Applying Visual Analytics to Develop a Clinical Workflow Analysis Tool (CWAT) to Explore Time and Motion Data in Healthcare

Danny T.Y. Wu, PhD*
Department of Biomedical Informatics
College of Medicine
University of Cincinnati

Derek Shu, BS
Department of Biomedical Informatics
College of Medicine
University of Cincinnati

Khanh Le, BS
Department of Biomedical Informatics
College of Medicine
University of Cincinnati

Ruthik Abbu, BS
Department of Biomedical Informatics
College of Medicine
University of Cincinnati

Kai Zheng, PhD
Department of Informatics
School of Information and Computer Science
University of California, Irvine

Abstract

Understanding clinical workflow is a crucial first step to improve the quality, safety, and efficiency of patient care delivery. It enables quality improvement processes and provides a basis to compare and quantify workflow improvements. A common source of data for studying clinical workflow is through time and motion studies, which generates multi-dimensional datasets that are challenging to analyze. Visual analytics can be an effective technique to show patterns and bottlenecks in the time and motion data. Moreover, workflow analysis often involves mixed-method design. The triangulation between the quantitative and qualitative data would require the support of a powerful data exploration tool. To address these challenges, we applied visual analytics to develop a clinical workflow analysis tool (CWAT) that allows for easy identification of significant workflow patterns. In this system demonstration paper, we describe the visualization design choices and validation through case studies.

Keywords: clinical workflow, visual analytics, time and motion studies, electronic health records.

Index Terms: C.3 [Special-purpose and Application-based Systems]; D.2.0 [Software Engineering]: General; J.5.0 [Pattern Recognition]: General;

1 Introduction

Analyzing clinical workflow to detect bottlenecks and optimize processes has great potential to improve quality, safety, and efficiency of patient care delivery. Clinical workflow is commonly characterized using data collected via time and motion observation, which has been a gold standard for quantitative workflow studies [1]. Because time and motion data contain many dimensions, such as locations, timestamps, activities, and clinical roles, specific techniques are required to effectively analyze such data. Moreover, due to the dynamic nature of the clinical environment, the analysis of clinical workflow data oftentimes requires multiple datasets and the involvement of domain experts to create a comprehensive picture about a clinical team's work patterns and issues. Currently, there is no easy-to-use and widely disseminated tool to support researchers and practitioners to conduct clinical workflow analysis, even though this topic has been researched in the medical informatics field for a decade. This motivated us to design and develop a self-service tool that integrates essential workflow analysis methods, metrics, and visual analytics techniques and to promote this tool to allow for a more standardized analysis of clinical workflow. In our tool, the visualizations are designed to provide an easier and more effective human interpretation of patterns related to physical movements, relationships between locations and activities, and the magnitude of change in workflow. In this system demonstration paper, we present the related work, describe the visualization design choices, and summarize the four major visual analytics components of this tool. We then demonstrate the effectiveness of this tool through two case studies. At the end, we discuss the limitations and future work of the system development.

2 Related Work

2.1 Clinical Workflow Analysis

Clinical workflow analysis has become a major research topic in medical informatics in the past decade. Such analysis usually employs a mixed-method study design. Qualitative research methods, such as semi-structured interviews and direct observations, have been commonly used to study care delivery and team collaborations [2]. For example, Unertl et al. in 2009 conducted a 10-month study in ambulatory clinics to develop an in-depth understanding of the workflow and the information flow in chronic disease care [3]. Qualitative data collections are usually time-consuming, not representative, and cannot scale up. However, they can capture the context of the workflow and facilitate a deeper understanding of clinicians' behaviors and root causes of the bottlenecks and delays [4]. Direct observations can be conducted as ethnographic studies, where clinicians' interactions with each other as well as with computer systems in a real environment are observed [5]. Direct observations can also be conducted through a time and motion study (TMS hereafter), where clinicians' actions, tasks, locations are recorded as timestamp data for further quantitative analysis [6]. On the other hand, quantitative workflow analysis has been studied in the past decade. Vankipuram et al in 2011 developed a system in critical care to automatically capture, analyze, and visualize workflow using radio identification tags [7]. The same researchers in 2018 proposed a framework to transform, analyze, and visualize location-tracking data [8]. The analysis methods included entropy estimation, probability modeling, and interactions. However, this framework focused on the massive location-tracking data and did not consider other timestamp data nor the integration of qualitative and quantitative data. Meanwhile, Zheng et al. highlighted the methodological inconsistency in measuring clinical workflow and called for standardized research [9].

2.2 Time and Motion Data

A TMS is a common method to collect activity and location data in healthcare. TMSs observe clinicians during their clinical routines to improve care quality and outcomes. TMSs originated in

* wutz@ucmail.uc.edu
231 Albert Sabin Way, ML0840, Cincinnati OH 45040, USA.

industrial engineering with a goal of collecting workers' time spent and movement in completing a series of tasks. TMSs have been widely adopted and frequently used to analyze healthcare workflow in recent years [1]. As of December 2021, a preliminary search in PubMed [10] with the keywords, "time and motion study" OR "time motion study", yielded 435 studies, in which more than 80% of the studies (N=352) were conducted after year 2000. TMSs usually require a person (observer) to shadow the study participants and continuously record when, where, and what tasks are performed in that workspace. Several informatics tools have been invented to support the TMS data recording with features to facilitate the capture of complex workflow behaviors and to detect the workflow patterns. These tools include, but are not limited to, the Time Capture Tool (TimeCaT) [11], WOMBAT [12], and CRISS T&M Logger [13]. Some of them have visual analytics capabilities. For example, TimeCaT shows multi-tasking and inter-observer reliability through horizontal bar charts and generates real-time reports with data visualizations. However, since most of the TMS tools focus on data collection, very few of them have the capacity to conduct detailed analysis to identify, quantify, and visualize workflow patterns.

2.3 Visual Analytics Applications

In the healthcare domain, there have been studies developing visual analytics application to support clinical and research work [14], [15]. Several studies have investigated the usability and workflow of artificial intelligence (AI)-based visual analytics applications in supporting medical decision making. These studies took a human-centered approach in determining user needs, designing a display, and assessing the effectiveness of the translation of algorithm outputs [16]–[18]. One such example is a medical imaging diagnosis tool called "BreastScreening", which was designed and evaluated to optimize human-AI interactions [19]–[21]. Such AI-based applications can be further refined by utilizing CWAT's analytics capacity to improve their workflow efficiency and quality [22].

3 Method

This system demonstration paper focused on the activity and location data collected from TMSs and developed a generalizable Clinical Workflow Analysis Tool (CWAT hereafter; pronounced as See-What). The CWAT can take timestamp data as input and generate interactive data visualizations to support workflow analysis. The visualization design followed Munzner's nested model [23] and generated four visual analytics components, including task analysis, sequential pattern analysis, location analysis, and task-location analysis. The visualization was validated through three case studies.

3.1 Visualization Design

The CWAT originated from a workflow redesign study funded by the Agency of Healthcare Research Quality (AHRQ) [24]. The study focused on six rural ambulatory clinics and aimed to understand how health information technology (HIT) changes may lead to workflow redesigns. TMSs were conducted before and after the HIT changes along with ethnographic observations and semi-structured interviews. The main problem was to create an interactive visualization that can quickly demonstrate workflow patterns to support the triangulation between the qualitative and quantitative data. The TMS data were abstracted to quantify the task and location duration by sites and clinical roles and to compare the numbers before and after the HIT intervention. The TMS data were also manipulated to form sequences of tasks or locations to examine frequent patterns and calculate transaction probabilities. In addition, the location and task data were combined to investigate potential correlations. Next, the TMS data abstraction was mapped to filters and charts to create four visual analytics components. Lastly, the CWAT included algorithms to turn multi-tasking data into sequences and three measures to quantify the time allocation, frequency, and continuous time of tasks and locations.

3.2 Four Visual Analytics Components

3.2.1 Task Analysis

The first visual analytics component of the CWAT focused on what the clinicians were doing (activities or tasks) and for how long using the three measures: time allocation, frequency, and continuous time. <u>Time allocation</u> was defined as the percentage of time of a task in an observation session. <u>Frequency</u> was defined as the number of recordings of a task in an observation session. <u>Continuous time</u> was defined as the average duration of a task in an observation session. For example, assuming a task is observed three times in a 60-minute observation session with durations of 3, 5, and 7 minutes, respectively, the analysis will show 25% for time allocation ((3+5+7)/60), 5 –minutes for continuous time ((3+5+7)/3), and 3 times per hour for frequency. The CWAT was able to aggregate the tasks into categories or themes depending on pre-defined rules. For example, the tasks "EHR documentation" and "App documentation" can be merged into the same category "Documentation" and further generalized into the theme "Clinician Activities". When multi-tasking happens, the overlapped time can either be attributed equally to all the tasks involved or separated as a new task, which was automatically performed by the CWAT.

After generating the measures, the observations can be grouped and compared on a task/category/theme basis. Statistical analyses are conducted automatically in the CWAT to examine any significant difference between the groups using either Student's T-test or Mann-Whitney U depending on the variable distribution. For example, in a pre-post study design, in which an outcome measure is prior to and following an intervention, the CWAT can automatically test significant differences between the pre- and post-observations (Figure 1).

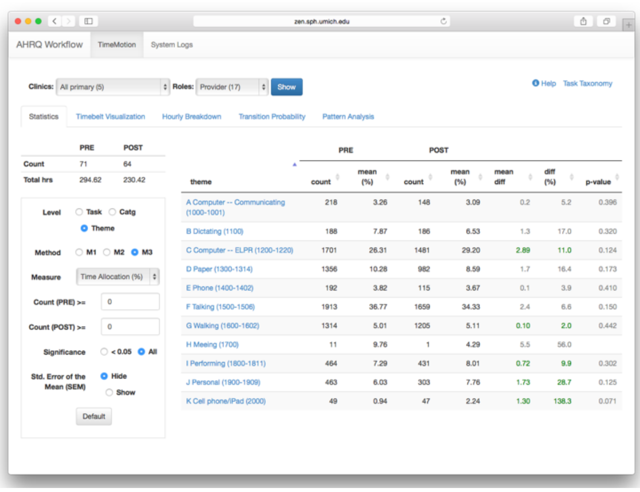

Figure 1: CWAT task analysis page. [24] In addition to the statistical summary, users can navigate the visualizations using other tabs: Timebelt Visualization (2nd tab, details in Figure 3), Transition Probability (4th tab, details in Figure 4), and Pattern Analysis (5th tab, details in Figure 5).

As shown in Figure 1, the CWAT provided a list of filters to allow slice-and-dice data exploration to overcome the high-dimensionality of workflow data. The statistical results will turn into the CWAT's first visual analytics component - a positive negative bar chart (Figure 2). The bars can be tasks or locations, which were ordered based on the magnitude of the differences from the most positive to the most negative.

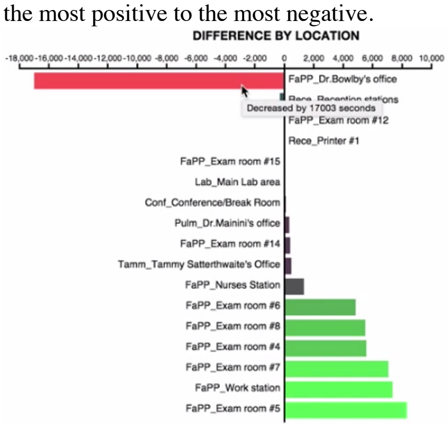

Figure 2: Positive and negative bar chart (magnitude of changes)

3.2.2 Sequential Pattern Analysis

The second visual analytics component of the CWAT focused on the sequences of tasks, which were presented in a time-belt visualization (Figure 3). Each task is colored based on the mapping rules defined by the CWAT users. This visualization can help users identify patterns that are easily caught by human eyes. The same filters in the task analysis were applied to this sequential pattern analysis. The CWAT users were able to perform drill-down analysis and compare the observations of a subset of the workflow data.

Figure 3: Time-belt visualization of task sequences [24]

Moreover, the CWAT calculated the transition probability of task pairs and present the probability in a heatmap (Figure 4). The transition probability was defined as the fraction of the frequency of a task sequence over the total number of sequences. For example, for a sequence of A-B-A-B-C, the sub-sequence A-B appears two times over the total of four sub-sequences (A-B, B-A, A-B, B-C). Therefore, the transition probability from A to B is 0.5 or 50%. Of note, in the CWAT the transition probability was calculated based on a set of observed (and selected) sequences, not on a single sequence. In addition to the transition probability that focuses on the relationship between two adjacent tasks, the CWAT calculated the frequent sequences of two or more tasks using traditional data mining techniques (frequent itemset mining) [25], and allowed users to change the threshold of support and confidence of the frequent sequences to explore the data. The frequent sequences were presented in a tabulate format. For example, frequent sequences with three tasks (e.g., A -> B -> C) were presented in a table with three columns.

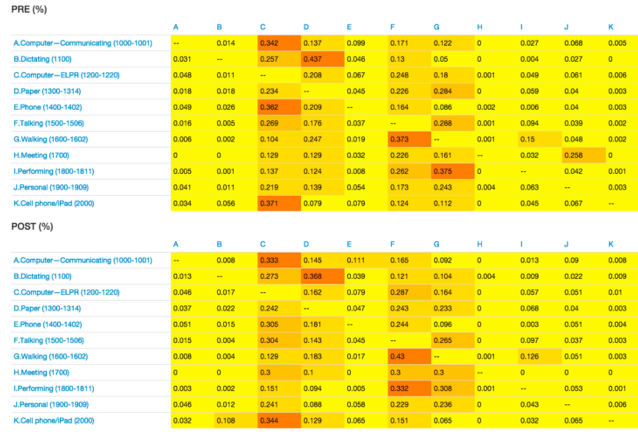

Figure 4. Heatmap of task sequences [24]

3.2.3 Task-Location Analysis

The fourth visual analytics component of the CWAT connected the activities and locations through a sunburst chart (Figure 5). Specifically, the locations were presented in the inner circle and the activities (tasks) were presented in the outer circle. Due to the limited space in the sunburst chart, only the top two or three frequent tasks were included per location. The CWAT users can click a location to perform drill-down analysis, where all the tasks associated with the selected location will be presented in a donut chart. The users can click the central empty circle to change the location-specific donut chart back to the task-location sunburst chart. This visual analytics component can help users explore potential correlations between the tasks and the locations.

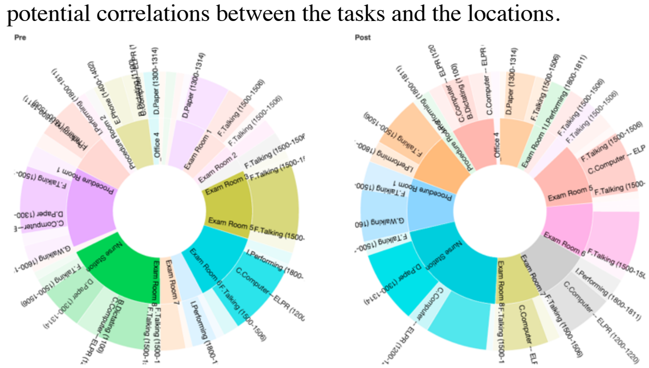

Figure 5. Sunburst chat of task-location analysis [24]

3.3 Validation

3.3.1 Case Study 1

The first case study was an AHRQ-funded project [24], which aimed to examine the relationships between HIT changes and ambulatory care workflow redesign. The HIT changes involved the launch of new components of the EHR system. Ethnographic observations and TMSs were conducted three months before and after the HIT changes. In the post-stage, semi-structured interviews were added to collect more feedback from the clinicians. The TMS data were analyzed using the CWAT and compared with the qualitative analysis results. This case study showed the validity of the CWAT in supporting TMS data analysis and triangulation and providing empirical evidence for the casual relationship between the HIT changes and the ambulatory workflow redesign.

3.3.2 Case Study 2

The second case study aimed to develop a clinical decision support (CDS) tool for the antimicrobial stewardship programs in an academic pediatric emergency department (PED) [26]. Prior to develop the CDS tool, a TMS was conducted to collect the workflow data, which were analyzed using the CWAT. The study involved 23 clinicians in four clinical roles (attending physician, nurse practitioner, physician assistant, and resident). This case study demonstrated the applicability of the CWAT in supporting a similar workflow project with minimal modifications to the tool.

4 Results

In Case Study 1, the CWAT successfully analyzed the TMS data and supported the triangulation of qualitative and quantitative analysis results. Specifically, the CWAT was able to identify shifting time allocation across tasks, multi-tasking events, and workflow workarounds in addition to quantifying the impact of health IT on workflow efficiency and changes in computer work hours during on- and off-hours.

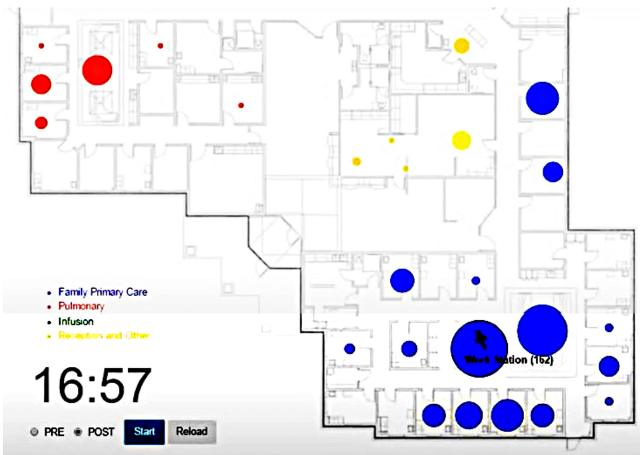

Figure 6. Map visualization of the location change.

Moreover, the visual analytics provided supporting evidence to the qualitative analysis results and their potential lack of statistical significance. For example, the qualitative analysis showed that after the health IT changes, the clinicians were more likely to gather in a new location. However, this change was not statistically significant. Through the location analysis and map visualization of the CWAT, the researchers were able to see the growth of the hotspot via an animation. (Figure 6).

In Case Study 2, CWAT successfully supported the TMS data analysis without any changes to its underlying data manipulation, analysis principals, or procedures. CWAT was able to quantify the tasks through the three measures (i.e., time allocation, continuous time, and frequency). The collaborating researchers found the sequential pattern analysis the most useful and suggested a visualization enhancement. As shown in Figure 7, the frequent patterns (e.g., S1-> C6 -> S9) derived from the sequential pattern analysis of a clinical role were presented in a network-based circular graph with the tasks being the nodes and the connecting steps being the directed edges. The S1 and S9 were defined as pseudo starting and ending points. The left graph circular graph shows the frequent patterns of the attending physicians while the right circular graph shows the frequent patterns of the residents. These graphs supported the interpretation of the workflow differences between the observed clinical roles and informed the three recommendations of the study.

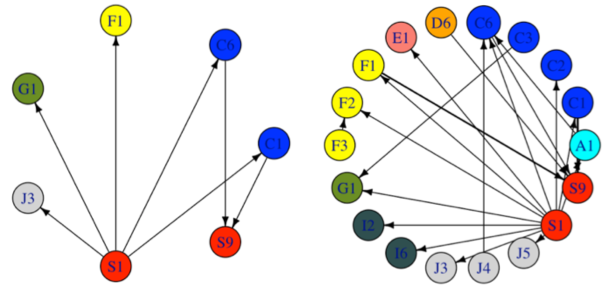

Figure 7. Network circular graph of the frequent patterns [26]. Left: attending physicians, Right: residents

5 Discussion

The system demonstration paper described the visualization design and case study validation of the CWAT. The two case studies demonstrated the face validity and potential applicability of the CWAT to other clinical domains. The case studies also identified additional visualization opportunities (e.g., Figure 7) and enhancements (e.g., adding a hierarchical tree structure to list all tasks in each location in Figure 5; adding time navigation such as pause button and time-slider in Figure 6). The CWAT has been re-engineered to allow users to upload their time and motion data following a pre-defined format and can run analysis automatically.

This study has at least three limitations. First, the case study validation only demonstrated the face validity of the CWAT. No validation was conducted with domain experts or end users directly. That is, we did not interview CWAT users, nor did we conduct usability testing on CWAT to assess its learnability, efficiency, risk for errors, and user satisfaction. Therefore, the current visualizations in CWAT can be improved or re-designed. Second, the case studies only included time and location data from a TMS but did not include other types of timestamp data from EHRs or real-time location systems (RTLS). Such massive datasets may not be fully supported by the data manipulation and analysis procedures of the CWAT. Third, the CWAT requires users to generate and import three types of data files. The current study did not demonstrate the easiness of this task although tutorials and manuals have been created.

We are in the process of creating a web-based portal for researchers to upload their configuration files and data to the CWAT and allow them to directly interact with the analysis results. At the time of publishing this system demonstration paper, we have used CWAT to analyze EHR and RTLS timestamps and demonstrated its usefulness in other studies, which are reported elsewhere [27]. In our future work, we will conduct usability testing with potential and real CWAT users and include more advanced methods on sequential pattern mining and visual analytics to extract and present workflow processes and bottlenecks. These methods will be driven by the literature, such as [8], [28], and from our collaborations. We anticipate CWAT to become an easy-to-use and widely accepted tool to help healthcare researchers and practitioners to improve care quality in their institutions.

6 Acknowledgement

CWAT was initially supported by the AHRQ-funded project (PIs: Elizabeth Ciemins and Kai Zheng) [24], and further enhanced by the corresponding author (Wu)'s lab at the University of Cincinnati College of Medicine.

References

[1] M. Lopetegui, P.-Y. Yen, A. Lai, J. Jeffries, P. Embi, and P. Payne, "Time motion studies in healthcare: what are we talking about?," *J Biomed Inform*, vol. 49, pp. 292–299, Jun. 2014, doi: 10.1016/j.jbi.2014.02.017.

[2] S. Staras *et al.*, "Using a Clinical Workflow Analysis to Enhance eHealth Implementation Planning: Tutorial and Case Study," *JMIR Mhealth Uhealth*, vol. 9, no. 3, p. e18534, Mar. 2021, doi: 10.2196/18534.

[3] K. M. Unertl, M. B. Weinger, K. B. Johnson, and N. M. Lorenzi, "Describing and modeling workflow and information flow in chronic disease care," *J Am Med Inform Assoc*, vol. 16, no. 6, pp. 826–836, Dec. 2009, doi: 10.1197/jamia.M3000.

[4] L. Barrick *et al.*, "Improving Care Delivery: Location Timestamps to Enhance Process Measurement of a Clinical Workflow," *Pediatric Quality & Safety*, vol. 6, no. 5, p. e475, Sep. 2021, doi: 10.1097/pq9.0000000000000475.

[5] D. Swinglehurst, "Displays of authority in the clinical consultation: A linguistic ethnographic study of the electronic patient record," *Social Science & Medicine*, vol. 118, pp. 17–26, Oct. 2014, doi: 10.1016/j.socscimed.2014.07.045.

[6] C. Sinsky *et al.*, "Allocation of Physician Time in Ambulatory Practice: A Time and Motion Study in 4 Specialties," *Ann. Intern. Med.*, vol. 165, no. 11, pp. 753–760, Dec. 2016, doi: 10.7326/M16-0961.

[7] M. Vankipuram, K. Kahol, T. Cohen, and V. L. Patel, "Toward automated workflow analysis and visualization in clinical environments," *J Biomed Inform*, vol. 44, no. 3, pp. 432–440, Jun. 2011, doi: 10.1016/j.jbi.2010.05.015.

[8] A. Vankipuram, S. Traub, and V. L. Patel, "A method for the analysis and visualization of clinical workflow in dynamic environments," *J Biomed Inform*, vol. 79, pp. 20–31, Mar. 2018, doi: 10.1016/j.jbi.2018.01.007.

[9] K. Zheng, M. H. Guo, and D. A. Hanauer, "Using the time and motion method to study clinical work processes and workflow: methodological inconsistencies and a call for standardized research," *J Am Med Inform Assoc*, vol. 18, no. 5, pp. 704–710, Oct. 2011, doi: 10.1136/amiajnl-2011-000083.

[10] "PubMed." National Center for Biotechnology Information, U.S. National Library of Medicine, Mar. 04, 2018. [Online]. Available: https://www.ncbi.nlm.nih.gov/pubmed/

[11] M. Lopetegui, P.-Y. Yen, A. M. Lai, P. J. Embi, and P. R. O. Payne, "Time Capture Tool (TimeCaT): development of a comprehensive application to support data capture for Time Motion Studies," *AMIA Annu Symp Proc*, vol. 2012, pp. 596–605, 2012.

[12] J. I. Westbrook and A. Ampt, "Design, application and testing of the Work Observation Method by Activity Timing (WOMBAT) to measure clinicians' patterns of work and communication," *Int J Med Inform*, vol. 78 Suppl 1, pp. S25-33, Apr. 2009, doi: 10.1016/j.ijmedinf.2008.09.003.

[13] M. B. Weinger, O. W. Herndon, M. H. Zornow, M. P. Paulus, D. M. Gaba, and L. T. Dallen, "An objective methodology for task analysis and workload assessment in anesthesia providers," *Anesthesiology*, vol. 80, no. 1, pp. 77–92, Jan. 1994.

[14] D. Wu, S. Deoghare, Z. Shan, K. Meganathan, and K. Blondon, "The Potential Role of Dashboard Use and Navigation in Reducing Medical Errors of an Electronic Health Record System: A Mixed-Method Simulation Handoff Study," *Health Systems*, 2019, doi: 10.1080/20476965.2019.1620637.

[15] M. F. Rey and C. M. D. S. Freitas, "Interactive Visualizations to Support Randomized Clinical Trial Monitoring," in *2021 34th SIBGRAPI Conference on Graphics, Patterns and Images (SIBGRAPI)*, Gramado, Rio Grande do Sul, Brazil, Oct. 2021, pp. 144–151. doi: 10.1109/SIBGRAPI54419.2021.00028.

[16] C. J. Cai *et al.*, "Human-Centered Tools for Coping with Imperfect Algorithms During Medical Decision-Making," in *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, Glasgow Scotland Uk, May 2019, pp. 1–14. doi: 10.1145/3290605.3300234.

[17] R. Fogliato *et al.*, "Who Goes First? Influences of Human-AI Workflow on Decision Making in Clinical Imaging," in *2022 ACM Conference on Fairness, Accountability, and Transparency*, Seoul Republic of Korea, Jun. 2022, pp. 1362–1374. doi: 10.1145/3531146.3533193.

[18] S. Chiang *et al.*, "Evaluation and recommendations for effective data visualization for seizure forecasting algorithms," *JAMIA Open*, vol. 4, no. 1, p. ooab009, Mar. 2021, doi: 10.1093/jamiaopen/ooab009.

[19] F. M. Calisto, A. Ferreira, J. C. Nascimento, and D. Gonçalves, "Towards Touch-Based Medical Image Diagnosis Annotation," in *Proceedings of the 2017 ACM International Conference on Interactive Surfaces and Spaces*, Brighton United Kingdom, Oct. 2017, pp. 390–395. doi: 10.1145/3132272.3134111.

[20] F. M. Calisto, N. Nunes, and J. C. Nascimento, "BreastScreening: On the Use of Multi-Modality in Medical Imaging Diagnosis," in *Proceedings of the International Conference on Advanced Visual Interfaces*, Salerno Italy, Sep. 2020, pp. 1–5. doi: 10.1145/3399715.3399744.

[21] F. M. Calisto, C. Santiago, N. Nunes, and J. C. Nascimento, "BreastScreening-AI: Evaluating medical intelligent agents for human-AI interactions," *Artificial Intelligence in Medicine*, vol. 127, p. 102285, May 2022, doi: 10.1016/j.artmed.2022.102285.

[22] F. M. Calisto, C. Santiago, N. Nunes, and J. C. Nascimento, "Introduction of human-centric AI assistant to aid radiologists for multimodal breast image classification," *International Journal of Human-Computer Studies*, vol. 150, p. 102607, Jun. 2021, doi: 10.1016/j.ijhcs.2021.102607.

[23] T. Munzner, "A Nested Model for Visualization Design and Validation," *IEEE Trans. Visual. Comput. Graphics*, vol. 15, no. 6, pp. 921–928, Nov. 2009, doi: 10.1109/TVCG.2009.111.

[24] Zheng, K, Ciemins, E, Lanham, H, and Lindberg, C, "Examining the Relationship Between Health IT and Ambulatory Care Workflow Redesign. (Prepared by Billings Clinic under Contract No. 290-2010-0019I-1)." AHRQ Publication No. 15-0058-EF. Rockville, MD: Agency for Healthcare Research and Quality, 2015.

[25] J. Han and M. Kamber, *Data mining: concepts and techniques*, 3rd ed. Burlington, MA: Elsevier, 2011.

[26] M. Ozkaynak, D. T. Y. Wu, K. Hannah, P. S. Dayan, and R. D. Mistry, "Examining Workflow in a Pediatric Emergency Department to Develop a Clinical Decision Support for an Antimicrobial Stewardship Program," *Appl Clin Inform*, vol. 9, no. 2, pp. 248–260, Apr. 2018, doi: 10.1055/s-0038-1641594.

[27] F. Ehrler, P. Ducloux, D. T. Y. Wu, C. Lovis, and K. Blondon, "Acceptance of a Mobile Application Supporting Nurses Workflow at Patient Bedside: Results from a Pilot Study," *Stud Health Technol Inform*, vol. 247, pp. 506–510, 2018.

[28] K. Zheng, H. M. Haftel, R. B. Hirschl, M. O'Reilly, and D. A. Hanauer, "Quantifying the impact of health IT implementations on clinical workflow: a new methodological perspective," *J Am Med Inform Assoc*, vol. 17, no. 4, pp. 454–461, Aug. 2010, doi: 10.1136/jamia.2010.004440.