Multivariate Time Series Visualization for a Single Individual: A Scoping Review Using PRISMA-ScR

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Abstract: The digitization of hospital information systems is becoming widespread, enabling the increasing integration of interactive visualization methods into decision support systems. This development facilitates the anticipation of critical risks in monitored patients and helps reduce the workload of healthcare providers. However, Electronic Health Records (EHRs) contain large, heterogeneous, and temporal data. Then, providing tools to understand these complex data is a challenge. Using PubMed and Google Scholar, we conducted a search for articles using keywords related to time, visualization, and data. Out of 3,197 retrieved articles, we identified 111 relevant ones through clustering. Applying exclusion criteria to focus on implemented prototypes, we manually annotated 21 articles for our review. This exploratory literature analysis reveals that while this research area has garnered recent interest, it demonstrates limitations in the proposed solutions. Few approaches employ temporal axis distortion, and no approach in the medical domain visually integrates model predictions. The study highlights preferred functionalities for the visual representation of multivariate temporal data, such as parallel time series and hierarchical views.

1 INTRODUCTION

The digitization of healthcare systems has recently experienced significant development. It promises to reduce diagnostic and treatment errors, avoid redundant testing, and guide more efficient allocation of healthcare resources, while fostering innovation in preventive and therapeutic approaches. Healthcare professionals use them daily to make critical decisions and monitor the effects of treatments or medical procedures in typically high-pressure environments. These records improve the continuity and relevance of care while facilitating communication and coordination between patients and healthcare professionals. Researchers leverage them to extract medical data, for instance, to improve patient inclusion rates in clinical trials, while data engineers use them to correct errors, among other applications. While the main limitations of EHRs, such as integration within a single information system and interoperability, are now being addressed, current EHR implementations can still be improved.

The global assessment of a patient's condition is generally performed by analyzing the variations over time of one or several heterogeneous variables. For instance, if the measured white blood cell count and the patient's temperature increase simultaneously, an ongoing infection is suspected. Similarly, if hemoglobin levels and platelet counts decrease rapidly, a hemorrhage is likely suspected in the patient. The goal of the current study is to identify visual features for representing temporal and multivariate data, i.e., involving more than two distinct

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variables evolving over time. More specifically, our aim is to explore visualizations that provide both a global and detailed view of heterogeneous multivariate temporal data. To achieve this, we conducted an exploratory review of the literature.

The motivations and state-of-the-art analyses conducted on similar topics are discussed in Section 2. The protocol and criteria used for the analysis are detailed in Section 3. The results obtained through manual annotation are presented in Section 3.6. Finally, Section 4 synthesizes these results and concludes this part with a discussion.

2 RELATED WORK

The visual analysis of multivariate temporal data is used in various fields, such as financial analysis (Yue et al., 2019), history (Zhang et al., 2023), and storytelling support (Shin et al., 2023). In the medical field, specifically, the visualization of data from Electronic Health Records (EHR) has been extensively studied. Previous research has synthesized the common characteristics of these visualizations and their associated functionalities, which will serve as the foundation for this literature review.

During the 2010s, several reviews focused on the visual representation of multivariate temporal data in the medical domain. Specifically, the following section highlights reviews addressing EHR visualization. (Combi et al., 2010) established a taxonomy of visualization methods, distinguishing whether they represent a single individual, such as a patient, or an entire cohort. (Aigner et al., 2011)[1] provided a detailed study of approaches for representing temporal data for one or more individuals. Their study extended beyond the medical domain. (Rind et al., 2013) focused on 14 specific approaches applied in the medical field, also distinguishing between individual and cohort representations. Finally, (West et al., 2015) employed the PRISMA protocol (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) (Moher et al., 2009) for a systematic review of EHR data visualization approaches. They highlighted an increase in publications in this domain up until 2012, when their work was conducted. The authors emphasized the need for further research focused on representing large-scale multivariate data on a single screen and addressing the representation of missing data, which remain relevant challenges.

Since 2019, new reviews have been proposed. (Scheer et al., 2022) utilized an extension of the PRISMA protocol, PRISMA-ScR (PRISMA Extension for Scoping Reviews) (Tricco et al., 2018), to describe 22 approaches focused on cohorts, differing from the patient-centered approach that is the focus of this chapter. (Wang and Laramee, 2022) proposed a detailed taxonomy of 51 studies restricted to the medical domain. The authors noted that the inclusion of machine learning models is a recent trend. However, their study did not distinguish between approaches designed for individual patients and those for cohorts. The systematic review by (Turchioe et al., 2019) focused on patient-oriented visualizations, highlighting the current lack of solutions. Their taxonomy of displayed data, visual encodings, and evaluation methods compared 39 approaches, 80% of which represented longitudinal data using line charts.

The review of these studies reveals the absence of a synthesis specifically dedicated to visualizing patient trajectories characterized by multivariate temporal data.

3 METHODOLOGY

We conducted an exploratory literature review focusing on visualizations representing a single individual. Our approach extends the protocol proposed by (Scheer et al., 2022), which is based on the PRISMA-ScR protocol (Tricco et al., 2018). To assess the presence of functionalities not yet implemented in medical approaches, we also included studies from fields outside of healthcare to explore the representation of multivariate records of a single individual on a timeline in a broader context. The complete protocol is represented by a flow diagram adapted from (Haddaway et al., 2022), as illustrated in Figure 1. The diagram details the successive steps of the protocol, described in the following sections.

3.1 Information Sources and Query Definition

To identify relevant articles across all application domains, we queried the specialized healthcare database PubMed[2] as well as the generalist database Google Scholar[3]. This search was conducted on November 13, 2023, using the Python libraries Pymed[4] and

[1] See https://browser.timeviz.net/, accessed 01/08/2024, for a comprehensive directory of techniques.

[2] https://pubmed.ncbi.nlm.nih.gov/, accessed on 05/04/2024.

[3] https://scholar.google.com/, accessed on 05/04/2024.

[4] https://github.com/gijswobben/pymed, accessed on 05/04/2024.

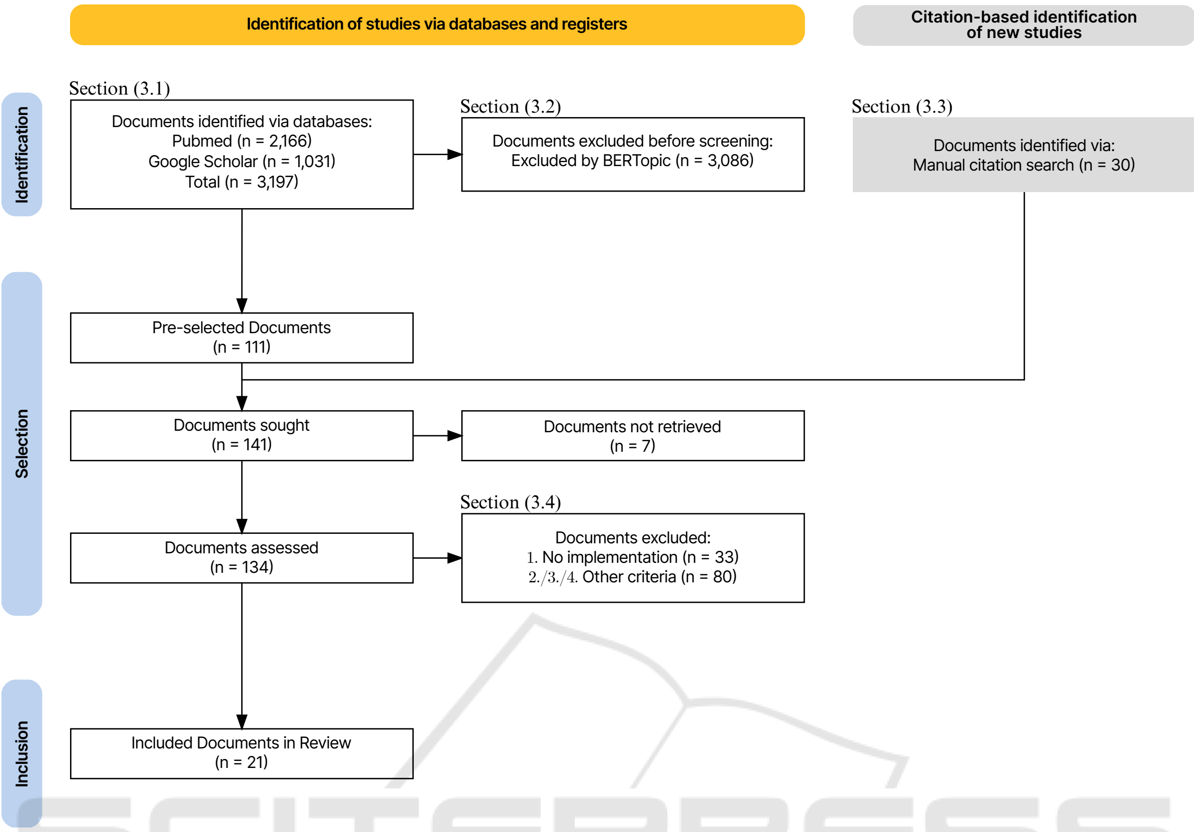

Figure 1: Flow diagram illustrating the number of documents at each stage of the PRISMA-ScR process. Diagram adapted from the work of (Haddaway et al., 2022).

Scholarly[5]. The query used in (Scheer et al., 2022) incorporates four key concepts: time, visualization, data, and medicine. To broaden our scope and identify approaches for visualizing temporal data across all fields, we retained only the keywords for the three concepts: "time", "visualization", and "data". The query is detailed in Table 1. At the end of this step, we obtained 3,197 documents.

3.2 Semi-Automatic Preselection of Articles

Among the query results, a significant number of articles were unrelated to temporal data visualization interfaces. Manually annotating thousands of documents to select relevant articles is a costly process, feasible only with a large team of evaluators. For this reason, we opted for an initial selection using semi-automatic tools.

We applied a topic extraction algorithm called BERTopic (Grootendorst, 2022). BERTopic is based on BERT (Bidirectional Encoder Representations from Transformers), an unsupervised deep language representation model that has shown strong performance in topic extraction tasks (Devlin et al., 2019). BERTopic uses a variation of TF-IDF to extract relevant topics from texts and clusters them according to these topics. The application of BERTopic to the titles, abstracts, and keywords of the documents obtained in the previous step, categorized the articles into 11 clusters, each corresponding to scientific themes. To ensure that the automatic clustering aligned with our preselection criteria, we included 19 articles cited in the reviews within our target domain[6]. These reviews, described in Section 2, all pertain to medical data visualization. Of the 19 articles, 14 were placed in the same cluster, which we selected for further analysis. This cluster contained a total of 111 documents and was associated with keywords such as data, visualization, and visual. At the end of this step, we retained 111 documents.

[5] https://github.com/scholarly-python-package/scholarly, accessed on 05/04/2024.

[6] These 19 articles were manually identified through citation analysis and literature reviews conducted at both the national and international levels.

Table 1: Search keywords by theme used in the PubMed engine. Due to the limitations of the Google Scholar search engine, the suffix "[tiab]", which restricts the search to the title and abstract content only, was removed from each keyword. Additionally, keywords containing the "*" were expanded (e.g., "timeframe*" becomes "timeframe OR timeframes").

Time
("temporal data"[tiab] OR "temporal sequence*"[tiab] OR "temporal pattern*"[tiab] OR "temporal abstraction*"[tiab] OR "temporal event*"[tiab] OR "time sequence*"[tiab] OR "time series"[tiab] OR "time period*"[tiab] OR "time frame*"[tiab] OR "timeframe*"[tiab] OR timeline*[tiab] OR time-oriented[tiab] OR (time[tiab] AND events[tiab])) AND
Visualization
(visuali*[tiab] OR "visual analy*"[tiab]) AND
Data
(data[tiab] OR information[tiab])

3.3 Manual Citation-Based Search for Articles

To complement the semi-automatic approach and ensure the most comprehensive selection of documents, we manually extracted citations from review articles dedicated to the representation of temporal data in the medical domain (Combi et al., 2010) (Aigner et al., 2011) (Rind et al., 2013) (West et al., 2015) (Turchioe et al., 2019) (Scheer et al., 2022). Documents identified in these literature reviews that were not included in the results of the previous step were retained. This additional search identified 30 additional documents, bringing the total number of selected documents to 141.

3.4 Evaluation by a Reviewer

To ensure that the selected articles aligned with our context, they were analyzed by a reviewer specializing in interface development for the medical domain. Of the documents identified in the previous steps, 7 could not be retrieved, resulting in a final total of 134 documents. Articles were retained if they met the following four criteria:

1. They present an implemented application tested on real or simulated data. This excludes articles describing a proof of concept, evaluation protocol, assessment of a visual or technical aspect, or a literature review.
2. They provide a view of an individual targeted by the user, extracted from a dataset. This excludes articles presenting only a synthetic view of the entire dataset or a subset of it.
3. They project data onto a single or synchronized temporal axis across different views.
4. They display multivariate or multimodal data related to the targeted individual.

Among the 134 documents reviewed, 33 were excluded for failing to meet the first criterion, and 80 did not meet the other three criteria. At the end of this step, 21 documents were retained.

3.5 Information Extraction from Articles

To extract relevant information, we developed a questionnaire that was refined over two successive iterations to characterize the content of the articles. These criteria are presented in the following two paragraphs: first, the functionalities, and then the evaluation methods used. Specifically, the functionalities describe the visual encodings chosen to represent the data or the interactions enabling the user to modify the display. In all cases, a criterion is satisfied if the stated assertion applies to the content of the annotated article. The assertion must be explicitly confirmed within the article text or illustrations.

Functionalities. The following criteria describe the interface's ability to present the entirety of the data within the pathway in a detailed and readable manner:

- **Context and Focus:** The user can choose to display a specific area or element in detail while always being able to assess the context in which the targeted area is embedded.
- **Expansion and Reduction:** The interface offers the choice between a compact or detailed view of an element.
- **Minimum Granularity:** The interface displays the finest possible representation of the data.

The following criteria describe the visual methods used to represent patient pathway records. Two criteria describe the heterogeneous or structured nature of the records:

Table 2: Synthesis of the content of the 21 identified articles on functionalities and interactions, based on the criteria developed in Section 3.5.

	Functionalities														
	Context and Focus	Expansion and Reduction	Minimum Granularity	Multimodal	Hierarchy	Temporal Distortion	Time Series	Importance	Plages standard	Standard Ranges	Missing Values	Proximity Map	Prediction	Open Environment	General Individual Information
Medical															
LifeLines (Alonso et al., 1998)			✓		✓										✓
KNAVE-II (Martins et al., 2004)			✓		✓		✓								
MIDGARD (Bade et al., 2004)	✓					✓	✓		✓	✓					✓
Caregiver (Brodbeck et al., 2005)	✓					✓	✓	✓		✓					
CareVis (Aigner and Miksch, 2006)	✓	✓	✓			✓			✓	✓					
Lung Transp. (Pieczkiewicz et al., 2007)	✓						✓			✓					✓
TimeLine (Bui et al., 2007)			✓	✓	✓		✓							✓	✓
MIVA (Faiola and Newlon, 2011)			✓	✓			✓		✓						✓
VisuExplore (Rind et al., 2011)			✓		✓		✓								✓
CareCruiser (Gschwandtner et al., 2011)			✓		✓		✓			✓					
UHS Lifelines (Hales et al., 2019)				✓	✓										
Tumor Board (Steinhauer et al., 2020)					✓				✓						✓
ClinicalPath (Linhares et al., 2023)	✓		✓		✓		✓	✓	✓	✓					
LastHistory (Baur et al., 2010)			✓	✓	✓										
ChronoLenses (Zhao et al., 2011)	✓		✓			✓	✓							✓	
Temporal MDS (Jäckle et al., 2016)			✓				✓	✓						✓	
BitExtract (Yue et al., 2019)	✓						✓					✓			
PromotionLens (Zhang et al., 2022)	✓		✓				✓					✓	✓		✓
Roslingfier (Shin et al., 2023)			✓				✓			✓		✓			
Life Mountain (Zhang et al., 2023)					✓		✓	✓		✓		✓			✓
LiveRetro (Wu et al., 2023)				✓	✓		✓					✓	✓		
Total :	8	1	13	5	11	4	16	4	5	8	0	5	2	3	9

- **Multimodal:** The interface displays numerical or categorical data alongside data of different types, such as text, images, etc.
- **Hierarchy:** The interface displays data organized hierarchically with two or more levels. This structure must be visible.

Two additional criteria describe the temporal aspect of the records:

- **Temporal Distortion:** The interface displays the temporal axis on a non-linear scale to emphasize certain areas.
- **Time Series**: The interface shows the evolution of multiple continuous variables along a temporal axis.

Four criteria describe the interface's ability to highlight key elements important for decision-making or understanding trends and data quality. Visual emphasis can be applied as follows:

- **Importance:** The interface draws attention to important values, with importance determined by variable criteria.
- **Standard Ranges:** The interface visually distinguishes measurements whose values fall outside standard ranges.
- **Missing Values:** The interface highlights data types or points that might be missing in the presented data. It also visually represents the absence of numerical values in series.

Two criteria describe the interface's ability to leverage an underlying predictive model to provide additional information:

- **Proximity Map:** The interface includes a panel showing relationships or proximity of the targeted

Table 3: Synthesis of the content of the 21 identified articles on evaluation methods, based on the criteria developed in Section 3.5.

		Accuracy	Resolution Time	Graded Questions	Open-Ended Questions	Open Feedback	Think-Aloud Protocol	Case Study
Medical	LifeLines	✓	✓	✓				
	KNAVE-II	✓	✓	✓				
	MIDGARD							✓
	Caregiver							✓
	CareVis				✓			
	Lung Transp.	✓	✓					
	TimeLine							
	MIVA	✓	✓	✓				
	VisuExplore				✓			✓
	CareCruiser							✓
	UHS Lifelines							
	Tumor Board			✓				
	ClinicalPath	✓	✓	✓		✓		✓
Non-medical	LastHistory				✓	✓		✓
	ChronoLenses							
	Temporal MDS							✓
	BitExtract							✓
	PromotionLens			✓		✓		✓
	Roslingfier			✓		✓		✓
	Life Mountain	✓		✓	✓			✓
	LiveRetro							✓
Total :		6	5	8	4	4	0	1

individual to other individuals. These relationships are derived from a predictive model or directly from the data.

- **Prediction:** The interface visually integrates predictions from an underlying model into the data presentation.

Two additional criteria complete the set of criteria already outlined:

- **Open Environment:** The interface displays data from an open data model or allows the user to upload their data in an interoperable format.
- **General Individual Information:** The interface includes a panel displaying general information about the targeted individual.

Evaluation. The following seven criteria describe the evaluation process for the interface:

- **Accuracy:** Participants are required to solve closed tasks using the interface, and the success rate in resolving these tasks is measured.
- **Resolution Time:** Similarly, the time required to complete each task is measured.
- **Graded Questions:** Participants respond to targeted questions about specific aspects of their interface usage on a predefined scale. This can be binary options (Yes/No), a numerical scale like the Likert scale (Likert, 1932) (1–5), a criticality scale, etc.
- **Open-Ended Questions:** Similarly, participants answer questions without constraints on their responses.
- **Open Feedback:** After using the interface, participants are invited to share their experience without restrictions.
- **Think-Aloud Protocol:** During interaction with the interface, participants are encouraged to articulate their thought process, exploration, and interaction strategies, as well as any factors aiding in problem resolution.
- **Case Study:** The usage scenario of the interface by a participant is described in detail. The participant's interaction with the interface is directed toward solving a pre-identified task.

3.6 Results

The results are presented in Tables 2 and 3. We distinguish studies originating in the medical domain from those in other fields, sorted by publication date.

The following observations are derived from the data presented in Table 2, which addresses functionalities and interactions. According to our findings, no approach facilitates easy identification of missing values. Most approaches display multivariate temporal data as parallel time series (16 out of 21). Few approaches are compatible with open environments (3 out of 21). Temporal distortion is rarely utilized (4 out of 21). Not all approaches display raw data with the finest possible granularity (13 out of 21 do). Few approaches support multimodal data visualization (5 out of 21). Additionally, none of the approaches in the medical domain provide latent space exploration through predictions or the projection of similar individuals.

The following observations are based on the data presented in Table 3, which focuses on methods for evaluating the needs that visual solutions should address. Some approaches incorporate user-centered design (9 out of 21), but all address identified user needs.

Qualitative and quantitative evaluations are combined only in the most recent approaches. None of the approaches identified in this study report collecting participants' think-aloud reflections to supplement qualitative results. Methods for collecting user-centered needs are challenging to classify, as each identified study presents a distinct protocol.

4 DISCUSSION

The methodology presented in this section, although based on the principles of the PRISMA-ScR method, has certain limitations. First, the query defined in Section 3.1 resulted in documents that were unrelated to the research question addressed in this chapter. Refining the combination of keywords could reduce the number of irrelevant documents. Furthermore, the success of using a semi-automatic approach, as described in Section 3.2, to filter similar approaches depends on the quality of the partitioning algorithm. In this work, we used only the BERTopic algorithm (Grootendorst, 2022), but it could be compared to other approaches, particularly LDA (Blei et al., 2003). Enhancing the representation of articles by incorporating full-text analysis and illustrations into multimodal models (Lopez, 2009) is another avenue to improve partitioning quality. Finally, the choice of data sources, PubMed and Google Scholar, was driven by the respective coverage of these sources in the medical and general domains. Alternative sources, such as Web of Science or DBLP, could also have been considered.

5 CONCLUSION

We studied 21 visualizations of multivariate time series for a single individual using the PRISMA-ScR protocol. This exploratory literature analysis reveals that this research area has gained recent interest but exhibits limitations in the proposed solutions. Notably, few approaches utilize temporal axis distortion to allow users to examine records at the minimal granularity level. Moreover, no approach in the medical domain visually integrates model predictions, a functionality present in non-medical approaches such as (Zhang et al., 2022) (Wu et al., 2023), which could be valuable for proactive patient care. Finally, the number of interoperable approaches remains limited. This study highlighted preferred functionalities for the visual representation of multivariate temporal data, including parallel time series and hierarchical views.

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