A User-Centric Adaption Model for Document Visualizations with Different Levels of Detail within a Consumer Health Information System

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Abstract
After receiving a diagnosis, patients often seek detailed information about causes, treatments, and consequences through health information materials such as websites and brochures. However, navigating these resources and finding specific information on their diagnosis and ways to respond, can be time-consuming and challenging. Text visualizations can help users access relevant information, but typically require knowledge of health literacy and visualization concepts. To address this, we propose a user-centric adaptation model for visualizations with varying Levels of Detail (LoD) in health-related text visualizations to enhance users' ability to explore health information materials. The initial LoD is personalized based on a user's visualization literacy, assessed during the onboarding phase. Heuristics derived from interaction metrics, such as dwelling time and mouse clicks, guide subsequent LoD adaptations, enabling the system to respond dynamically to user behavior. This combined approach balances user-driven customization with system-driven adaptability, aiming to improve engagement, accessibility, and comprehension. Our work establishes a foundation for future research on adaptive LoD visualizations tailored to individual abilities and preferences in health information systems.

Keywords
Consumer Health Information Systems, Adaptive User Interface, Interaction Tracking, Text Visualization, Level of detail

1. Introduction

When individuals are diagnosed with a disease, they often face an urgent need to understand its causes, treatment options, and potential impact on their daily lives. Many turn to online resources as their first point of reference, yet accessing and comprehending this information requires a certain level of *digital health literacy*–defined as the "capabilities [...] to use and benefit from digital health resources" [1]. Furthermore, health information materials are often dense, detailed, and lengthy, which can overwhelm patients and make navigation challenging. This complexity discourages engagement, hinders informed decision-making, and lowers user satisfaction [2]. Text visualizations offer a promising solution by helping users navigate large documents, identify areas of interest, and obtain overviews [3, 4]. However, effectively interpreting visualizations requires a degree of visualization literacy, which refers to the "ability and skill to read and interpret visually represented data and to extract information from data visualizations" [5]. Shortcomings in users' visualization literacy levels can further restrict access to critical information.

To address this issue, visualizations should be adapted to users' specific needs and abilities. One promising approach involves tailoring the Level of Detail (LoD)—the amount and complexity of information shown in the visualization—to match individual user capabilities. Selecting an appropriate LoD is essential to ensure that visualizations are both effective and accessible.

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Figure 1: Text visualizations with different LoD in our CHIS. The document is analyzed using *Latent Dirichlet Allocation* (LDA) applied to its paragraphs. (First column) A word cloud visualizing the most dominant terms across several topics. The size of each word represents its relevance, while the color indicates its associated topic. (Second column) A topic cloud displaying the most relevant terms within each topic, offering a more focused view of the topic structure. (Third column) Text snippets highlighting terms that signify specific topics, providing contextual insights. (Fourth column) A tile bar designed to help users localize terms within the document, offering a compact overview of term frequency and distribution. (Fifth column) Infographic-based visualizations convert important content from the document into graphical representations. Each row corresponds to the different LoDs for each visualization method.

In this work, we present a concept for user-centric adaptation of LoD in text visualizations to support users in accessing health information materials. Figure 1 illustrates the visualizations integrated into our approach. The initial global LoD for each user is determined using the *Mini-VLAT* [6], an assessment tool that quantifies visualization literacy. During user interaction, behavioral data such as dwelling time and the number of mouse clicks are collected to gain additional insights. Two heuristics leverage this interaction data to suggest adjustments to the LoD of individual visualizations dynamically. At the same time, users retain the ability to manually adjust LoDs, ensuring flexibility and maintaining user control. We validate our approach using a carefully selected digital health information brochure [7].

2. Related Work

Our presentation of the related work is divided into two parts. First, we review existing work on adaptive user interfaces (UIs), particularly in the domain of Consumer Health Information Systems (CHIS), to highlight strategies for tailoring interfaces to individual users' abilities and preferences. Next, we explore visualization techniques developed for navigating medical documents, focusing on their application to Electronic Health Records (EHRs) and their relevance to our study.

2.1. Adaptive User Interfaces for Consumer Health Information Systems

End users have varying levels of visualization literacy, so UIs should be able to adapt to their individual needs. This adaptation can be managed manually by the user or automatically by the system (through an adaptive UI) e.g., by taking user profiles and application context into account [8]. Akiki et al. [9] introduced an approach to improving UIs by adjusting elements such as layout and font size based on user preferences and the context of use. Similarly, Gajos et al. [10] framed the adaptation process as an optimization problem, taking into account both the user's abilities and the device being used. Although the solution space is vast, their algorithm efficiently delivers quick and effective adaptations. Hussain et al. [11] proposed an additional adaptation model that is independent of both the application domain and the device. This model provides a more flexible approach to user interface adaptation, allowing for broader applicability across diverse systems and environments. Adaptive UIs can significantly enhance accessibility, as demonstrated by systems like *Easy Reading* by Heumader et al [12]. This system supports users with cognitive disorders in reading webpages by tracking user interactions and tool usage to adapt the webpage and help users extract information from text. However, while Easy Reading focuses purely on text, our system takes it a step further by providing a more abstracted visualization of text, enabling users to engage more effectively with complex visual content. Our approach goes beyond just textual data to encompass non-text information, showcasing its relevance across various contexts. For example, we have created interactive versions of static infographics that can be dynamically adjusted through aggregation, significantly improving the user experience. Martin-Hammond [13] presented an adaptive UI designed specifically for individuals with pointing disabilities caused by physical impairments. In a design study, Eslami et al. [14] demonstrated that user preferences within a CHIS vary between user groups, further emphasizing the importance of adaptive UIs. In their paper, "The presence of a well-designed, user-friendly interface in healthcare is critical, as it can directly impact patient health. A poorly designed interface may lead to incorrect system usage or increased user errors, potentially causing the system to be abandoned. Since users with different abilities, skills, and needs interact with the system, it is essential to adapt the interface to suit those needs." Our work presents directions toward an adaptable and adaptive UI for CHIS by integrating in the interactive system methods for choosing the LoD of different visualizations that aim to help users explore health documents. However, adaptive UIs and visualizations remain rare in CHISs. For the specific case of type-2 diabetes mellitus—the focus of our study—a survey by Krenn et al. [15] revealed that out of 114 reviewed informational materials, only 24 provided any form of adaptability to meet individual user needs. Among these, just one interactive website incorporated different LoDs, highlighting a significant gap in the integration of adaptive features in this domain.

2.2. Visualizations for Exploring Medical Documents

The treatment of a patient is continuously documented in a so-called *patient chart* within an EHR [16]. To help physicians navigate and analyze the documents contained in them, various text visualization techniques have been developed. Hirsch et al. [17] introduced a system that generates word clouds, linking the displayed terms to their corresponding relevant documents. Building on this, Sultanum et al. [18], in a design study, proposed a catalog of requirements tailored to such tasks and devised an enhanced design that incorporates a temporal dimension into Hirsch's approach. In a further work, their derived system *Doccurate*, presents vertically arranged word clouds that illustrate the frequency of terms over specified time periods [19]. In addition, the system supports varying LoDs and enables users to trace the information back to the original documents. In a subsequent design stage conducted in collaboration with practitioners, Sultanum et al. [20] further extended Doccurate, resulting in a system called *ChartWalk*. This enhanced tool refines the exploration and analysis of patient charts, making it even more effective for clinical use. For a comprehensive survey of visualization approaches for clinical chart reviews, we refer to the work of Ramalho et al. [21]. A recent state-of-the-art report on the broader domain of visualization and visual analytics for EHR data was presented by Wang and Laramee [22]. Tytarenko et al. [23] presented a visualization approach for the localization of topics, i.e., semantic concepts, within a document. Their technique, *Hierarchical Topic Maps*, is based on a Tile-Bar approach arranged in a binary tree layout, which provides multiple LoDs. As opposed to previous works, their approach is not limited to clinical chart review but can be applied agnostically to various types of documents.

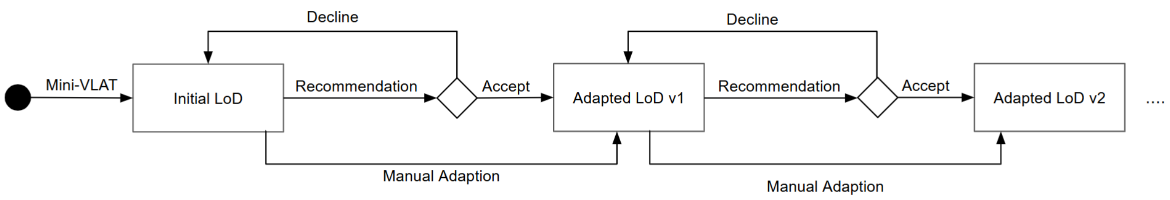

Figure 2: UML for the process of adapting the LoD. The initial LoD is determined according to the visualization literacy score from the Mini-VLAT. Based on the dwelling time and mouse clicks, the system recommends adaptions to the LoD to the user. Furthermore, the user can choose the LoD manually.

3. User Adaption

The visualizations within our A^+CHIS system provide several LoD. The displayed LoD depends on the individual preferences and visualization literacy of a particular user. To better align the LoD with the user's ability to extract meaningful insights, we introduced three approaches for adapting it. These methods adapt the LoD in a heuristic manner, enhancing the likelihood of quickly identifying a level that meets the user's needs. The initial LoD is set according to the visualization literacy score from the Mini-VLAT. Based on the dwelling time and mouse clicks, our system recommends adaptions to the LoD, which can be accepted by the user. At any time, users also may change the LoD themselves. The workflow is illustrated in Figure 2.

3.1. Adaption based on Visualization Literacy Assessment

The *Visualization Literacy Assessment Test* (VLAT), developed by Lee et al. [5], is widely regarded as the standard for quantifying a user's visualization literacy. The VLAT includes 12 fundamental two-dimensional data visualizations and 53 multiple-choice questions for assessment. However, its larger number of tests demands substantial time and cognitive effort from participants. To address this, Pandey and Ottley introduced the Mini-VLAT [6], a condensed version comprising 12 questions—one per visualization—from the original VLAT. An experimental study demonstrated a strong positive correlation between the scores of the VLAT and Mini-VLAT, validating the latter as an effective measure of visualization literacy. In our approach, we employ the Mini-VLAT to determine the initial global LoD for users new to the system. The Mini-VLAT score serves as the basis for tailoring the initial visualization experience to the user's literacy level.

3.2. Manual Adaption

The purpose of manually adjusting the complexity of the visualizations is to enable users to determine whether a preset or recommended LoD meets their needs or requires further customization [15]. The manual adaptation concept in A^+CHIS utilizes a matrix-based approach for arranging the visualizations (rows) with their different LoDs (columns). This matrix view provides a concise overview of available options, showing how the appearance of the visualization changes with modifications to its LoD. Users can choose to apply a global LoD across all visualizations simultaneously or individually customize the LoD for each visualization.

3.3. Rule-Based Automatic Adaption

During the exploration phase, our system continuously tracks user interactions, specifically monitoring dwelling times and mouse clicks for each visualization [24]. Our heuristics for adapting the LoD rely on the premise that higher dwelling times and click counts reflect greater user experience, while lower values suggest less experience. Since the provided visualization components require interaction through clicks, these metrics serve as key indicators of user engagement and familiarity. If a user falls within the top or bottom third for both dwelling time and click count, the system recommends adjusting the LoD accordingly–either increasing it for highly engaged users or decreasing it for those with lower engagement. Following the guidelines by Peissner and Edlin-White [25], in both cases, a recommendation in the form of a modal dialogue will appear to the user, as shown in Figure 4. The user can review the suggestions and choose which changes to accept, allowing for a more controlled adaptation process. In particular, this process prevents sudden workflow interruptions, but to minimize them, we aim to enhance adaptation triggers by utilizing behavioral cues such as scrolling and revisit patterns, while also considering less intrusive alternatives [26].

4. Use Case

We demonstrate a user's interaction with our A$^+$CHIS system using the document "*Den Diabetes im Griff*", provided by the German health insurance company AOK [7]. This scenario constitutes a patient utilizing a digital health system to gain a clearer understanding of their condition, with the document acting as a diabetes education resource. This document was chosen due to the high prevalence and growing global impact of diabetes. According to the *World Health Organization* (WHO), the number of people with diabetes increased from 200 million in 1990 to 830 million in 2022 [27]. In 2021 alone, diabetes accounted for over two million deaths worldwide. As of 2022, an alarming 59% of adults aged over 30 diagnosed with diabetes were not taking medication to manage their condition. These statistics underscore the critical need for accessible and adaptive health information systems like A$^+$CHIS to better support individuals in understanding and managing their health.

A user begins their interaction with the system by taking the Mini-VLAT. Based on these results, the user is directed to a tailored exploration page that aligns with their evaluated visualization literacy, as shown in Figure 3. In the exploration interface, the user can choose different text visualization techniques. In our example it is a word cloud that outlines the document's main themes derived from LDA [28]. When the user clicks on a specific tag in the word cloud, such as "Insulin", the system responds by displaying relevant text snippets in a nearby panel and by showing the distribution of the term within the document using a tilebar [29]. The occurrences of the term within these snippets are highlighted to improve focus and aid in quick understanding.

Upon entering this exploration page, the system starts monitoring users interactions, such as which tags they click, how long they hover, their engagement with snippets, and the total time spent. Based on the data collected, the system present a modal dialog with related recommendations, as shown in Figure 4. The modal dialog clearly explains the recommendation and allows the user to choose whether to accept or decline it. The user decides to accept the adjustment, resulting in a simplified word cloud with fewer, more general terms, while still keeping the functionality of text snippet previews for the selected terms.

5. Discussion & Next Steps

There are several directions for enhancing our system with respect to its functionality and usability. One immediate improvement is the integration of additional text visualization techniques, particularly those explored in prior research focused on clinical chart review. This allows for a broader variety of visual complexity and provide a more tailored experience for both novice and advanced users. Additionally, expanding the LoD options within the existing visualizations would further enrich the system's adaptability and offer a more granular approach to information presentation.

Another key area for improvement is refining the rule-based system for automatic adaptation recommendations. While the current method offers a basic framework, it could be replaced with more advanced algorithms to better assess user behavior and tailor LoD adjustments accordingly. For instance, the rules governing adaptations based on mouse clicks could be refined to better capture the specific interaction patterns for different visualization components. Various visualizations have distinct interaction requirements, and a "one-size-fits-all" method may not provide optimal results. For example,

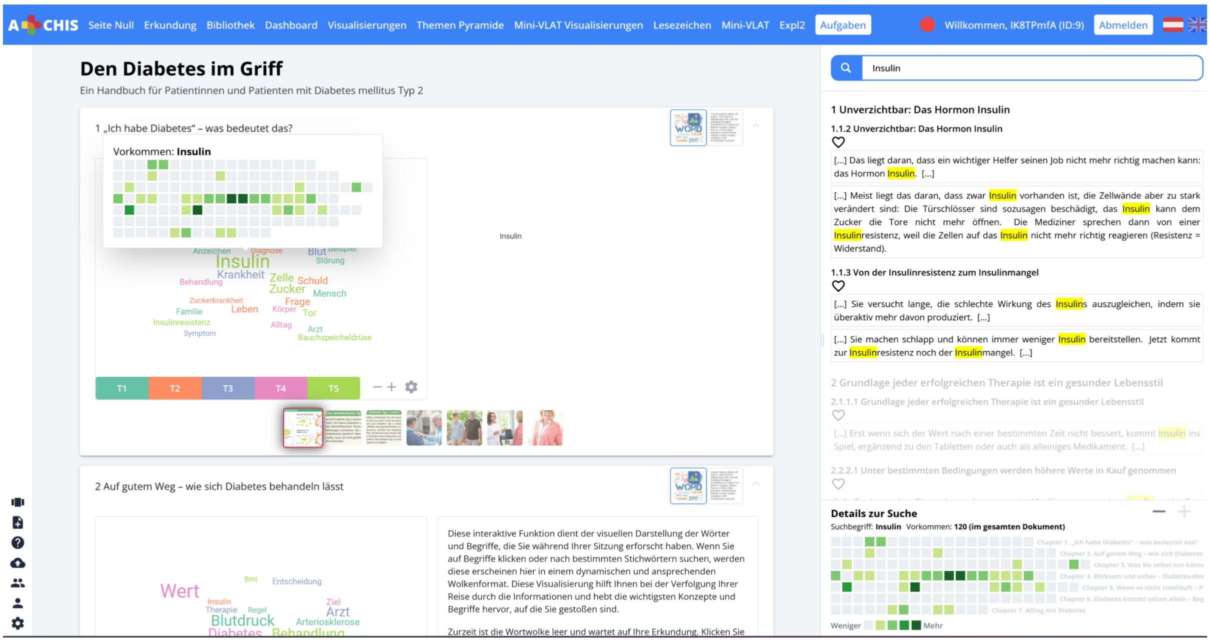

Figure 3: The user interface of our A$^+$CHIS system allows for intuitive interaction. In this example, the user hovers over the term "Insulin" from the word cloud, triggering the display of several text snippets revealing the contexts the term appears in. Additionally, the tile bar visualization provides an overview of the term's distribution throughout the document, enabling the user to quickly locate relevant sections.

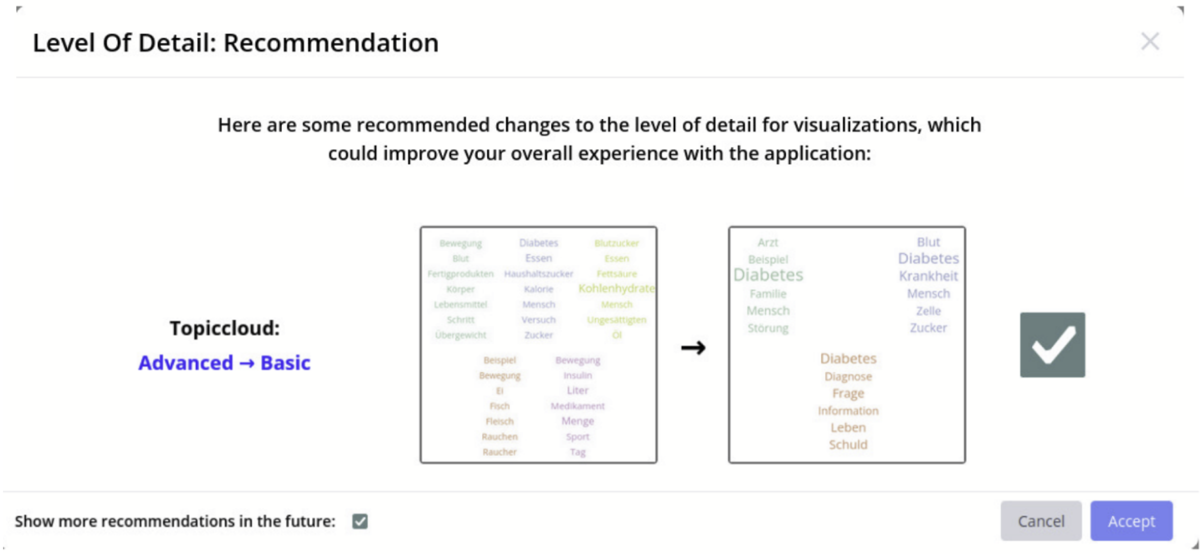

Figure 4: The user is prompted with a modal dialog, showing the potential changes in LoDs determined through the rule-based adaptation. On a per-component basis (checkbox) they can decide which proposals they want to accept.

tile bars—often used as tooltips to display term frequencies when hovered over—may see more mouse movement than actual clicks. In contrast, visualizations like topic or word clouds typically require more direct engagement, such as clicks, to reveal underlying information. By creating distinct rules that account for the unique interaction styles of each visualization, we can ensure more accurate and context-aware adaptations. Moreover, the heuristics currently applied to adapt LoD may not always align with individual user behaviors. For example, frequent mouse clicks might indicate a user's enthusiasm about the current LoD, suggesting they are highly motivated to explore the material further.

Conversely, the same behavior could signal indecision or confusion, leading to excessive clicks as a sign of frustration with the chosen LoD. As a result, the heuristics used may not be universally applicable and refining them could improve the accuracy of adaptation recommendations and enhance the system's responsiveness to user needs. While we recognize the limitations of our current rule-based heuristics, we want to highlight that they mainly demonstrate our adaptation pipeline. In future iterations, these heuristics can easily be substituted with more advanced detection methods.

Although informal tests conducted during development suggest that the system is functional, a formal evaluation is crucial to assess its performance across diverse user groups. Future work should involve both quantitative and qualitative methods to determine how well the system accommodates users with varying levels of visualization literacy, health literacy, and personal preferences. A rigorous user study will be essential to evaluate how the system functions in real-world scenarios.

Finally, we envision applying our approach to support tasks beyond health information exploration—specifically, by assisting patients in navigating and understanding their health record data as mentioned by Kambhamettu et al. [30]. This would demonstrate the broader applicability of the system and its potential to enhance user engagement, accessibility, and understanding in various healthcare contexts.

6. Conclusion

Exploring health information materials can be a time-intensive process that demands a certain level of digital health literacy. Text visualizations offer valuable support by providing an overview of a document and aiding in information retrieval. However, their effective use often presents an entry barrier and impedes full engagement with the system, particularly for users with limited visualization literacy. To address this challenge, we propose an adaptation model that semi-automatically adjusts the LoD of text visualizations to suit individual user needs. The initial LoD is determined based on the Mini-VLAT. During document exploration, the system monitors user interactions, such as mouse clicks and dwelling times, which serve as inputs for two heuristics that recommend LoD adjustments. This hybrid approach–combining manual control with system-driven adaptability–allows users to customize their experience while ensuring the system dynamically responds to their actions. By enhancing adaptability, our method fosters greater engagement and understanding, making CHISs more accessible to users with varying levels of visual literacy. Our approach is implemented within a CHIS, as demonstrated in a use case involving large-scale health information material. Notably, this work lays the groundwork for innovative methods to support users in efficiently navigating and comprehending health information, with potential extensions to related domains such as personal health record exploration.

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