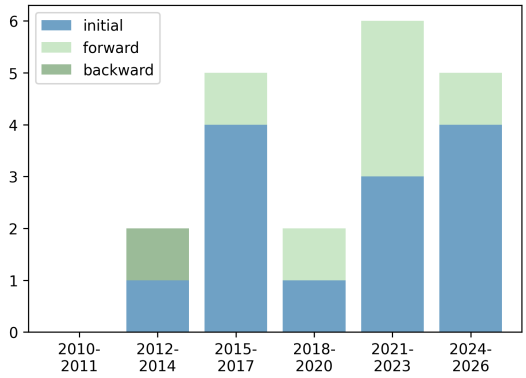


Figure 3: Distribution of publications by period.

A large proportion of the publications, as well as the underlying data, originate from Europe and North America. At the country level, the U.S. account for the largest number of studies, while European contributions are distributed across multiple countries, including Italy, England, and Germany. Journal articles account for 70% of all publications, with the remaining 30% being conference proceedings.

Figure 4 presents the distribution of publications across the Journal Citation Reports categories un-

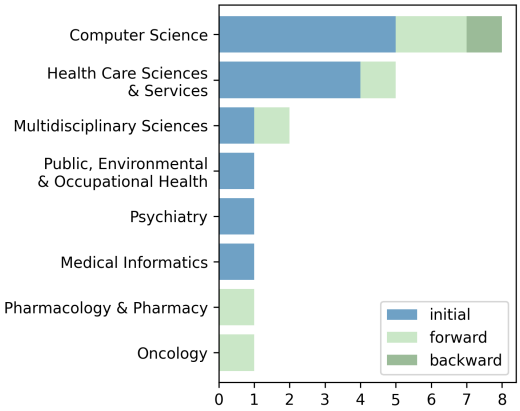


Figure 4: Distribution of publications by Journal Citation Reports categories.

der which each article is indexed. The eight categories are Computer Science, Health Care Sciences & Services, Multidisciplinary Sciences, Public, Environmental & Occupational Health, Psychiatry, Medical Informatics, Pharmacology & Pharmacy, and Oncology. For simplicity, all subfields within Computer Science – such as Artificial Intelligence, Information Systems, and Software Engineering – are aggregated into a single category. The figure indicates that the majority of publications fall within Computer Science, followed by Health Care Sciences & Services.

3.2 Process characteristics

As described in Section 1, considerable diversity exists in the terminology used across the literature. The publications were therefore examined with respect to the type of process on which they are based, as illustrated in Figure 5.

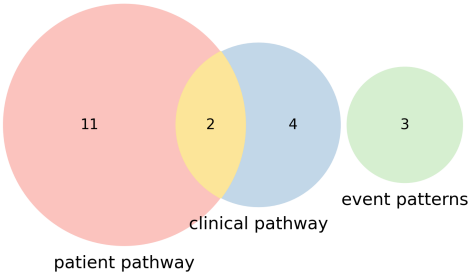


Figure 5: Overlap of process types across publications.

Most studies rely on patient pathways, some on clinical pathways, and two [34, 35] on a combination of both. A further category, *event patterns*, was introduced in the course of forward and backward citation tracking. Although the three papers focusing on event patterns [33, 36, 37] do not employ pathway-related terminology, their visualizations are nevertheless used to analyze pathways in terms of patterns or trajectories derived from event data.

The level of analysis is documented alongside the process type. In 14 of 20 publications, analyses were conducted at the aggregate level, while individual patient-level analyses were less common, accounting for four papers. The remaining two papers combined both levels [38, 39].

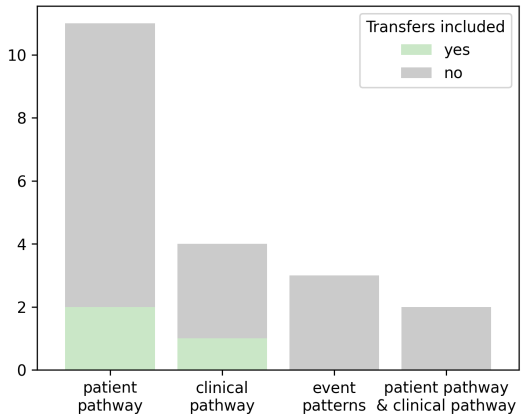


Figure 6: Inclusion of transfer information by process type.

The inclusion of patient transfer information along the analyzed pathway is shown in Figure 6. Transfers were incorporated in only 15% (3) of the publications [40–42], all within the patient pathway or clinical pathway categories. No publication assigned to the event patterns category incorporated transfer information.

3.3 Context and application

The selected publications are analyzed with respect to their contextual and application-related characteristics, specifically data type, data origin, clinical domain, and care setting. Figure 7 illustrates that almost all studies rely on real-world electronic health record (EHR) data. Only a single study utilizes data extracted from a mobile health application [43], while two additional studies are based on interview data: one drawing on real-world data [40] and one employing theoretically derived data [44]. Additionally, Borg et al. [39] uses a combined dataset comprising EHR data and cancer registry records.

The clinical domains addressed in the included studies fall into three broader categories: chronic somatic diseases, neuropsychiatric disorders, and acute or specialized care. With respect to care settings, Figure 8 shows that chronic somatic diseases are represented across several settings, including studies in which the care setting is not explic-

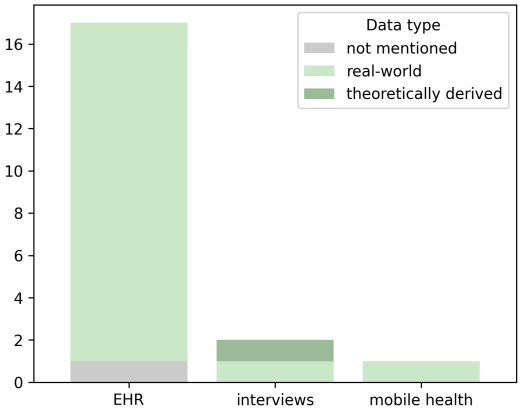


Figure 7: Distribution of data origins across data types.

itly stated, as well as inpatient and outpatient contexts. Neuropsychiatric disorders are mainly associated with outpatient care, while acute and specialized care spans a broader range of settings, including emergency room, inpatient, and outpatient care. Overall, the figure indicates heterogeneous reporting of care settings, as a substantial proportion of studies either do not explicitly specify the setting or refer only to inpatient and/or outpatient care.

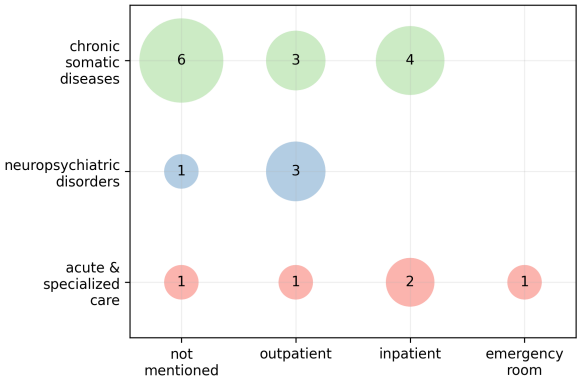


Figure 8: Relationship between clinical domains and care settings.

As shown in Figure 9, the majority of publications concentrate on chronic somatic diseases, with particular emphasis on oncology [34–36, 39, 45], cardiovascular diseases – including cardiac disorders, heart failure, and stroke [46–48] – respiratory diseases such as respiratory infections and asthma [33, 36, 49], and musculoskeletal disorders, notably rheumatoid arthritis and hip arthroplasty [38, 40]. Within this group, oncology represents the most extensively represented application domain.

Fewer reviewed publications address neuropsychiatric disorders, including mental health conditions such as attention-deficit hyperactivity disorder and major depressive disorder [44, 50], as well as neurological conditions such as tinnitus [43]. Other

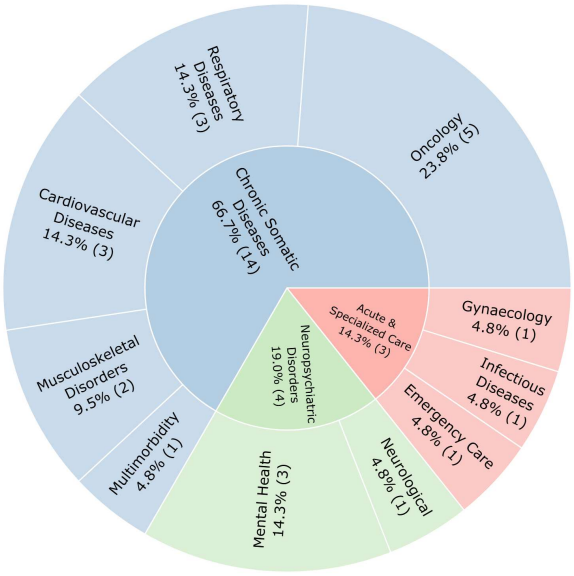


Figure 9: Hierarchical distribution of clinical domains and subdomains.

studies focus on acute and specialized care settings, including emergency and trauma care [51], infectious diseases such as sepsis [52], and gynaecological procedures such as total laparoscopic hysterectomy [42]. Taken together, the reviewed literature indicates that the modeling and visualization of patient pathways are particularly prominent in oncology and other chronic somatic conditions, whereas applications in emergency care contexts occur less frequently.

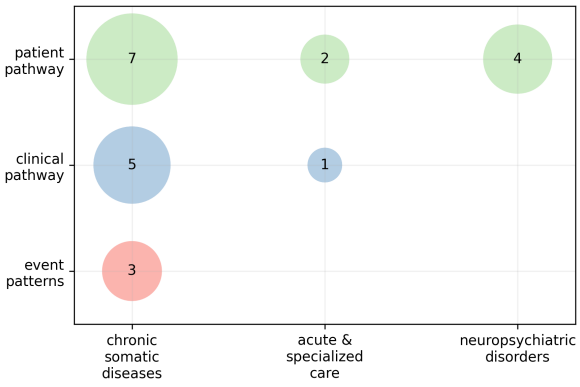


Figure 10: Relationship between clinical domain and process characteristics.

Figure 10 further presents a cross-analysis of two analytical categories – context and application, represented by clinical domain, and process characteristics. The most frequent combination in the reviewed publications is the analysis of patient pathways in the context of chronic somatic diseases. Patient pathways are also the only process characteristic represented in studies on neuropsychiatric disor-

ders. By contrast, clinical pathways are always examined in relation to chronic somatic diseases, with only one publication addressing acute and specialized care [52]. Event patterns are even more narrowly represented, as all three corresponding publications focus exclusively on chronic somatic diseases. Overall, the figure indicates that chronic somatic diseases constitute the broadest application area across the identified process characteristics, whereas neuropsychiatric disorders are limited to patient pathway analyses in the reviewed literature.

3.4 Methods and modeling approaches

The third analytical category focuses on the methods and modeling approaches employed to analyze patient pathways and process the underlying data. The methodological and modeling techniques identified in the selected publications were classified into four overarching groups: probabilistic modeling, rule-based modeling, process mining, and temporal sequence analysis.

As shown in Figure 11, the most frequently used approaches are process mining and probabilistic modeling, followed by temporal sequence analysis. By contrast, rule-based modeling is represented by a single publication [35], which models treatment pathways using the Business Process Model and Notation standard, deriving pathway rules from clinical guidelines, and executed on a newly developed open-source workflow software system that maps medical knowledge onto patient-specific data. This distribution indicates that the reviewed literature is predominantly shaped by data-driven and exploratory approaches, whereas explicitly guideline-based or rule-based modeling approaches are comparatively underrepresented.

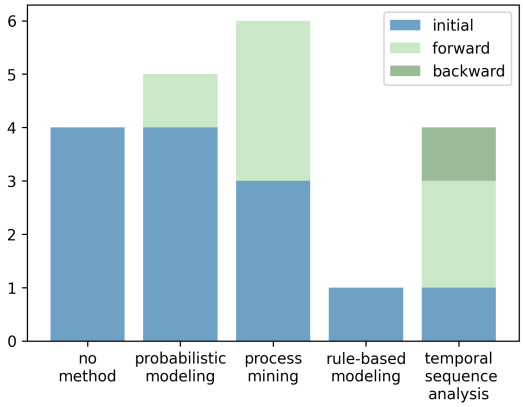


Figure 11: Distribution of publications by type of approach.

Common probabilistic models include Markov or state-transition models [39], as well as Bayesian networks, for which various learning algorithms are used, including constraint-based, score-based, and hybrid algorithms that combine both [47]. Other probabilistic or data-driven techniques include natural language processing for extracting relevant variables [34] and a purpose-built algorithm for clinical pathway learning [37].

Almost all studies employing temporal sequence analysis, and approximately half of those using process mining, were identified through forward and backward citation screening. In the initial screening phase, most of the included studies relied on probabilistic modeling or employed no formal modeling method. Studies lacking explicit methods or modeling approaches instead present and structure their data through alternative means. For instance, Kaushal et al. [38] uses a database to filter and retrieve selected data, while Balatsoukas et al. [48] clusters patient processes into events and states based on standard clinical codes, such as SNOMED (Systematized Nomenclature of Medicine), representing conditions, investigations, and treatments. Oosterholt et al. [40] applies a visual mapping tool, whereas Harris et al. [44] reports no formal methodological framework.

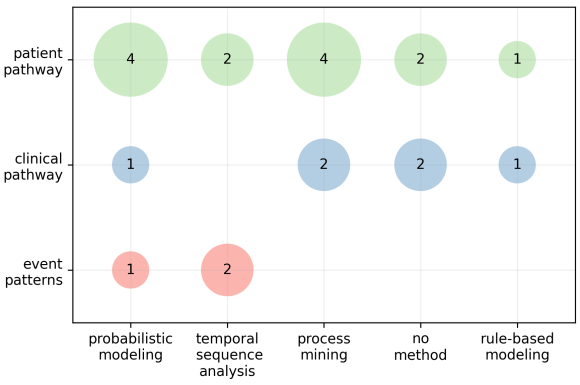


Figure 12: Relationship between process characteristics and modeling approaches.

The cross-analysis presented in Figure 12 indicates that patient pathways are associated with the broadest range of modeling approaches, occurring across all identified methodological categories. This observation reflects the overall dominance of patient pathway–oriented studies within the analyzed body of literature. Consequently, the combinations of patient pathways with probabilistic modeling and process mining are also among the most frequent, given that these two modeling approaches are the most commonly used overall.

Clinical pathways are primarily associated with process mining, no explicitly reported method, and rule-based modeling, whereas event patterns are mainly associated with probabilistic modeling and temporal sequence analysis. Given the small number of included publications, however, these differ-

ences should be interpreted as descriptive patterns rather than statistically meaningful differences.

3.5 Visualization techniques

The fourth and final analytical category focuses on visualization techniques, examining how analytical results are visualized in the selected publications, considering the type of visualization, the interaction mode, and the representation of data points.

The most commonly used visualization techniques are graph-based representations, particularly directed graphs. These include process mining trajectories [43], directly-follows graphs combined with tables [41], based pathway models based on established business model standards [35], streamlined clinical journey diagrams [44], and directed acyclic graphs [47]. Network graphs are used less frequently as a separate graph-based representation [37].

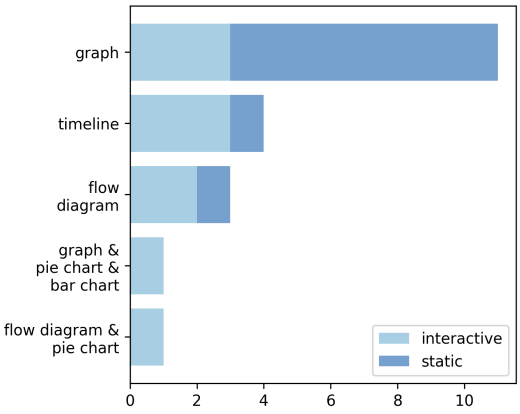


Figure 13: Distribution of publications by visualization technique.

A further finding concerns the type of interaction, distinguishing between static and interactive visualizations. As shown in Figure 13, almost all static visualizations are graphs. Techniques such as timeline-based visualizations – including timelines and stacked area charts [39] – pie charts [38, 48], bar charts, and flow diagrams – including Sankey diagrams [34, 38, 46] and rule-based flow charts [45] – are more commonly used as interactive visualizations among the included publications. Combinations of multiple visualization types are also used: Balatsoukas et al. [48], for example, uses a graph model to visualize an individual patient's pathway and, for specific states and events, conducts statistical analyses across all patients using bar and pie charts. This corresponds to the use of both aggregated and individual levels of analysis in the process characteristics category. By contrast, Kaushal et al. [38] combines Sankey diagrams with parallel coordinates and sunburst charts, the latter a specific form of pie chart.

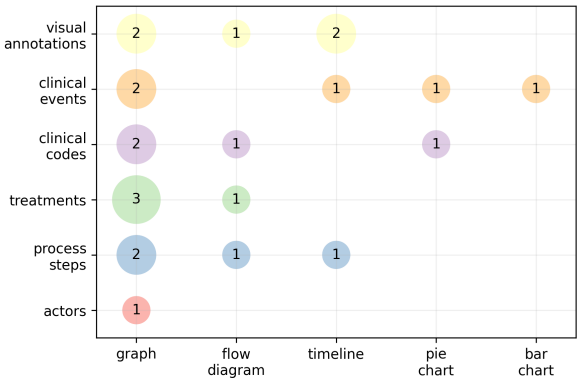


Figure 14: Relationship between visualization techniques and representation of data points.

Figure 14 presents the relationship between visualization techniques and the types of data points[5] represented. Graph-based visualizations cover the broadest range of representation types and depict actors,[6] process steps, treatments, clinical codes, clinical events, and visual annotations. This broad distribution reflects the flexibility of graph-based approaches for representing different aspects of patient pathways and care processes. Treatments are most frequently represented through graphs, while clinical events and clinical codes are distributed across several visualization types, including graphs, timelines, and pie charts. Timeline visualizations are mainly associated with visual annotations and clinical events, consistent with their role in representing temporal patterns and event sequences. Overall, the figure shows that graph-based techniques provide the most flexible representation, whereas other visualization types are more strongly linked to specific types of data points.

A further cross-analysis between visualization techniques and process characteristics was conducted, considering both the level of analysis and the process type. As shown in Figure 15, no clear distinction between static and interactive visualizations emerges across aggregated, individual, and combined levels of analysis. Interaction types are distributed relatively evenly across the levels of analysis, except for two publications that combine aggregated and individual analyses while using interactive visualization techniques [38, 48]. Although aggregated analyses constitute the largest group overall, both static and interactive visualizations are also used in individual-level analyses.

Figure 16 shows the relationship between visual-

[5]Representation of data points refers to the specific way in which data and analytical outcomes are encoded and represented in the visualizations.

[6]The actors represented in Oosterholt et al. [40] comprise the patient, radiologist, anesthetist, nurse specialist, pharmacist, orthopedic surgeon, physiotherapist, nurse, physician, and a digital patient information application.

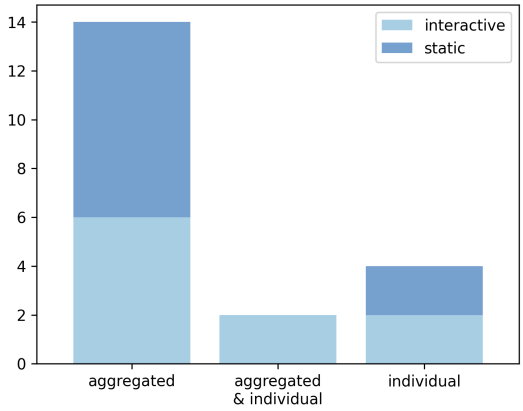


Figure 15: Distribution of publications by level of analysis.

ization techniques and process characteristics, represented by process type. The most common approach is visualizing patient pathways using graph-based techniques. Other frequent combinations include clinical pathways represented as graphs and patient pathways represented through flow diagrams. While patient pathways and clinical pathways cover almost all identified visualization types and are most often visualized as graphs or flow diagrams, event patterns are limited to graphs and timelines.

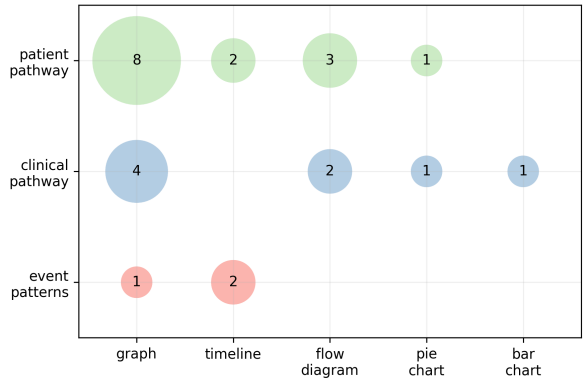


Figure 16: Relationship between visualization and process types.

Among event patterns, Monroe et al. [33] and the related work by Plaisant [36] both use interactive EventFlow-based, timeline-oriented visualizations with symbols, colors, and text annotations to represent diagnoses and treatments in different settings, such as patient drug data before and after stroke or prescription patterns of asthma medication. By contrast, Zhang and Padman [37] uses interactive network graphs, in which each node represents a clinical visit and captures information on encounter types, diagnoses, and prescribed medications, represented through nodes, edges, and additional information provided as hover text.

A cross-analysis of the categories context and application and methods and modeling approaches was also conducted. Context and application are represented by clinical domain and compared with the type of visualization. This cross-analysis reveals clear descriptive patterns, as illustrated in Figure 17. As chronic somatic diseases represent the most frequently addressed clinical domain among the included publications, they are correspondingly distributed across all visualization types, with the highest number of publications in this domain using graphs, followed by flow diagrams and timelines.

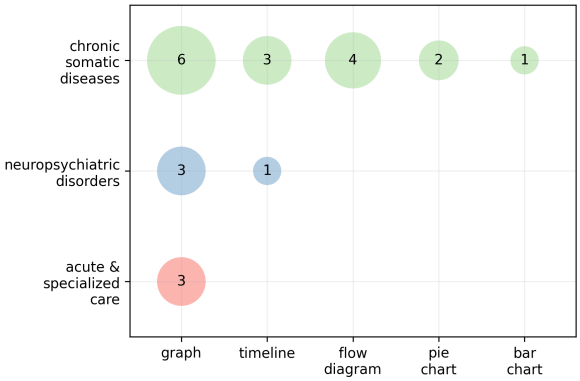


Figure 17: Relationship between visualization techniques and clinical domains.

Neuropsychiatric disorders are mainly visualized using graphs [41, 43, 44], with the exception of Zhang et al. [53], who developed an algorithm identifying medical events leading to sub-cohorts with distinct temporal sequence patterns in patients with major depressive disorder, implementing these patterns as an interactive flowchart of medical events. In the domain of acute and specialized care, all three publications use graph-based visualizations [42, 51, 52], covering emergency care, gynecology, and sepsis. Overall, graph-based visualizations appear across all clinical domains, whereas the broader range of visualization types is mainly observed in studies of chronic somatic diseases.

When comparing visualization types with modeling approaches, the relationships are more dispersed, as shown in Figure 18. The most frequent combinations are graph-based visualizations with process mining and probabilistic modeling, again highlighting the central role of graphs as a visualization type. Timeline visualizations are mainly associated with temporal sequence analysis, consistent with their purpose of representing temporal patterns and event sequences. Flow diagrams occur across several methodological categories, including process mining, probabilistic modeling, temporal sequence analysis, and studies without an explicitly reported method. By contrast, pie charts and bar charts are only associated with publications

that report no formal modeling approach. Overall, the figure indicates that graph-based visualizations are used across the widest range of modeling approaches, while timelines are more closely linked to temporal sequence analysis.

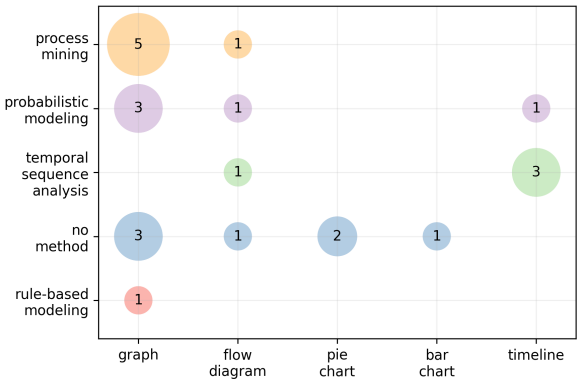


Figure 18: Relationship between visualization techniques and modeling approaches.

4 Discussion

As outlined in Section 1, the concept of PJM has gained increasing attention in healthcare research and practice [17]. The 1 193 records retrieved from Web of Science further reflect this broad interest. However, the review revealed a marked discrepancy between the large number of publications referring to patient journeys or related concepts and the limited number of studies analyzing and visualizing patient pathways from an organizational or institutional perspective within which the patient journey unfolds. This discrepancy is reflected in the final corpus of 20 publications meeting the defined inclusion criteria. Because the search strategy incorporated various synonymous terms for patient pathways, it retrieved numerous studies focused primarily on the patient-centered perspective – individual experiences and perceptions of care – that did not address the clinical and organizational processes through which patients move and were therefore excluded during initial screening. Among the remaining publications, many applied analytical or modeling approaches to healthcare processes but did not visualize either the underlying data or the resulting models, and were likewise excluded in accordance with the scope of this review. The findings therefore indicate that, despite growing interest in patient journeys, comparatively little research has focused on the integrated analysis and visualization of real-world patient pathways as they unfold across clinical and organizational structures, revealing a substantial gap in applied research in this area.

The findings are discussed below across the four major analytical categories identified in this review.

4.1 Process characteristics

Across the included publications, patient pathways are addressed more frequently than clinical pathways or event patterns, possibly reflecting the broader and more flexible use of the term *patient pathway*, whereas clinical pathways and event patterns appear to describe more specific analytical concepts. At the same time, the reviewed literature suggests that terminology is not applied consistently: similar processes are described using different terms, while the same term may refer to different levels of abstraction or analytical objectives. This conceptual overlap complicates direct comparisons between publications and highlights the need for clearer distinction and more consistent terminology.

Another notable finding is the limited consideration of transfers. Only a small number of publications explicitly represent cross-departmental care transitions, which are particularly relevant given that patient pathways frequently extend beyond a single department or care setting. Consequently, existing pathway representations may provide only a partial view of the actual care trajectory.

4.2 Context and application

The reviewed studies predominantly rely on real-world EHR data, indicating that patient pathway analysis is strongly data-driven and oriented toward routinely collected clinical information. Such data reflect actual treatment trajectories and organizational processes, but their analytical value depends on the completeness and quality of clinical documentation and local information systems. Events that are not recorded cannot be incorporated into the resulting pathway models, and differences between institutions may reduce the comparability and transferability of findings.

Chronic somatic diseases, particularly oncology, represent the most prominent clinical application area in the included publications, possibly because these conditions often involve long, complex, and multidisciplinary treatment processes with recurring diagnostic and therapeutic steps, making them particularly suitable for pathway analysis and visualization.

4.3 Methods and modeling approaches

The methods and modeling approaches identified in this review are heterogeneous, but probabilistic modeling and process mining are especially prominent, underscoring the field's data-driven character. By contrast, rule-based modeling appears only rarely, revealing a gap between the analysis of real-world pathways and the representation of

guideline-based reference pathways. Although clinical guidelines are highly relevant to the motivation for pathway analysis, only limited work combines observed real-world pathways with formalized guideline-based reference pathways. Closer integration of these perspectives could help identify deviations between expected and actual care.

The results also show that not all pathway visualizations rely on an explicit analytical or modeling method, suggesting that pathway visualization should not be understood solely as the output of a computational analysis; it can also function as a design and communication tool that supports shared understanding among clinicians, researchers, and other stakeholders.

4.4 Visualization techniques

Graph-based representations, particularly directed graphs, are the most widely used visualization techniques in the reviewed literature, occurring across all process types, clinical domains, and most modeling approaches, and used to represent a broad range of data points, including process steps, clinical events, treatments, and codes, mostly via static and occasionally interactive visualizations. This broad applicability indicates the suitability of graphs for visualizing pathway processes and dependencies; however, their flexibility is also a limitation: as the number of nodes, edges, and process variants increases, graph-based representations can quickly become visually complex and difficult to interpret. In addition, the wide variety of data-point representations limits comparability across studies and complicates the transfer of visualization approaches between applications. Their usefulness therefore depends strongly on appropriate aggregation, filtering, and interaction mechanisms.

The relationship between interaction type and level of analysis was less systematic than might be expected. One might assume that aggregated pathway data require interactive functions such as filtering, comparison, and drill-down, whereas individual pathways could be presented more easily in static form. However, the included publications show no clear distinction between static and interactive visualizations across aggregated and individual analyses, suggesting that interaction type may be determined less by the level of analysis than by the intended application purpose – exploratory analysis, decision support, or communication. This distinction may also partly reflect reporting practices, as publications may present static figures even when the underlying visualization is interactive, and interaction mechanisms are not always described in sufficient detail.

4.5 Limitations

Several limitations must be considered when interpreting these findings. The final number of included studies is relatively small, so the observed relationships should be interpreted as descriptive patterns rather than statistically meaningful associations. This small corpus may reflect a genuine scarcity of research on modeling and visualizing clinically detailed patient pathways.

The number of included publications is also shaped by the search strategy, the defined eligibility criteria, and the heterogeneous terminology used in the literature. Relevant studies may have been excluded because they applied different terms to comparable concepts. Furthermore, study classification depends on the quality and level of detail reported in the original publications; methodological approaches, interaction mechanisms, and levels of analysis were not always described consistently.

4.6 Future research

Future research should address both conceptual and technical gaps identified. Clearer, more consistent terminology would improve comparability across studies and support the development of shared classification frameworks.

Future pathway models should also represent transfers and transitions between departments and care settings more explicitly to capture continuity of care. Greater integration of observed real-world patient pathways with guideline-based reference pathways could facilitate comparisons between actual and recommended care processes. Future studies should evaluate the usability and clinical usefulness of visualizations with actual end users.

Particular attention should be given to scalable, interactive approaches that can handle complex graph structures while enabling users to navigate between cohort-level overviews and individual patient pathways. Such approaches should integrate real-world clinical data with guideline-based information within a standardized representation of clinical pathways, allowing observed patient pathways to be compared across different healthcare infrastructures and against reference care processes, ultimately supporting clinically meaningful pathway analysis and contributing to improved medical treatment.

5 Conclusion

This systematic review provides a structured synthesis of the visualization in data driven approaches that analyze or model patient pathways. Although patient pathway research has received considerable attention, as reflected by the 1 193 records identi-

fied in the initial search, only 20 studies explicitly visualize the underlying pathways or analytical results. Moreover, the visualizations are rarely evaluated, leaving their contribution to the interpretation of pathway data largely unexamined. Among the included studies real-world EHR data predominate, particularly in oncology, while process mining and probabilistic modeling are the most frequently applied analytical approaches and graph-based representations dominate the visualization techniques. Few studies adopt an organizational or institutional perspective and several aspects remain underexplored, including transfers between care settings, integration of observed pathways with guideline-based reference processes, and scalable visualizations of complex pathway structures. Future research should therefore prioritize interactive, clinically evaluated visualization approaches that scale to complex pathways, combine cohort- and individual-level perspectives, and support comparisons between actual and guideline-recommended care. Such approaches may improve the transparency, interpretability, and clinical usefulness of patient pathway analysis.

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Declaration of Generative AI and AI-assisted technologies in the writing process

The authors declare that generative AI was used for proofreading and language editing during the preparation of this manuscript. No AI-generated content was included in the original writing of this work.

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A Appendix

Table A1: Overview of the reviewed publications.

Reference	Region	Key contents and main results
Balatsoukas et al. [48]	England	• Limited knowledge on requirements for user-friendly and usable electronic care pathways is addressed. • Evaluation of a collaborative online care pathway investigation tool (COCPIT). • Demonstration of usefulness of modular visualization and direct manipulation.
Becker et al. [35]	Germany	• Develops guideline-based clinical algorithms for colorectal cancer. • Usage of BPMN and UMLS to formalize treatment pathways. • Mapping of patient data onto individualized treatment positions.
Borg et al. [39]	Sweden	• Usage of a state-transition model for cancer pathways. • Visualization of investigation time and pathway outcomes. • Demonstration of usefulness of standardized cancer pathways.
Cascini et al. [51]	Italy	• Directed graph compares expected and actual patient pathways. • Predictive model generates probability-based pathway alternatives. • Structured data is required for algorithmic modeling.
Harris et al. [44]	Canada	• Integrated journey-mapping tool for attention-deficit hyperactivity disorder care. • Application of a design science approach to clinical journey mapping. • Usage of UML-inspired diagrams and color coding.
Kaushal et al. [38]	India	• Combination of multiple visualizations for different stakeholders. • Interactive filtering of patient records is enabled. • Parallel coordinates scale better than Sankey and Sunburst.
Korolkov et al. [34]	USA	• Introduction of a real-world-data-based treatment analyzer. • Combination of guideline summaries, matched cohorts and treatment visualization. • Usage of machine learning for mortality prediction.
Kurniati et al. [49]	Indonesia	• Process mining can help visualize disease trajectories. • Process mining can help improve performance through process statistics. • Representation of diagnoses and resources as directed process models.
Liu et al. [47]	USA	• Presentation of an interactive recommender for personalized pathways. • Demonstration of pathway support for heart failure readmission reduction. • Usage of Bayesian Networks to model causal relationships.
Lupia et al. [52]	Italy	• A process mining method with background knowledge is proposed. • Usage of a heuristic algorithm for scalable model discovery. • Visualization of resulting pathways as dependency graphs.
Monroe et al. [33]	USA	• Introduction of user-driven simplification of event sequences. • Extension of timestamped life event sequences (LifeFlow) for complex process log data. • Visual complexity measurement by number and size of elements.
Oosterholt et al. [40]	Netherlands	• Key phases modeling of the outpatient THA care pathway. • Suggestion that visual modeling is transferable to other settings. • Care pathway models considered suitable for both regular and teaching hospitals.

Continued on next page

Table A1: Overview of the reviewed publications (continued).

Reference	Region	Key contents and main results
Park et al. [42]	Korea	• Event log extraction from OMOP CDM is proposed. • Demonstration of process mining across multiple care settings. • Process mining-based visualizations are more effective than OHDSI visualizations such as Sankey diagrams and sunburst plots.
Perer et al. [46]	USA	• Care Pathway Explorer for EMR-based pathway analysis is developed. • Usage of frequent sequence mining on clinical event data. • Focus on temporal clinical event patterns.
Plaisant [36]	USA	• Presentation of visualization techniques for temporal patient record patterns. • Usage of EventFlow to analyze treatments and outcomes. • Demonstration of use across diagnosis and treatment, and prescription patterns.
Savino et al. [45]	Italy	• Translation of rectal cancer guidelines into Pseudo-Workflow formalism (PWF). • Demonstration of the importance of PWF to evaluate clinical guidelines adherence. • Identification of reasons for deviations during a treatment process found important.
Schlüter et al. [43]	Germany	• Application of process mining to analyze tinnitus treatment processes. • Patterns in the relationship between stress levels and tinnitus progression are revealed. • Exploratory value but limited medical-statistical validation is highlighted.
Yardley et al. [41]	England	• Application of process mining to referral records from two sites. • Identification of common mental health care pathway routes. • Mapping of patient flows from routinely collected data.
Zhang et al. [50]	USA	• Development of an interactive interface for temporal health record patterns. • Integration of diagnoses, procedures and prescriptions in timeline views. • Identification of subgroup-specific temporal sequence patterns.
Zhang and Padman [37]	USA	• Development of an interactive platform for pathway visualization. • Integration of analytics for pathways across demographics and comorbidities. • Scalability limits for dense graph layouts are noted.

Table A2: Overview of the categories covered in the reviewed publications.

			Balatsoukas et al. [48]	Becker et al. [35]	Borg et al. [39]	Cascini et al. [51]	Harris et al. [44]	Kaushal et al. [38]	Korolkov et al. [34]	Kurniati et al. [49]	Liu et al. [47]	Lupia et al. [52]	Monroe et al. [33]	Oosterholt et al. [40]	Park et al. [42]	Perer et al. [46]	Plaisant [36]	Savino et al. [45]	Schlüter et al. [43]	Yardley et al. [41]	Zhang et al. [50]	Zhang and Padman [37]	**Count**
Process characteristics	Process type	Patient pathway		✓	✓	✓	✓	✓	✓	✓	✓				✓	✓			✓	✓	✓		13
		Clinical pathway	✓	✓					✓			✓		✓				✓					6
		Event patterns											✓				✓					✓	3
	Level of analysis	Aggregated	✓	✓	✓	✓	✓	✓	✓	✓			✓		✓	✓		✓	✓	✓	✓	✓	16
		Individual	✓					✓			✓	✓		✓			✓						6
	Transfers	Yes												✓	✓					✓			3
Context and application	Care setting	Inpatient		✓					✓		✓	✓			✓	✓							6
		Outpatient					✓						✓	✓	✓			✓	✓	✓			7
		Emergency room													✓								1
	Data type	Real-world	✓	✓	✓	✓			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	18
		Theoretical					✓																1
	Data origin	EHR	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓		✓	✓	✓	✓		✓	✓	✓	17
		Interviews					✓							✓									2
		mHealth																	✓				1
	Clinical domain	Acute & specialized				✓						✓			✓								17
		Chronic somatic	✓	✓	✓			✓	✓	✓	✓		✓	✓		✓	✓	✓				✓	2
		Neuropyschiatric					✓												✓	✓	✓		1
Methods and modeling app.		Probabilistic			✓	✓			✓		✓											✓	5
		Rule-based		✓																			1
		Process mining								✓		✓			✓			✓	✓	✓			6
		Temporal sequence											✓			✓	✓				✓		4
Visualization techniques	Visualization type	Graph	✓	✓		✓	✓			✓	✓	✓		✓	✓				✓	✓		✓	12
		Timeline			✓								✓				✓				✓		4
		Flow diagram						✓	✓							✓		✓					4
		Pie chart	✓					✓															2
		Bar chart	✓																				1
	Interaction	Yes	✓					✓	✓		✓		✓			✓	✓		✓		✓	✓	10
	Representation of data points	Visual annotations					✓						✓			✓	✓					✓	5
		Clinical events	✓															✓		✓			3
		Clinical codes		✓				✓		✓													3
		Treatments							✓		✓	✓								✓			5
		Process steps			✓	✓									✓			✓					4
		Actors												✓									1