GLIMPSE-Med: Single-Screen Visualization of Multivariate Time Series for a Single Individual

Hugo Le Baher[1,2,4][a], Jérôme Azé[1][b], Sandra Bringay[1,3][c], Pascal Poncelet[1][d], Arnaud Sallaberry[1,3][e] and Caroline Dunoyer[4,5][f]

[1] *LIRMM, UMR 5506, University of Montpellier, CNRS, Montpellier, France*

[2] *5 DEGRÉS, Paris, France*

[3] *AMIS, Paul-Valéry University of Montpellier, Montpellier, France*

[4] *Health Data Science Unit, Public Health Service, Centre Hospitalier Universitaire de Montpellier, Montpellier, France*

[5] *Desbrest Institute of Epidemiology and Public Health, UMR UA11, University of Montpellier — Inserm, Montpellier, France*

{*hlebaher, aze, sandra.bringay, poncelet, arnaud.sallaberry*}*@lirmm.fr, c-dunoyer@chu-montpellier.fr*

Keywords: Visualisation Design and Techniques, Temporal Data, Multivariate Data, Healthcare.

Abstract: The widespread digitization of hospital information systems is paving the way for the integration of interactive visualization methods into decision support systems. This progress enhances the ability to anticipate critical risks in monitored patients and alleviates the workload of healthcare providers. However, Electronic Health Records (EHRs) encompass large, heterogeneous, and temporal records, making it a significant challenge to develop tools that enable effective understanding trajectories embedded in these complex data. We introduce GLIMPSE-Med, an interactive timeline-based visualization interface for temporal and heterogeneous events in the EHR, incorporating a score generated by a predictive model. The evaluation of this interface, conducted with healthcare professionals, confirmed that it meets two essential needs: (1) Assess the quality of data collected in an EHR ; (2) Estimate the patient's condition over time.

SCIENCE AND TECHNOLOGY PUBLICATIONS

1 INTRODUCTION

Healthcare systems have recently undergone significant digitization, promising reduced diagnostic and treatment errors, fewer redundant tests, and more efficient resource allocation, while driving innovation in preventive and therapeutic methods. Paper records have largely been replaced by electronic health records (EHRs), integrated into healthcare facilities after major organizational and technical shifts. EHRs are critical tools for healthcare professionals, aiding in decision-making, treatment monitoring, and enhancing care continuity and coordination. Researchers use them to extract data for clinical trials, while data engineers leverage them to address errors. Despite progress in integration and interoperability, EHR systems still have room for improvement.

In a medical setting, the use of existing systems raises several challenges. The evaluation of a patient's condition through existing dedicated interfaces can be difficult, even for experienced healthcare professionals. While interactive systems are recognized as indispensable, their use can sometimes lead to uncomfortable user experiences. In the context of temporal and multivariate data in particular, achieving a comprehensive understanding of individual trajectories within these datasets is challenging. Additionally, the progressive integration of predictive models into these systems to support clinicians' decision-making can sometimes lack clarity. It is therefore essential to propose visualizations that address these needs and are tailored to the daily practices of healthcare professionals.

We propose GLIMPSE-Med (Graphical Longitudinal Interface for Multimodal Pathways Search and Expertise in Medicine). This novel visualization interface aims to facilitate the understanding of individual pathways by compressing multivariate time series into a single, unified view. Applied to a medical con-

[a] https://orcid.org/0000-0003-3107-7070
[b] https://orcid.org/0000-0002-7372-729X
[c] https://orcid.org/0000-0002-2830-3666
[d] https://orcid.org/0000-0002-8277-3490
[e] https://orcid.org/0000-0001-7068-176X
[f] https://orcid.org/ 0000-0002-6789-4075

Le Baher, H., Azé, J., Bringay, S., Poncelet, P., Sallaberry, A. and Dunoyer, C.
GLIMPSE-Med: Single-Screen Visualization of Multivariate Time Series for a Single Individual.
DOI: 10.5220/0013373300003912
Paper published under CC license (CC BY-NC-ND 4.0)
In *Proceedings of the 20th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2025) - Volume 1: GRAPP, HUCAPP and IVAPP*, pages 765-775
ISBN: 978-989-758-728-3; ISSN: 2184-4321
Proceedings Copyright © 2025 by SCITEPRESS – Science and Technology Publications, Lda.

text, the presented prototype aims to help the evaluation a patient's journey within a healthcare facility.

2 RELATED WORK

Multivariate temporal data visualization is widely utilized across various fields, including healthcare, where it has been extensively applied to the study of Electronic Health Records (EHRs). The development of EHR visualization techniques has been shaped by successive contributions in the past 25 years. Lifelines (Alonso et al., 1998) pioneered representation of personal history records, enabling users to explore events along a timeline while maintaining context. Approaches such as MIDGARD (Bade et al., 2004), CareVis (Aigner and Miksch, 2006) or MIVA (Faiola and Newlon, 2011) offers extensions of Lifelines with various improvements such as integration of computerized protocols or use of iconographic elements. Recently, ClinicalPath (Linhares et al., 2023) introduced an efficient compressed, day-to-day summary view, but it lacks support for detailed data exploration. Notably, while non-medical domains such as e-commerce employ advanced predictive visualization tools (Zhang et al., 2022), (Wu et al., 2023), similar innovations are yet to be fully adopted in healthcare settings.

Several frameworks have been proposed to classify visualization methods, distinguishing between individual and cohort-focused approaches (Combi et al., 2010), (Aigner et al., 2011), (Rind et al., 2013), (West et al., 2015). Recent reviews emphasize the importance of addressing gaps in current methods, such as the representation of missing data and the integration of predictive models (Scheer et al., 2022), (Wang and Laramee, 2022). However, no existing synthesis focuses specifically on multivariate temporal data of single individuals.

3 REQUIREMENTS

In practice, following the recommendations of Munzner (Munzner, 2009) and the design process proposed by Sedlmair et al. (Sedlmair et al., 2012), the design of visual systems is conducted through successive iterations involving: **(1)** defining user needs and appropriate data structures, **(2)** proposing visual encodings and interactive functionalities to address these needs, and **(3)** presenting the results to users to gather feedback and refine the requirements. To develop GLIMPSE-Med, we identified a set of requirements derived from existing literature and through collaboration with the targeted end users. We focus on two primary audiences: **(1)** data engineers or statisticians responsible for data integration, data quality, and the development of automated indicators, and **(2)** healthcare professionals who require rapid and comprehensive understanding of patient trajectories. The experts involved were affiliated with the Montpellier University Hospital.

- R1 – Global and Detailed View: To facilitate understanding and enable informed decision-making, the interface must provide both a synthetic and detailed visualization of the patient's condition. This requires offering a global summary of the context while providing easy access to specific details on demand. Additionally, for practical use in healthcare settings, it is crucial that the information density fits realistically on a standard screen, such as a desktop computer.
- R2 – Trajectory: The interface must depict changes in the patient's condition over time by consistently displaying all individual measurements. By presenting a chronological sequence of these measurements, healthcare professionals can observe trends and variations in the patient's health.
- R3 – Heterogeneity: The interface must manage a variety of data types related to the patient's health, including numerical or categorical values from diverse and often structured sources
- R4 – Quality: Users must be able to evaluate the completeness, validity, consistency, and conformity of the displayed records.
- R5 – Importance: The interface must highlight specific records based on predefined criteria. By emphasizing critical data points, the interface enables healthcare professionals to quickly identify and interpret essential information even within large datasets.
- R6 – Prediction: This need involves integrating a third-party predictive model into the interface. Predictions regarding the patient's health should be visually presented alongside traditional records and clearly distinguishable from them.

While all these needs target the two identified audiences, (**R4**) primarily addresses the concerns of data engineers and statisticians.

4 GLIMPSE-Med

In this section, we present our interface, GLIMPSE-Med, whose design prioritized the compression of

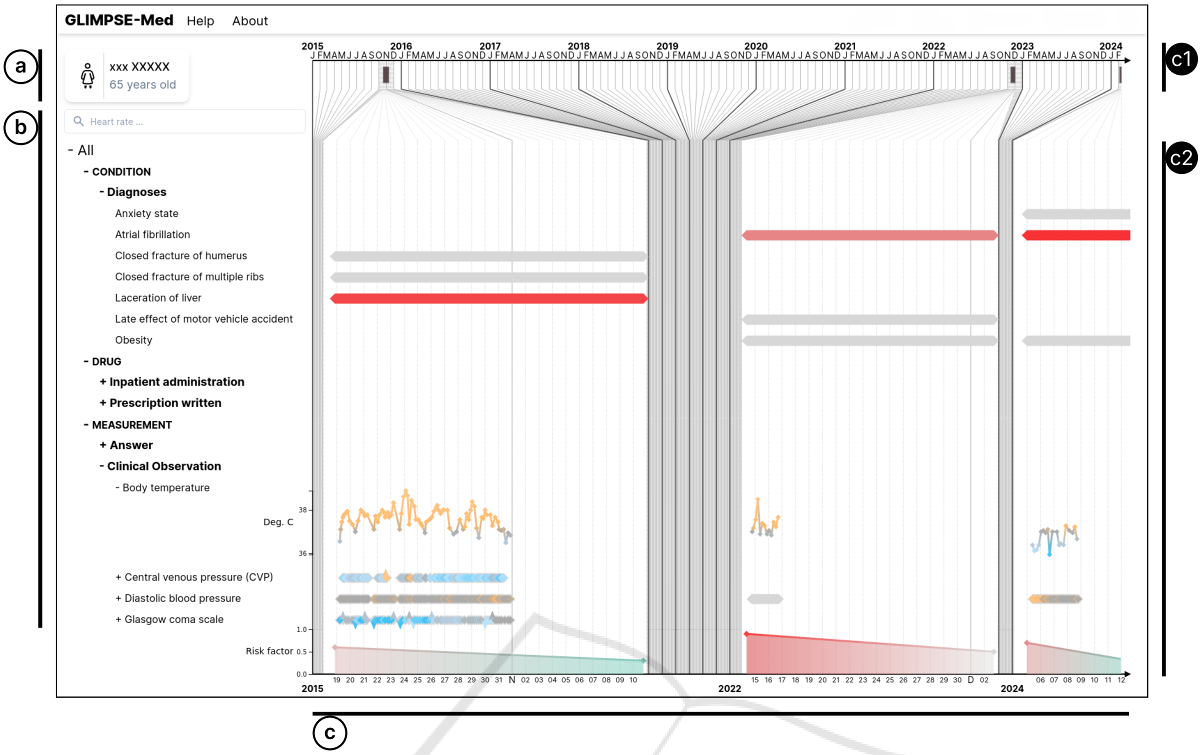

Figure 1: Screenshot of GLIMPSE-Med, showing a patient whose journey contains 7,885 data points covering three hospital stays. (a) General patient information panel (anonymized). (b) Dropdown menu displaying measured modalities grouped by categories and subcategories. A search bar allows users to filter displayed modalities. (c) Main data display in timeline form. (c1) Linear time axis. (c2) Distorted time axis.

temporal axes and modalities. According to the taxonomy of (Aigner et al., 2011), our interface uses an abstract reference frame, multivariate variables, linear time arrangement, both instant and interval temporal primitives, static visual correspondence, and two-dimensional dimensionality. The source code is available in a public repository[1].

The interface is illustrated in Figure 1, where it displays data from a specific patient from MIMIC-III, a publicly available database provided to the scientific community free of charge upon request. It contains clinical data from patients admitted to the Beth Israel Deaconess Medical Center in Boston, Massachusetts, from 2001 to 2012. Its primary advantage lies in the extensive anonymization of the data. The dataset is accessible on the PhysioNet platform (Goldberger et al., 2000) under the name MIMIC-III Clinical Database (Johnson et al., 2015), (Johnson et al., 2016). The database includes records for 38,597 adult patients, covering a total of 53,423 hospital stays. Here, this anonymized data is from a 65-year-old woman. The interface consists of three main parts: a panel displaying general patient information (Fig. 1.a), a dropdown menu for navigating between different modalities (Fig. 1.b), and a timeline (Fig. 1.c). In terms of implementation, the interface uses React[2], D3[3], and Tailwindcss[4]. The following paragraphs provide an in-depth exploration of available features and visual encodings.

General Information. A panel, illustrated in Figure 1.a, displays static patient information, encompassing data without temporal dynamics requiring quick access. This panel serves as a dedicated space for individual patient examination (**R1**), facilitating quick access to demographic details (**R2**) for efficient monitoring.

Modalities. Modalities (e.g., diagnoses, prescriptions, vital signs) are organized in an expandable tree menu (Figure 1.b). Users can click to expand or collapse categories, with the leaf nodes representing specific records stored in the patient files. Only modalities relevant to the patient are displayed. Selecting a leaf node opens a detailed view of that modality.

[1]https://gite.lirmm.fr/advanse/glimpse-med/

[2]https://react.dev/ accessed on 21/03/24.

[3]https://d3js.org/ accessed on 21/03/24.

[4]https://tailwindcss.com/ accessed on 21/03/24.

While the hierarchy is typically based on medical taxonomies like the International Classification of Diseases (ICD) for diagnoses, it is not required; all items can simply be grouped under a single root if needed. This organization helps users explore the data structure (**R3**) and spot potential errors or misclassifications (**R4**).

Search Bar. A search bar (Figure 1.b) is available above the modalities menu. Users can filter modality or category titles not containing the term entered in the bar, case-insensitively. Users can quickly find desired elements within a dense structure (**R1**) and identify data types that may not have been stored and displayed (**R4**).

Timeline. Temporal data is displayed on a timeline spanning from the first to the most recent measurements, with margins to account for varying temporal granularities. Vertical lines of different shades and widths indicate subdivisions like years and months (Figure 1). The timeline consists of three sections: a linear axis (Figure 1.c1), a distorted axis (Figure 1.c2), and a transition region connecting the two. The distortion compresses empty spaces where no data was recorded, magnifying periods with patient activity and collected data. This allows users to navigate all measurements in full temporal context (**R2**) while maintaining global awareness of temporal relationships (**R1**). The timeline dynamically adjusts using a custom algorithm that recursively subdivides it into a tree structure. Nodes represent calendar intervals tailored to the temporal extent, optimizing screen space utilization by adapting displayed data within predefined axis parameters.

Hospital Stays and Zoom. Each stay within the patient's journey is displayed on the linear axis with a rectangular symbol (Figure 1.c1), with the left and right sides corresponding to admission and discharge dates respectively. As illustrated in Figure 2, clicking a symbol expands the display to the corresponding admission while maintaining the predefined portion of the display. Users control the desired level of detail by zooming in on an admission (**R1**).

Records. On the timeline, each record is represented by a diamond-shaped symbol. For instantaneous records indicating zero duration, the upper corner of the diamond aligns with the corresponding temporal coordinate (Fig. 3.a1). For temporal periods, the diamond extends horizontally, with left and right peaks indicating start and end temporal coordinates

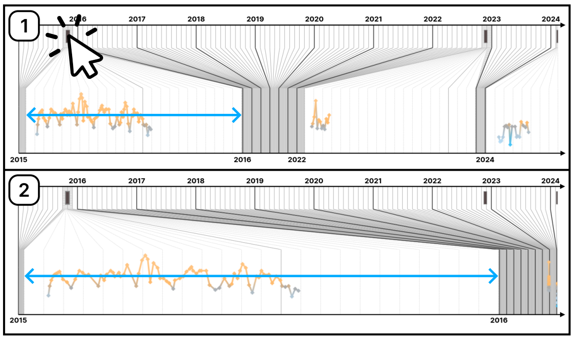

Figure 2: Illustration of zoom interaction. (1) The upper figure shows the default view, where all hospital stays are represented on the same scale within the distorted axis. (2) The lower figure shows the display after clicking on the first stay symbol. The distorted axis is then focused on the temporal range of this admission.

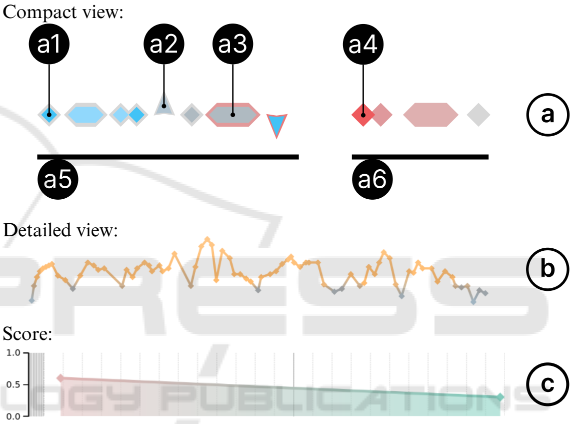

Figure 3: Symbolic representation of records. (a) Compact view. (a1) Example of instantaneous record. (a2) Example of significant increase. (a3) Example of interval. (a4) Example of important data. (a5) Numerical records. (a6) Non-numerical records. (b) Detailed view of a numerical series. (c) Risk score.

respectively (Fig. 3.a3). For each recorded modality, a sequential arrangement of corresponding records is displayed on the interface as a series. Users choose to display a series in either compact or detailed format. Clicking the corresponding series toggles between the two views. The characteristics and functionalities of these two views are discussed in the following sections.

Compact Series View. When data is displayed in compact view, it is distributed along a horizontal line. If the record includes a numerical value, a small concentric diamond is inserted inside (Fig. 4.a2). Additionally, to indicate significant evolution of the series' numerical value compared to the previous value, the diamond shape transforms into a triangle, with trian-

SCITEPRESS SCIENCE AND TECHNOLOGY PUBLICATIONS

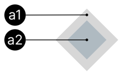

Figure 4: Components of the symbol representing a recording, including the external (a1) and internal (a2) parts. The internal component is only visible if the recording has a numerical value.

gle orientation (upward or downward) indicating increase or decrease, respectively (Fig. 3.a2). In our context, significant evolution corresponds to a change greater than the standard deviation of the dataset for the considered modality. Users can thus quickly discern the nature (**R3**) of a displayed series and identify potential anomalies such as missing values, duplicates, or outliers (**R4**). Furthermore, users capture the global dynamics of the series (**R2**) at a glance.

Detailed View of a Series. During the detailed visualization of a series containing numerical recordings, the data are displayed as a linear graph. The spatial coordinate Y of each symbol corresponds to the numerical value of the associated recording, if available. Successive points are connected by straight segments (Fig. 3.b). However, only points belonging to the same admission are connected, to avoid interpolation between distinct data collection periods. This method allows users to analyze the dynamics of measurements (**R2**) and identify anomalies (**R4**) and variations (**R5**), while maintaining a contextual overview (**R1**).

Highlighting of Recordings. Each recording is represented by a symbol with two parts: the contour and the internal component (Fig. 4). The internal component is visible only if a numerical value is present (Fig. 4.a2). Both parts use independent color schemes:

(1) Internal diamonds are colored based on standard value ranges. Due to the diverse semantics of medical modalities, defining universal interpretations for values is impractical. For example, while maximum values indicate stability in some measures (e.g., Glasgow Coma Scale), for others (e.g., heart rate), values near the mean suggest a healthy state. To avoid semantic bias regarding health impact, the palette uses blue for below-normal values, orange for above-normal values, and gray for values within the norm. This palette, inspired by temperature-related colors, leverages intuitive associations with "hot" and "cold."

(2) Contours are highlighted in red to indicate importance (Fig. 3.a4), a color chosen for its effectiveness in signaling critical or negative factors (**R6**). While the importance criterion is adaptable and context-dependent, in general, recordings flagged by

Figure 5: Illustration of a tooltip appearing when hovering over a recording. Additionally, when hovering, a series is highlighted with a light gray background.

the prediction model as contributing to patient deterioration are emphasized using this palette.

Predicted Score. In conjunction with the display of recordings, an estimate of the patient's risk is displayed at the bottom of the interface (Fig. 3.c) (**R6**). These predictions are independent of the models but should be generated either by statistical estimators or by machine learning models capable of temporal predictions. The prediction label is adaptable to correspond to the application context, which requires adjusting the color palette and its semantics. Here, a binary color gradient using shades of red and green has been adopted, where the score represented indicates a general estimate of the patient's deterioration (e.g., risk of mortality, cardiac insufficiency, or reintubation).

Tooltip. When the mouse cursor hovers over an element, a tooltip is revealed to provide complete information about it. This feature allows users to evaluate the content of a particular recording **(R1)**.

5 USER STUDY

5.1 Design

To evaluate the effectiveness of our interface, we conducted a user study involving 14 participants on-site. This diverse panel consisted of healthcare professionals from the Montpellier University Hospital, including doctors, statisticians, and data engineers, comprising nine women and five men. Participants received no financial or privileged treatment. This study was approved by the Montpellier University's ethics committee, opinion number UM 2023-041bis. The experiments were conducted using real patient trajectories from the MIMIC-III dataset (Johnson et al., 2015) (Johnson et al., 2016). The information displayed on the interface includes demographic data, vital signs, laboratory test results, procedures, diagnoses, medications, and various clinical notes.

Each evaluation session, lasting approximately 40 minutes, began with a complete presentation of the

SCITEPRESS SCIENCE AND TECHNOLOGY PUBLICATIONS

study, providing an overview of the interface's features. Participants had access to two distinct patient files, accessible via separate browser tabs. The experience consisted of three steps:

Step 1: Participants responded to closed-ended questions through a multiple-choice questionnaire of 15 questions, interacting with the interface. The questions assigned to participants for task completion are accessible in Table 1. These questions were designed to encourage participants to explore all features. Sometimes, advanced medical knowledge was required (questions 14 and 15). Although participants responded without assistance, they had the opportunity to ask clarifying questions to the evaluator. Additionally, participants were encouraged to verbalize their thoughts, sharing any reflections or challenges encountered during navigation in the interface.

Step 2: Participants completed the SUS (System Usability Scale) questionnaire (Brooke, 1996). Since all participants were French-speaking, we used the French version of the questionnaire, F-SUS (Gronier and Baudet, 2021). Comprising 10 questions, visible in Table 2, this standard questionnaire aims to evaluate the effectiveness, efficiency, and satisfaction of the interface. Participants responded to each question on a 5-point Likert scale. The questionnaire generates a score ranging from 1 to 100.

Step 3: Participants participated in open discussions, responding orally to questions posed by the evaluator. These questions were designed to gather comments on general or specific aspects of the interface. They provided an opportunity for participants to express their thoughts openly.

5.2 Results

This section presents both quantitative and qualitative analyses of the experimental results.

5.2.1 Quantitative Analysis

Table 1 presents the results of the quantitative analysis. Participants were presented with a multiple-choice questionnaire designed to assess their ability to extract information from the presented data. The average accuracy across all questions was 89%. This high accuracy suggests that the system effectively conveys relevant patient information and enables users to accurately answer questions related to the presented data. As shown in Table 1, participants achieved an overall accuracy of 89% in answering closed-ended questions using the interface. Accuracy was calculated as the proportion of correct answers to a given question out of the total number of participants. As anticipated, the results were high, aligning with the intentional accessibility of the questions, which served as a means for participants to explore the interface with clear objectives in mind. As expected, participants demonstrated lower performance on the last two questions (79% and 14% for questions 14 and 15, respectively), which required advanced medical knowledge and familiarity with medical coding. Only one participant had experience with medical coding. They successfully answered the questions related to this domain. Furthermore, it is important to note that some participants overlooked recordings of high importance, leading to performance below the average for question 9.

In addition to the closed-ended questionnaire, participants' satisfaction with the interface was assessed using the System Usability Scale (SUS) questionnaire. Based on the SUS score, participants expressed satisfaction with their experience using the interface. As shown in Table 2, the average score is 79.62, placing it in the highest quartile in terms of absolute scores. When compared to other studies (Bangor et al., 2008), our interface also falls within the highest quartile, receiving ratings between "good" and "excellent" on the adjective scale.

5.2.2 Qualitative Analysis

In addition to the quantitative evaluation, participants were encouraged to share their thoughts aloud as they completed the tasks and responded to open-ended questions. This section presents a synthesis of these feedback comments.

Visual Features. Numerous comments were gathered regarding interface elements, particularly concerning the primary contribution of our approach: the compression of the two axes of representation for temporal and multivariate measures - the temporal axis and the modality menu.

A synthesis of these comments is presented in Table 3. In this synthesis, we chose to extract positive and negative opinions and represent them visually in green and red, respectively. Participants were encouraged to express aloud any obstacles they encountered and their opinions on features they disliked. The results show that they did not hesitate to do so. We therefore represented the absence of comments as relatively positive, with a green and gray hatch, under the assumption that participants validated the features about which they did not express negative feedback. The presented synthesis summarizes only the opinions regarding the main features.

The majority of participants appreciated the distortion of the temporal axis (Fig. 1.c2) since 10 expressed positive sentiments. All participants seem to

Table 1: Multiple-choice questionnaire used during task-based evaluation. The average accuracy is calculated based on the responses of the 14 participants.

№	Questions	Acc.
1.	What is the patient's age?	100 %
2.	How many years are displayed on the screen?	100 %
3.	How many admissions are shown on the interface?	100 %
4.	What is the discharge modality for the second admission?	93 %
5.	Among these choices, which diagnosis was identified in two different admissions?	100 %
6.	What is the last measured value of "Heart Rate"?	100 %
7.	Among these choices, which "Clinical Observation" does not vary during the last admission?	93 %
8.	Which admission shows the peak risk?	93 %
9.	What is the most important modality for risk estimation?	79 %
10.	What is the date of the "Heart Rate" value shown as important?	93 %
11.	How many values have a coding error in "Fluid output miscellaneous route"?	100 %
12.	Which modality has coding errors only during the first admission?	93 %
13.	What is the current risk level of the patient?	100 %
14.	Could the diagnosis "Obesity" be coded for the patient's admission?	79 %
15.	Could the diagnosis "Essential hypertension" be coded for the patient's admission?	14 %
	Overall average accuracy:	**89 %**

Table 2: F-SUS Questionnaire. Scores calculated based on the original guidelines by (Brooke, 1996) and averaged across 14 participants.

№	Questions	Score
1.	I would like to use this interface frequently.	7.67
2.	This interface is unnecessarily complex.	7.50
3.	This interface is easy to use.	7.85
4.	I would need the support of a technician to be able to use this interface.	8.75
5.	The different functionalities of this interface are well-integrated.	7.67
6.	There are too many inconsistencies in this interface.	8.22
7.	Most people would learn to use this interface very quickly.	8.02
8.	This interface is very cumbersome to use.	8.02
9.	I felt very confident using this interface.	7.67
10.	I needed to learn a lot of things before I could use this interface.	8.22
	Overall Score:	**79.62 /100**

confirm the readability of this feature. The reservation expressed indicates that in some cases, there would be an advantage to keeping a linear temporal scale, since the spaces between the measures would have semantic importance.

Participants appreciated the presence and functionality of the search bar. They successfully used the tooltips (Fig. 5). The other features are more mixed, such as the display of units, zoom interaction (Fig. 2), navigation in the modality tree (Fig. 1.b) and the visual representation of the series (Fig. 3) even if these features seem to be mostly readable and understandable.

The most contested element is the semantics of the risk curve (Fig. 3.c) and the "important" values (Fig. 3.a4). For example, three participants could not understand the link between the two, stating they were unable to see which elements are involved in the risk calculation and were unable to identify if a given red value refers to the current or next stay.

Usage. The interface was designed for two main objectives: **(1)** consulting patient electronic health records in a clinical setting and **(2)** the ability to assess data quality within these records. We then questioned participants about the use of the interface based on their experience. We aimed to confirm the interface's response to the requirements of these tasks and also to identify new, unexpected applications of the interface.

As expected, two physicians expressed their intention to use the interface in a clinical setting. For example, upon arrival at the service, they wish to observe the vital signs of the previous day to connect with the patient. During the service, they could monitor the evolution of a specific parameter. They also highlighted its usefulness in a consultation scenario,

Table 3: Summary of user remarks provided during oral discussions, grouped by features in the form of horizontal bar diagrams. Negative opinions are shown on the left in red and positive opinions on the right in green. No opinions are shown in green hatch in the center. A total of one comment per participant, or 14 comments, are expected per feature.

Feature	Negative	Positive
Temporal Axis		
Distortion	1	10
Unit and Zoom	2	1
Modalities Tree		
Clarity and Navigation	1	1
Arrangement	2	
Search Bar		4
Series		
Symbols	1	1
Colors	1	1
Tooltip		1
Risk and Importance		
Sémantics	3	

Negative *No Feedback* *Positive*

stating it would help find analysis results, reports or determine if a particular test was performed.

As expected, four data engineers or statisticians expressed their intention to use the interface for data quality assessment, for applications such as preparing a study when working with clinicians or verifying their work. They mentioned they could conduct research in health warehouses, observe typical patient cases to assess data availability and identify potential inconsistencies. For quality control purposes, they could use it to verify data loading and inspect patient data. We also identified an unexpected third use case during the evaluation: six participants would use the interface for retrospective studies, where researchers need to explore patient trajectories a posteriori. According to participants, the interface would be useful for developing hypotheses, for example, by observing correlations, planning the variables to analyze and how, or determining if a genetic variant is causal. One participant argued it would be faster than going into the existing hospital software for these tasks. One participant recommended using the interface for medical coding. Another expressed the intention to use it for machine learning, highlighting the interface's ability to show and explain a predictive score.

5.3 Discussion

The open-ended questionnaire and think-aloud feedback collected during the experiment provided valuable insights into the components users need to complete tasks effectively. This feedback also highlighted potential uses for the interface. These participant responses complement the quantitative analysis and are essential for identifying precise areas for improvement in the evaluated interface. Based on this evaluation, the general aesthetics were refined, and certain functionalities were adjusted to incorporate participant feedback.

The evaluation demonstrated that the interface could serve as a faster and simpler alternative to the current hospital software for retrospective studies or for assessing the quality of medical records. Its single-screen presentation allows users to explore data with fewer clicks and less prerequisite knowledge of the software. A task-based comparative study would be necessary to confirm differences in the number of clicks required.

To the best of our knowledge, and beyond the medical domain, GLIMPSE-Med is the only interface that visually integrates data quality assessments or prediction outputs with multivariate time series on a single screen. In the medical field, this approach is the first to contextually and focally compress both temporal and modality axes.

Limitations. Some participants appeared to struggle to evaluate the interface independently of the data displayed or the predicted risk values used for demonstration purposes. The discrepancy between the experimental setting and users' everyday configurations may have influenced their ability to envision regular use of the interface. Furthermore, while participants were French-speaking, the interface's labels and modalities were written in English. Although no participant reported linguistic difficulties, this factor may have impacted the results.

Due to the composition of the participant panel and the tasks evaluated, the effectiveness of the interface in a clinical context cannot yet be validated. However, participant feedback has been positive and opens avenues for further interface development. A new evaluation phase should include additional features such as data export capabilities and the integration of textual content. Clinical transmissions or reports should be incorporated as records within the timeline, with a new interaction allowing users to view raw textual data in a dedicated window. Moreover, the interface's clinical effectiveness should be studied with a panel of healthcare professionals (e.g., doctors, nurses) who work in daily clinical environments.

The primary issue identified during the evaluation was the exploration of the modality menu (Fig. 1.b): participants could only identify sub-elements of a category by clicking on it. To address this, we plan to implement a compact view for multiple series. Sub-

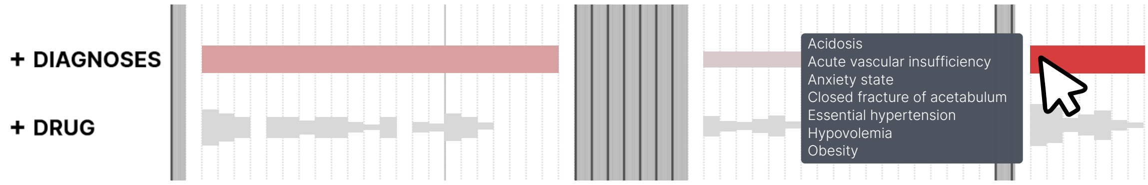

Figure 6: Proof of concept for a compact view of multiple series displayed as an unsmoothed violin density diagram: the records within a collapsed subtree are aggregated by temporal unit. Each aggregation is represented by a rectangle, with vertical height indicating the volume of measurements. In the example, the average importance is highlighted using a red color gradient. Additionally, details of the aggregated content are visible upon hovering.

elements of a collapsed tree node will be synthesized into a violin density diagram. An example of this concept is shown in Figure 6.

Future Works. In future versions, users will be able to pin desired series to the upper portion of the y-axis. Constant display of a user-selected set of series will enable personalized ordering and comparisons with other series. We also plan to incorporate data export capabilities to external files.

The addition of such features is straightforward, while other improvements present certain scientific challenges:

(1) While the readability of the risk score (Fig. 3.c) and important values (Fig. 3.a4) independently of each other was validated, the visual representation of their relationship requires further exploration. In particular, the interactions between these elements should be further refined to enhance their semantic clarity for users. For instance, when a user hovers over a prediction, the important values for that specific prediction should be dynamically highlighted using a new color palette, an extended tooltip, or spatial links.

(2) Currently, GLIMPSE-Med only presents numerical and categorical data. The EHR includes two additional modalities: clinical notes and medical imaging. To maintain visual consistency and make use of the compression features in our interface, these modalities must be adapted to the format of parallel timelines. Since the interface relies on compressing records visually while allowing users to view them fully on demand, it is necessary to design both a compact and a detailed view for each modality.

A simple approach would treat images and documents in the preview as simple records, without analyzing their content. Collections of documents or images could then be displayed as categorical timelines, as shown in Figure 3.a, using symbols representing an envelope or imaging icon to indicate their type. Clicking on a symbol could open the raw content in a sub-window. While this approach deviates from the single-window display principle, it is intuitive. However, it provides limited information, requiring users to open the full content to find what they need. To avoid this, both compact and detailed representations should offer as much useful information as possible. Using information extraction techniques could generate richer and more informative representations, such as extracting categorical or numerical data from texts and images. These could be displayed in timelines without major interface changes. For detailed views, compact representations could be achieved using summarization techniques. However, both information extraction and automatic summarization for texts and images remain challenging and require further research.

Medical texts are often structured into paragraphs with headings, which can guide information extraction. However, this structure varies between institutions and over time. Automatic methods, like named entity recognition or topic modeling (Vayansky and Kumar, 2020), can identify relevant information or keywords summarizing the content. For example, (Wu et al., 2023) track the evolution of online video comments by showing representative keywords and visualizing semantic changes using the BERT language model (Devlin et al., 2019).

For medical imaging, information extraction is more complex. Models are typically specialized for specific types of imaging, like MRI or CT scans (Jalali and Kaur, 2020). A common technique is segmentation, which classifies pixels to detect important shapes (Qureshi et al., 2023). This can highlight key regions of an image, offering an informative summary useful for visualization.

6 CONCLUSION

We proposed GLIMPSE-Med, a visual interface targeting two primary audiences: healthcare professionals and data engineers/statisticians. Through innovative visual encodings and interactive functionalities, the interface facilitated the presentation of large and multivariate medical records in a single on-screen view. Notably, its temporal distortion capabilities and the ability to toggle between compact and detailed views of data series provided users with a simplified navigation experience. An empirical evaluation was conducted with 14 healthcare professionals affiliated with the Montpellier University Hospital. Results indicated an accuracy rate of 89% in task resolution, while usability assessments using the SUS scale placed the interface in the top quartile for usability. Additionally, qualitative feedback obtained from open-ended questions identified potential areas for improvement. To the best of our knowledge, GLIMPSE-Med is the first interface across domains to visually integrate data quality and prediction outputs with multivariate time series in a single on-screen view. In the medical field, it is also the first to compress both the temporal axis and the modality axis. Although tested exclusively in a medical context, GLIMPSE-Med is not limited to this use case. The evaluation demonstrated that GLIMPSE-Med effectively addressed the problem at hand; however, qualitative feedback and discussions with users highlighted opportunities for further interface improvements.

REFERENCES

Aigner, W. and Miksch, S. (2006). CareVis: integrated visualization of computerized protocols and temporal patient data. *Artificial Intelligence in Medicine*, 37(3):203–218.

Aigner, W., Miksch, S., Schumann, H., and Tominski, C. (2011). *Visualization of Time-Oriented Data*. Human-Computer Interaction Series. Springer, London.

Alonso, D. L., Rose, A., Plaisant, C., and Norman, K. L. (1998). Viewing personal history records: A comparison of tabular format and graphical presentation using LifeLines. *Behaviour & Information Technology*, 17(5):249–262.

Bade, R., Schlechtweg, S., and Miksch, S. (2004). Connecting time-oriented data and information to a coherent interactive visualization. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, (CHI ’04), pages 105–112, New York, NY, USA. Association for Computing Machinery.

Bangor, A., Kortum, P. T., and Miller, J. T. (2008). An empirical evaluation of the system usability scale. *International Journal of Human–Computer Interaction*, 24(6):574–594.

Brooke, J. (1996). SUS - A quick and dirty usability scale. *CRC Press*.

Combi, C., Keravnou-Papailiou, E., and Shahar, Y. (2010). *Temporal Information Systems in Medicine*. Springer US, Boston, MA.

Devlin, J., Chang, M.-W., Lee, K., and Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186. Association for Computational Linguistics.

Faiola, A. and Newlon, C. (2011). Advancing Critical Care in the ICU: A Human-Centered Biomedical Data Visualization Systems. In Robertson, M. M., editor, *Ergonomics and Health Aspects of Work with Computers*, Lecture Notes in Computer Science, pages 119–128, Berlin, Heidelberg. Springer.

Goldberger, A. L., Amaral, L. A. N., Glass, L., Hausdorff, J. M., Ivanov, P. C., Mark, R. G., Mietus, J. E., Moody, G. B., Peng, C.-K., and Stanley, E. (2000). PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. *Circulation*, 101(23):E215–220.

Gronier, G. and Baudet, A. (2021). Psychometric evaluation of the F-SUS: Creation and validation of the french version of the system usability scale. *International Journal of Human–Computer Interaction*, 37(16):1571–1582.

Jalali, V. and Kaur, D. (2020). A study of classification and feature extraction techniques for brain tumor detection. *International Journal of Multimedia Information Retrieval*, 9(4):271–290.

Johnson, A. E. W., Pollard, T. J., and Mark, R. G. (2015). MIMIC-III Clinical Database.

Johnson, A. E. W., Pollard, T. J., Shen, L., Lehman, L.-W. H., Feng, M., Ghassemi, M., Moody, B., Szolovits, P., Celi, L. A., and Mark, R. G. (2016). MIMIC-III, a freely accessible critical care database. *Scientific Data*, 3:160035.

Linhares, C. D. G., Lima, D. M., Ponciano, J. R., Olivatto, M. M., Gutierrez, M. A., Poco, J., Traina, C., and Traina, A. J. M. (2023). ClinicalPath: A visualization tool to improve the evaluation of electronic health records in clinical decision-making. *IEEE Transactions on Visualization and Computer Graphics*, 29(10):4031–4046.

Munzner, T. (2009). A nested model for visualization design and validation. *IEEE Transactions on Visualization and Computer Graphics*, 15(6):921–928.

Qureshi, I., Yan, J., Abbas, Q., Shaheed, K., Riaz, A. B., Wahid, A., Khan, M. W. J., and Szczuko, P. (2023). Medical image segmentation using deep semantic-based methods: A review of techniques, applications and emerging trends. *Information Fusion*, 90:316–352.

Rind, A., Wang, T. D., Aigner, W., Miksch, S., Wongsuphasawat, K., Plaisant, C., and Shneiderman, B. (2013). Interactive Information Visualization to Explore and Query Electronic Health Records. *Foundations and Trends® in Human–Computer Interaction*, 5(3):207–298.

Scheer, J., Volkert, A., Brich, N., Weinert, L., Santhanam, N., Krone, M., Ganslandt, T., Boeker, M., and Nagel, T. (2022). Visualization techniques of time-oriented data for the comparison of single patients with multiple patients or cohorts: scoping review. *Journal of Medical Internet Research*, 24(10):e38041.

Sedlmair, M., Meyer, M., and Munzner, T. (2012). Design study methodology: Reflections from the trenches and the stacks. *IEEE Transactions on Visualization and Computer Graphics*, 18(12):2431–2440.

Vayansky, I. and Kumar, S. A. P. (2020). A review of topic modeling methods. *Information Systems*, 94:101582.

Wang, Q. and Laramee, R. (2022). EHR STAR: The state-of-the-art in interactive EHR visualization. *Computer Graphics Forum*, 41(1):69–105.

West, V. L., Borland, D., and Hammond, W. E. (2015). Innovative information visualization of electronic health record data: a systematic review. *Journal of the American Medical Informatics Association : JAMIA*, 22(2):330–339.

Wu, Y., Xu, Y., Gao, S., Wang, X., Song, W., Nie, Z., Fan, X., and Li, Q. (2023). LiveRetro: Visual Analytics for Strategic Retrospect in Livestream E-Commerce.

Zhang, C., Wang, X., Zhao, C., Ren, Y., Zhang, T., Peng, Z., Fan, X., and Li, Q. (2022). PromotionLens: Inspecting Promotion Strategies of Online E-commerce via Visual Analytics.

SCITEPRESS
SCIENCE AND TECHNOLOGY PUBLICATIONS