Patient Dashboards of Electronic Health Record Data to Support Clinical Care: A Systematic Review

Bárbara Ramalho
Human-Centred Design
Fraunhofer Portugal AICOS
Porto, Portugal
barbara.ramalho@aicos.fraunhofer.pt

Sandra Gama
HUMAN Lab, Graphics and Interaction,
INESC-ID, University of Lisbon
Lisbon, Portugal
sandra.gama@tecnico.ulisboa.pt

Francisco Nunes
Human-Centred Design
Fraunhofer Portugal AICOS
Porto, Portugal
francisco.nunes@fraunhofer.pt

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***Abstract*—Visualisations in Electronic Health Records (EHRs) are crucial for clinical care. Since clinicians need to quickly diagnose and treat their patients, having appropriate ways to visualise patients' characteristics and issues documented in the EHR, can be instrumental. However, the existing literature has not yet summarised the characteristics and lessons learned from the studies on patient dashboards for clinical care. Our review analysed patient dashboards, that visualised EHR data to support clinical care, and which were evaluated with end-users. We read papers from Human-Computer Interaction, Information Visualisation, and Medical Informatics, focusing on the user interfaces and the end-user evaluation results. From a set of 3545 articles, we selected 30 studies, which were analysed using Thematic Analysis. Results provide an understanding of the patient dashboard designs, the visualisation techniques employed, the data represented, as well as the lessons learned from this body work; which should contribute to future designs.**

***Index Terms*—Electronic Health Records, Electronic Medical Records, EHR, EMR, Data visualisation, Patient Dashboard.**

I. Introduction

Today's healthcare is characterized by fast decision-making. Decades of improvements in quality of life and care have led to greater longevity [1], and, with it, a greater number of chronic patients [2]. The number of clinicians in healthcare systems did not increase accordingly [3], which meant that the same professionals needed to attend to a higher number of patients within the same work schedules. The time pressure in medical appointments is detrimental to care [4], thus a number of studies have investigated technological solutions to support clinicians in their everyday work [5], [6].

The Electronic Health Record (EHR), defined as the set of technologies responsible for storing and displaying relevant clinical information [7]–[9], was often seen as key to the digitalization in healthcare and to the transformation of data into useful information [10], [11]. However, in several cases, EHRs became part of the problem. Getting an overview of the patient's status, at the beginning of the appointment, or searching for previously collected data became hard [12], [13] as data was scattered and represented in textual form [14], [15]. The use of the EHR has also been linked to increased burnout and "click fatigue", due to the effort needed to constantly navigate systems with low usability, and high cognitive demands [12], [16], [17]. Visualising data chronologically also raised issues because of the amount and variety of data entries [18].

The research community has worked on these problems, creating a number of patient dashboards to summarise patient data and issues, and support efficient clinical decision-making. Dashboards are defined here as "a visual display of data used to monitor conditions and/or facilitate understanding" [19]. The concept overlaps with information visualisation, but dashboards are usually seen as supporting analysis that "require a timely response to fulfil a specific role" [20]. Our use of the concept aligns with authors that attribute interactivity to dashboards [21]. Moreover, we use the concept of patient dashboards to refer to dashboards displaying data from a single patient, which could also be named patient summaries or patient data overviews. Existing research on patient dashboards has provided a number of appropriate examples (e.g., [22]–[24]), however, we currently lack a review that summarises the characteristics and lessons learned from the studies designing and evaluating patient dashboards for clinical care.

This study presents a systematic review of papers that discussed patient dashboards based on EHR data to support clinical care. Considering the interest of supporting clinical care, we focused on single-patient dashboards (we excluded systems that analysed a group of patients, as diagnosis and treatment is based on individual patient visits). Our review had a Human-Computer Interaction (HCI) lens and was based on publications from HCI, Information Visualisation, and Medical Informatics. The analysis of the papers was supported by Thematic Analysis [25] and led to six main themes: i) Dashboard aim, ii) Dashboard design and interactivity, iii) Visualisation techniques employed in dashboards, iv) Types of data represented in dashboards, v) Evaluation with end-users, and vi) Lessons Learned from studies. We expect our work to inform researchers and designers creating patient dashboards for clinical care, by understanding the characteristics of prior dashboards and learning from the insights of the studies.

Our review complements existing reviews of visualisation in/of EHR systems. While we believe this paper to be the first to offer a review analysing in-depth patient dashboards, previous work has looked at visualisations in EHR systems. The systematic reviews of Rind et al. [26], Rostamzadeh et al. [27], and West et al. [14] have all analysed the technical characteristics of visualisations present in EHR, outlining, for example what were the most common visualisation types or

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visual analytics used in the studies. Rind et al. [26] discuss clinical outcomes of using the visualisations; the remaining reviews focused solely on the artefacts and not the outcomes. Our work complements this literature by focusing on single-patient dashboards, designed for supporting clinical decisions, and which have been evaluated with end-users.

II. Methods

This section describes the setup of our literature review, including the focus, databases selected, search strategy, and the analysis approach. PRISMA diagram appears in Figure 1.

A. Focus and research questions

Our review focused on studies describing patient dashboards, that display EHR data to support clinical care, and which were used by clinicians[1]. The focus on actual use by clinicians excluded user research studies, data structure or framework developments, and visualisation exploration studies that did not assess the developed prototypes for their impact on clinicians and their work (e.g., [28]–[32]). The focus on systems to support clinical care further ensured the papers aimed to improve the work of clinicians, and not explore visualisation techniques or designs *per se* (e.g., [33]–[36]). Moreover, the focus on patient dashboards meant all visualisations catered to the needs of a clinician caring for a patient, the most common care scenario, and not focus on analysing patient groups which mostly serve research purposes (e.g., [37]–[40]).

Our work was oriented by three research questions: i) What were the characteristics of patient dashboards in the review? ii) What were the lessons learned from the studies in the review? and iii) How were studies evaluated with end-users?

B. Databases selected

The selected databases were ACM DL (Digital Library), IEEE Xplore, PubMed, and Eurovis. The ACM DL and the IEEE Xplore were selected because they index key visualisation conferences and journals, including IEEE VIS, IEEE VAST, ACM CHI, or IFIP Interact. PubMed was included to capture visualisation work performed in the context of medical informatics. EuroVis was searched due to the importance of the conference and its absence from the remaining indexes.

C. Search strategy

After multiple discussion sessions among the authors, we settled with the following search expression:

> (“information visualisation” OR “information visualisation” OR “data visualisation” OR “data visualization” OR “infovis” OR “visualisation” OR “visualization” OR “dashboard” OR “patient summary” OR “patient overview” OR “visual analytics”) AND (“electronic health record” OR “EHR” OR “electronic medical record” OR “EMR”).

The expression captures different ways of framing patient dashboards, including “dashboard”, or “data visualization”,

[1]The term clinician is used in this paper as a synonym for healthcare professional, which includes doctors, nurses, or physiotherapists.

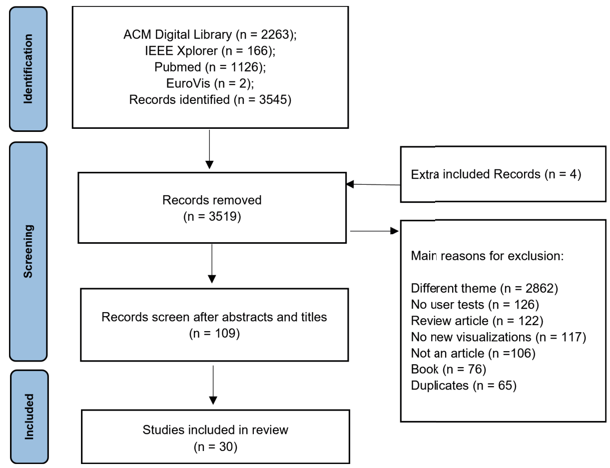

Fig. 1. PRISMA flow diagram [41].

TABLE I
Number of papers in the review identified with each keyword

Electronic Health Record	23	Data Visualisation	1
EHR	23	Data Visualization	16
Electronic Medical Record	11	Infovis	0
EMR	10	Visualisation	2
Information Visualisation	1	Visualization	23
Information Visualization	10	Patient Summary	2
Dashboard	11	Patient Overview	2
Visual Analytics	7		

and different ways of naming EHRs, including “electronic health record”, or “electronic medical record”. Searching for user evaluation was unnecessary as the used keywords yielded very broad works in visualisation. In total, the expression gathers 28-word pairing combinations, and caters both to British and US spelling variants.

Our search was conducted on December 5th, 2022, yielding 3545 papers: 2263 from ACM DL, 1126 from PubMed, 166 from IEEE Xplore, and 2 from Eurovis.

D. Selection strategy

The paper screening was supported by the Rayyan software [42]. Following each of the database searches, we exported the results to a .csv file or similar, and imported it to Rayyan. The titles and abstracts of all papers were read in Rayyan by the first author and the third author read 39% of the abstracts. Differences in the selection decisions were discussed and consensus was reached. The first screening resulted in 109 papers to potentially include in the review. Adding to this set, we included five articles retrieved through manual search [43]–[47]. Having read or skimmed selected papers, we obtained a review set composed of 30 papers.

The paper selection was based on two criteria. First, the paper should propose a prototype, system, or technology that visualizes data from the EHR and aims to provide an overview of patient data to support clinical care. Second, the Dashboard should have been subjected to user evaluation with clinicians.

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We excluded papers that: i) had a different topic, ii) were books or review articles, iii) missed an evaluation with users, iv) did not have visualisations, or v) that did not describe scientific studies (e.g., workshop proposals, proceedings). PRISMA diagram in Figure 1 further details the selection process.

E. Analysis

The 30 papers in the review were analysed using Thematic Analysis [25]. We used some existing categories in the analysis, e.g., for the dashboard design and interactivity, but coded the data openly to capture additional topics. Our coding process was supported by Microsoft Excel. We also made notes about the papers as we read them in a note-taking app. At the end of the analysis, our excel sheet had 72 columns, coding the papers of the review in a number of different aspects.

III. Results

A. Characterization

Our review is composed of 30 papers. The first papers appearing in the review date back to 2010 (see Figure 2). After 2010, most years had papers published in the review. The years of 2015, 2020, and 2021 were the ones with most papers published (4/year). It is curious to see that the first papers matching our search criteria are from 2010, considering the much earlier work on visualisation in healthcare (e.g., [48]). We shall come back to this issue in the Discussion, but it is important to remind that, to fulfil the selection criteria, the papers needed to visualise data from an EHR for a clinical purpose, and be evaluated with clinician end-users.

In terms of search keywords or expressions, there were varying results (see Table I). The search terms yielding more papers in the review were Electronic Health Records / EHR (23), Visualization (23), Data Visualization (16), or Dashboard (11). InfoViz did not return any paper in the review. Moreover, the American spelling of Visualization appeared more often.

The papers in the review were published in 19 venues (see Table II). We find 10 papers published in conferences and 20 papers published in journals. Three venues are tied as the most common venue with four publications: the BMC Medical Informatics and Decision-making journal, TVCG, and CHI. ACI and JAMIA feature two publications, and the other venues have one paper in the review set. Most publication venues find home in Medical Informatics or healthcare, but papers appear also in Information Visualisation and HCI venues.

In terms of affiliation, most papers feature a first author from a university from the USA or Canada. The other identified countries (Pakistan, Austria, France, Germany, UK, and Brazil) published between 1 and 3 studies on the review.

In terms of healthcare scope, the papers were very varied (see Table III). Papers in the review span chronic, acute, or emergency care. Some dashboards target single conditions, with the most common being hypertension (3 studies), diabetes (2 studies), or kidney injury (2 studies). Other dashboards aim to support specific hospital units or specialties, including primary care (8 studies), intensive care unit (5 studies), or inpatient care (3 studies).

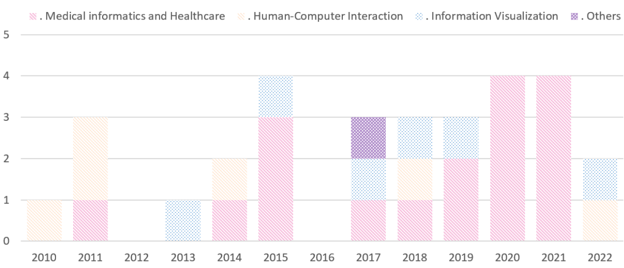

Fig. 2. Chart of venues of the papers analysed in the review, grouped by year

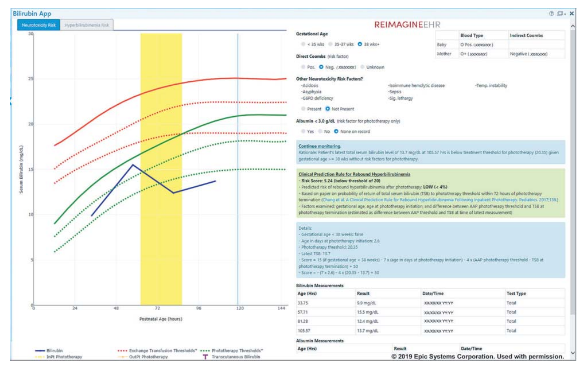

Fig. 3. Detail from screenshot of EHR showing the evolution of pediatric bilirubin data [22] ©JAMA Network Open.

B. Dashboard aim

The reviewed dashboards had a variety of clinical aims. Since the dashboards span chronic, acute, and emergency care (see Section III-A), it was expected for the dashboards to support varied work types and practices. Our analysis of the interfaces and technology descriptions highlighted three categories that group clinical aims: i) Dashboards to accelerate diagnosis, ii) Dashboards to support treatment decisions or adjustments; and iii) Dashboards to monitor patient values.

The **Dashboards to accelerate diagnosis** are systems that plot diagnostic relevant data from the EHR. By making available relevant data in an appropriate format, these dashboards are expected to support clinicians in diagnosing or ruling out a specific condition. For example, Kawamoto et al. [22] presented a dashboard that includes a line chart with the patients' values against a curve of the pathological threshold of bilirubin (see Figure 3). This provides a very fast visual comparison that supports clinicians during acute medical appointments. This category is composed of dashboards from 24 studies, namely: [22]–[24], [44]–[47], [49]–[65].

The **Dashboards to support treatment decisions or adjustments** consist of systems that represent current or evolving data, highlighting worrying values or measurements. The expectation is that clinicians gain visibility about certain health aspects and can adjust treatment or other decisions. One dashboard in this category is the study from Thayer et al. [66] that created an interactive timeline for accompanying children with asthma. The authors represented medication,

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TABLE II
VENUES OF THE PAPERS ANALYSED IN THE REVIEW.

Human-Computer Interaction	***CHI*** – ACM Conference on Human Factors in Computing (2010, 2014, 2018, 2022), ***HCI International*** – International Conference on Human-Computer Interaction (2011), ***INTERACT*** – IFIP International Conference of Human-Computer Interaction (2011)
Medical Informatics & healthcare	***AMIA annual symposium*** - American Medical Informatics Association (2015), ***Annals of Family Medicine*** (2011), ***ACI*** – Applied Clinical Informatics Journal (2019, 2020), ***AJH*** – American Journal of Hypertension (2021), ***BMC Medical Informatics and Decision-Making*** (2018, 2020, 2020, 2021), ***eGEMs*** – eGEMs The journal of electronic health data and methods (2015), ***Epilepsia Open*** (2021), ***IJMI*** – International Journal of Medical Informatics (2015), ***JAMA Network Open*** (2019), ***JAMIA*** – Journal of the American Medical Information Association (2014, 2021), Joint Commission journal on quality and patient safety (2017), ***MIE*** – Medical Informatics Europe Conference (2020)
Information Visualisation	***EVA*** – Electronic Visualisation and the Arts (2018), ***TVCG*** – Transactions on Visualisation and Computer Graphics (2013, 2015, 2019, 2022), ***IEEE VAHC*** – IEEE Workshop on Visual Analytics in Healthcare (2017)
Others	***ISADS*** – IEEE International Symposium on Autonomous Decentralized Systems (2017)

Note: Categorisation of venues into groups was made by the authors considering the conference or journal websites.

TABLE III
CONDITIONS OR MEDICAL SPECIALTIES TARGETED BY THE DASHBOARDS IN THE REVIEW.

Chronic	Hypertension (3), Diabetes (2), Stroke prevention (1), Asthma (1)
Acute	Kidney Injury (2), Hyperbilibinemia (1), Epilepsy (1)
Specialisation	Primary Care (8), Intensive Care (5), Inpatient care (3), Obstetrics (1), Pediatrics (1), Urologist/Gynecology (1)

visits to the clinic, and asthma plan updates, intending the timeline to support clinicians in adjusting treatment or self-care. Another type of dashboard under this category are the systems used in emergency care for keeping track of the evolution of patients' vital signs (e.g., [67]). These systems represent current values, averages, or trends, in a table like format colouring the cells displaying aggravations, so that emergency clinicians can shortly act on the patients' health. The category of dashboards to support treatment decisions or adjustments is made of 5 studies, namely: [43], [66]–[69].

The last category, **Dashboards to monitor patient values**, is not focused on diagnosis or treatment decisions, but rather on checking the alignment of patient values with certain normative values. By providing representations that show if a certain patient value is under range or deviating, they support clinicians with checking for different issues when the patient visits them. The dashboard under this category was designed by Khan et al. [70], who created a solution for clinicians monitoring the health of pregnant women. The expectation is that values are all in range, but by highlighting values that may be deviating it supports the work of clinicians. We expect this kind of dashboard to be mostly used in primary care, where people may attend the clinic for a checkup.

C. Dashboard design and interactivity

To better understand the affordances of the patient dashboards in the review, we analysed the design and interactivity characteristics of the dashboards. We draw on the work of Sarikaya et al.'s [21] who categorised dashboards regarding the possibility for users to: i) design or customise the dashboard, ii) filter or select the represented data, and iii) change the data under representation; and thus created the categories of Construction or Composition, Multipage, Interactive Interface, Highlight & Annotation, and Modify Data or the World. See analysis on Table IV.

Construction or Composition refers to dashboard functionalities that enable the user to personalize the data view, be it through adding, moving, resizing, or changing plots or representations using the dashboard interface. The papers in the review were very limited in terms of Construction or Composition. The great majority of dashboards did not enable users to personalise their data views in any way. The five exceptions were [47], [54], [56], [67], [68], which enabled users to drag diagrams to change their positioning, toggle buttons to show or collapse views, or use drag-and-drop mechanisms to choose which data to visualize.

Multipage refers to whether the dashboard consists of a single or a multipage interface, accessible for example with menu tabs. Almost all dashboards were implemented in a single page [22], [23], [44]–[47], [49], [51]–[56], [58], [59], [62]–[64], [66]–[68], [70]. Figure 3 is an example of single-page dashboard. There were six Multipage dashboards [49], [50], [60], [61], [65], [69], enabled by tabs or buttons that opened new dashboard windows when clicked.

Interactive Interface refers to whether users can use mechanisms such as filtering, selections and slicing to drill up or down the data hierarchies or control the data they visualize in other ways. This includes drop-down selections or the ability to slice timelines to the appropriate timeframe. Our analysis revealed that many dashboards had filters and included some selections [45]–[47], [50], [52], [54], [56], [59], [62], [64]–[66], [68], [69]. However, it was not very common to find dashboards that were interactive in the sense that data could be filtered by selecting it through the charts, as they usually employed drop downs, slicers, or buttons.

Highlight & Annotation refers to whether the dashboard enables users to signal important values. We included in this functionality the ability to enter free notes on certain data points or patients, which was enabled by [43]–[45], [49], [53],

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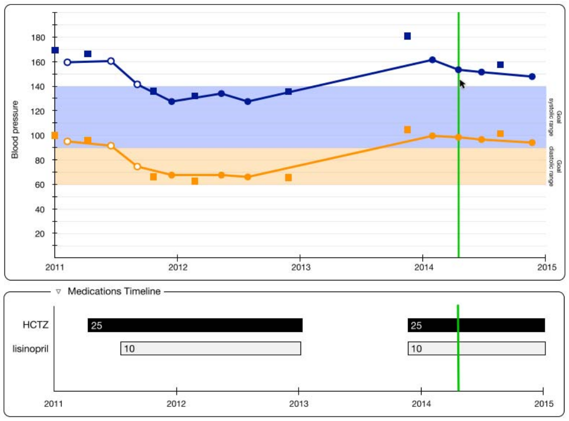

Fig. 4. Screenshot of the Home Blood pressure dashboard with line chart and timeline representations [24] ©BMC.

[55], [62]. One example in the group is the Harvest system by Hirsch et al. [53], where doctors could write down notes on the space on the right side of the screen, enabling them to comprehend the patient better at a future visit.

Lastly, the category of **Modify Data or the World** refers to whether the dashboard is merely for visualising data or whether it enables the addition of new data. Most dashboards analysed enabled clinicians solely to visualise data and not to add or edit existing data. Exceptions to this were [22], [43], [50], [51], [65], [69], [70], which enabled users to update user data directly on the dashboard.

Inspired by Sarikaya et al. [21], we also coded for the literacy requirements of dashboards. According to the authors, low literacy is composed of simple visualisations such as bar or line charts (see Figure 5 image B/D). Medium literacy introduces idioms[2] with more complexity, such as double axis, or cumulative measures (see Figure 4 or Figure 5 image B). Moreover, high literacy is composed of more technical visualisations such as tree maps, or scatterplots that are not as commonly seen outside of technical domains. Almost all dashboards fell in the low literacy category (21 examples), there were eight examples that could be categorised as having medium literacy, and one with high literacy.

D. Visualisation techniques employed in dashboards

Regarding the visualisation techniques employed (see Table IV), our first finding was that evolution and timeline visualisations were the most popular, which comes as no surprise, since identifying temporal trends is one of the main challenges of EHRs [72], [73]. Evolution visualisations, consisting of charts that show how data variables change over a period of time were present in 17 dashboards [22], [24], [43], [46], [49], [50], [55], [56], [59]–[61], [64], [65], [67]–[70]. Idioms for this category included line charts, stacked area charts, and theme rivers [56], [58]. Figure 3 shows an example of an evolution line chart idiom, which displays a patient's levels of bilirubin over time.

[2]Idioms are a way of visually representing and manipulating data [10].

Timeline visualisations, consisting of temporal representations of data, displaying or not the evolution of individual data points. It is a representation that organises heterogeneous data points in a chronological fashion, often using linear displays.

A majority of papers focused on showing the evolution of quantitative data, such as vitals or lab results, which is congruent with the data of Table IV. Figure 5 C and D, also show the difference between an evolution line chart, and a linear timeline. While evolution visualisations tend to have the same temporal spacing on their axis, timelines work differently since the occurrences they measure can happen at uneven time intervals [24], [52]–[57], [59], [63], [66]. Timelines commonly display days and years, with thirteen articles having the option to display days, and twelve displaying years. Often days are displayed to register the specific dates of medical procedures, while years are needed to limit the amount of information presented. It is not as common to see data displayed by hours, weeks, or months. Only four dashboards had the option to see data organised hourly, eight had the option to visualise it weekly, and five monthly.

Other visualisation techniques used included: i) rankings, consisting of visualisations where there is a relationship of relative superiority/inferiority in the comparison of the items displayed (e.g.: [47], [49], [50], [62]); ii) highlight numbers, consisting of large numeric displays of important data factors (e.g.: [49]–[51], [68]); iii) tables, consisting of a structured organization of multicolumn data elements (e.g: [23], [44], [49], [50], [53], [58], [60], [61], [64], [65]); iv) lists, consisting of a structured single column catalogation of elements (e.g.: [23], [24], [47], [49], [50], [58], [63]. Tables and lists were commonly used to represent textual data, while rankings were usually bar chart representations that compared the occurrence of specific data types, appearing few times. These visualisations appeared in a minority of papers, as did Highlight numbers, which only appeared four times, and represented numerical focal points of the dashboards.

Aggregate visualisations were also rare. Clusters, which include bubble charts, scatterplots, or density charts, were not used by the reviewed dashboards. Hierarchies, visualisations where there is a part-of-a-whole relationship, such dendrograms, treemaps, sunbursts and circular packing diagrams [74], were used in one dashboard [57]. The lack of clusters and hierarchical visualisations might mean that the task of understanding such relationships relies on the expertise of doctors, and is not necessary to display in such a way.

E. Types of data represented in dashboards

In terms of the represented data, the dashboards included Vitals, Medication, Lab Tests Results, Structured Notes, Unstructured Notes, and Personal Data (see Table IV).

Vitals such as body temperature, pulse rate, and respiration rate were the most common data type, represented 15 times [24], [44], [46], [50], [51], [55], [56], [58], [60], [61], [64]–[66], [68], [70]. Figure 5 E shows a table that displays a patients vital signs of the last 24 hours, showing the highest and the latest measured values.

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TABLE IV
FEATURES OF THE DATA TYPES, VISUALISATION TYPES, AND DASHBOARD CHARACTERISTICS OF THE STUDIES IN THE REVIEW.

	Data types						Visualisation types								Dashboard characteristics					
Study	Vitals	Medication	Labs	Struct. notes	Unstruct. notes	Demographics	Ranking	Hierarchy	Evolution	Highlight Numbers	Table	Lists	Timeline	Clusters	Literacy	Construct/ compose	Multipage	Interactive interface	Highlight annotation	Modify data or World
Bannach et al. [62]	-	x	-	-	-	x	x	-	-	-	-	-	-	-	B	-	-	x	x	-
Bersani et al. [60]	x	x	x	-	-	-	-	-	x	-	x	-	-	-	B	-	x	-	-	-
Buchhalter et al. [49]	-	x	-	x	x	x	x	-	x	x	x	x	-	-	B	-	x	-	x	-
Fadel et al. [64]	x	x	x	x	-	x	-	-	x	x	x	x	-	-	B	-	-	x	-	-
Faiola et al. [71]	-	-	x	-	-	-	-	-	x	-	-	-	-	-	M	x	-	-	-	-
Faiola et al. [68]	x	-	-	-	-	-	-	-	x	x	-	-	-	-	M	x	-	x	-	-
Febretti et al. [69]	-	x	-	-	-	-	-	-	x	-	-	-	-	-	B	-	x	x	-	x
Foraker et al. [51]	x	x	x	-	-	x	-	-	-	x	-	-	-	-	B	-	-	-	-	x
Hirsch et al. [53]	-	-	-	x	-	-	-	-	-	-	x	-	x	-	B	-	-	-	x	-
Howarth et al. [50]	x	x	x	x	-	-	x	-	x	-	x	-	-	-	M	-	x	x	-	x
Khan et al. [70]	x	x	x	-	-	-	-	-	x	-	-	-	-	-	B	-	-	-	-	x
Kawamoto et al. [22]	-	-	x	-	x	x	-	-	x	-	-	-		-	B	-	-	-	-	x
Koopman et al. [23]	-	x	x	-	x	-	-	-	-	-	x	x	-	-	B	-	-	-	-	-
Koopman et al. [24]	x	x	x	-	x	-	-	-	x	-	-	-	x	-	M	-	-	-	-	-
Ledieu et al. [59]	-	-	x	-	-	-	-		x		-	-	x	-	B	-	-	x	-	-
Linhares et al. [46]	x	-	x	-	-	-	-	-	x	-	-	-	x	-	B	-	-	x	-	-
Martignene et al. [54]	-	x	x	-	-	-	-	-	-		-	x	x	-	M	x	-	x	-	-
Mlaver et al. [61]	x	x	x	-	x	-	-	-	x	-	x	-	-	-	B	-	x	-	-	-
Nelson et al. [63]	-	x	-	x	-	-	-	-	-	-	-	x	x	-	B	-	-	-	-	-
Pao et al. [52]	-	-	x	-	-	x	-	-	-	-	-	-	x	-	B	-	-	x	-	-
Pickering et al. [58]	x	x	x	-	x	-	-	-	-	-	x	x	-	-	B	-	-	-	-	-
Pohl et al. [56]	x	-	x	-	-	-	-	-	x	-	-	-	x	-	B	x	-	x	-	-
Sultanum et al. [45]	-	x	-	-	x	x	-	-	-	-	-	-	x	-	B	-	-	x	x	-
Sultanum et al. [47]	-	-	-	x	x	x	x	-	-	-	-	x	x	-	M	x	-	x	-	-
Sultanum et al. [43]	-	x	x	x	x	-	-	x	x	-	-	x	x	-	M	-	-	-	x	x
Thayer et al. [66]	x	x	-	-	-	-	-	-	-	-	-	-	x	-	B	-	-	x	-	-
Wegier et al. [55]	x	x	-	-	-	-	-	-	x	-	-	-	x	-	M	-	-	-	x	-
Wilcox et al. [44]	x	x	x	x	-	x	-	-	-	-	x	-	-	-	B	-	-	-	x	-
Zhang et al. [57]	-	x	x	-	-	-	-	x	-	-	-	-	x	-	H	-	-	x	-	x
Zhang et al. [65]	x	-	x	-	-	x	-	-	x	-	x	-	x	-	B	-	x	x	-	x
Total	15	20	20	8	9	11	4	2	17	4	10	8	15	0	-	5	6	15	7	8

Literacy level: B – Basic, M – Medium, H – High.

Medication-related data, such as intake time or prescription lists appear in 20 papers [23], [24], [43]–[45], [49]–[51], [54], [55], [57], [58], [60]–[64], [66], [69], [70]. This points to a general goal of dashboard designers to support clinicians in visualising or updating patient prescriptions.

Lab test results appear in 20 examples [22]–[24], [43], [44], [46], [50]–[52], [54], [56]–[61], [64], [65], [68], [70]. As an example, Khan et al. [70] created a visualisation displaying lab results for Hemoglobin and WBC Count in an obstetrics dashboard. In this case, a stacked horizontal bar displays the values, and is colour coded to display the level of risk in the range of values. Figure 3 also displays the lab results for the levels of bilirubin, but through a line chart, to display the evolution of the values.

Structured data or notes usually entered in the EHR through a selection method were rare [43], [44], [47], [49], [50], [53], [63], [64]. Only eight dashboards enabled this option, of which Figure 3 serves as an example, since clinicians could select whether the patient had certain neurotoxicity factors and the risk factors of the Direct Coombs test results, on the right column section of the dashboard.

Unstructured notes refer to the ability to enter freely written notes into the EHR [22]–[24], [43], [45], [47], [49], [58], [61]. This type of clinical data poses a lot of challenges because of the slow process of insight extraction [6], [75], [76], however, it is an important source of information that can contain elements worth representing in EHR visualisations. Our analysis suggests that unstructured notes are often excluded in these systems, possibly because of their qualitative nature, which does not fit well to commonly used graphical elements or visualisation techniques.

Demographics refers to data that identifies the individual the EHR data refers to (e.g., age, sex, height) [22], [44], [45], [47], [49], [51], [52], [62], [64], [65]. This category also does

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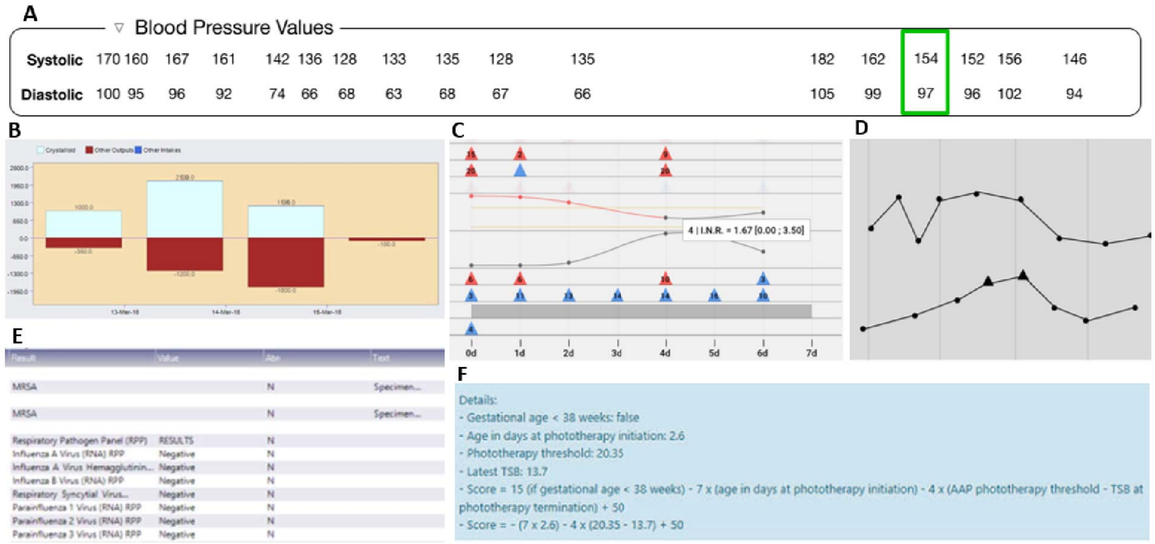

Fig. 5. Collage with screenshots from the dashboards in the review highlighting the visualisation techniques employed. From left to right, and from top to bottom. A- Highlighted Numbers [24]; B- Ranking [50]; C- Timeline [54]; D- Evolution [59]; E- Table [50]; F- Lists [22]

not appear often, which is a possible indication of the fact that when the dashboards were accessed they were already associated with a specific patient, and thus it was not necessary to re-identify the patient of the dashboard.

Our analysis shows that most EHRs visualisations are used to encode data on medication, lab test results and vitals. These results reflect a prioritization of displaying types of numerical data that enables clinicians to accompany patients over time, or detect changes in quantitative results. Fewer data of structured or unstructured notes was included, which leaves the question of whether that is the case simply because user needs are more highly aligned with quantitative data, or whether it is because the inclusion of textual visualisations to display quantitative data is under-explored [45], [77], [78]. Other types of data that did fit into this categorization were also found in some instances. For example, patient's bowel regimen [60], risk scores [64], and expected survival rate [37].

F. Evaluation with end-users

In general terms there was some variety in the evaluation (see Table V). 19 studies were cross-sectional and 11 were longitudinal. In terms of duration, cross-sectional studies lasted minutes to hours, while longitudinal studies varied between two months and 2 years. In the cases of longitudinal studies, the visualisations were often embedded into the EHR system of the hospital, and clinicians could use them as part of their routine, or, if that was not the case, there were multiple iterative tests to gather feedback from clinicians at various stages of the visualisations. Evaluations were mostly conducted in a laboratory environment, where conditions and setup were controlled. Nevertheless, 8 studies were conducted in everyday clinic practice or very close to real-world conditions.

The process of design creation often happened in an iterative fashion, where prototype evaluations occurred along the development of the product. Regarding the methods used, these were usually interviews, questionnaires, or usability tests. Most studies included usability tests, evaluating activities using Think Aloud [22], [23], [50], [53], [59], [66], [69], time on task, task accuracy, screen-recording or mouse clicks. Questionnaires were also a common method of evaluation, for example, asking participants to fill-in satisfaction surveys with Likert scale responses, over an agree/disagree, or positive/negative spectrum. Interviews were also often used, both individually and as part of a group, and using more informal or formal arrangements.

Regarding evaluations, we were also interested in reviewing the kinds of tasks given to clinicians during this phase of the process. Few were the papers that detailed them, but we can still gather some insights from the ones that did. Koopman et al. [23] gave users some very direct tasks for finding information on the system. These included the following examples: *"Date of last HbA1c level"*, *"Value of last HbA1c level"*, *"Date of last LDL cholesterol level"*, *"Value of last LDL cholesterol level"*. These examples show a focus on tasks related to finding values, and dates, which is are common tasks in the use of EHRs. Hirsh et al. [53] had another approach with more open-ended questions, such as *"How soon after [hospital] discharge did the patient have outpatient clinical follow up?"*, *"Does this patients have a history of rash?"*, *"What accounted for the change [in clinical problems over a period of time]?"*, *"What were the five most prominent or important problems [over a period of time]?"* These questions require a more complex interpretation of the data, and can test comprehension as well as usability.

Some studies used validated instruments as part of their

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TABLE V
EVALUATION CHARACTERISTICS OF THE EVALUATION OF THE STUDIES IN THE REVIEW.

Study	Evaluation type	Duration	Total N	Methods used	Validated instruments used	Compared against	Used in
Bannach et al. [62]	Cross-sec	-	-	U	-	-	Lab
Bersani et al. [60]	Longitud	18 months	53	U	QWL, PU, PEOU, UC, Health-ITUES	-	Real
Buchhalter et al. [49]	Longitud	3 months	91	U	Family Experience, Provider Satisfaction	ExistSol	Real
Faiola et al. [71]	Cross-sec	-	19	Q, U	-	-	Lab
Fadel et al. [64]	Longitud	2 months	35	Q, U	-	ExistSol	Lab
Faiola et al. [68]	Cross-sec	-	12	I, Q, U	-	MultiVers	Lab
Febretti et al. [69]	Cross-sec	-	24	U	-	MultiVers	Lab
Foraker et al. [51]	Longitud	1 year	119	I, Q, U	-	-	Real
Hirsch et al. [53]	Longitud	2 years	12	Q, U	-	ExistSol	Lab
Howarth et al. [50]	Cross-sec	-	43	U	SUS, UAT	-	Real
Kawamoto et al. [22]	Longitud	3 years	12	U	SUS	ExistSol	Real
Khan et al. [70]	Cross-sec	-	9	Q, U	SUS, SEQ	ExistSol	Real
Koopman et al. [23]	Cross-sec	-	10	I, U	-	ExistSol	Lab
Koopman et al. [24]	Cross-sec	-	40	I, Q	-	-	Lab
Ledieu et al. [59]	Cross-sec	-	6	U	SUS, vigiGrade Completeness Score	ExistSol	Lab
Linhares et al. [46]	Cross-sec	-	17	Q, U	-	-	Lab
Martignene et al. [54]	Cross-sec	-	2	U	-	MultiVers	Lab
Mlaver et al. [61]	Longitud	16 months	98	I, Q, U	Health-ITUES, QWL, PU, PEOU, UC	-	Real
Nelson et al. [63]	Cross-sec	-	5	U	-	ExistSol	Lab
Pao et al. [52]	Cross-sec	-	100	Q	-	ExistSol	Lab
Pickering et al. [58]	Longitud	9 weeks	169	U, Q	-	ExistSol	Lab
Pohl et al. [56]	Cross-sec	-	9	I	-	-	Lab
Sultanum et al. [45]	Cross-sec	-	11	I, Q, U	SUS	ExistSol	Lab
Sultanum et al. [47]	Cross-sec	-	6	I, Q	-	-	Lab
Sultanum et al. [43]	Cross-sec	-	28	I, U	-	-	Lab
Thayer et al. [66]	Longitud	1 year	62	U	NASA TLX, TAM	ExistSol	Real
Wegier et al. [55]	Cross-sec	-	40	I, U	-	MultiVers	Lab
Wilcox et al. [44]	Longitud	6 months	8	I, Q	-	ExistSol	Lab
Zhang et al. [57]	Cross-sec	-	18	U	-	ExistSol & MultiVers	Lab
Zhang et al. [65]	Longitud	6 months	10	Q, U	-	ExistSol	Real

Evaluation type: Cross-sec - Cross-sectional study, Longitud - Longitudinal study. ***Methods***: I - Interviews, Q - Questionnaires, U - Usability tests. ***Validated instruments***: Health-ITUES - Health Information Technology Usability Evaluation Scale, PU - Perceived Usefulness, PEOU - Perceived Ease-of-Use, NASA-TLX - NASA Task Load Index, QWL - Quality of Work Life, SEQ - Single Ease Questions, SUS - System Usability Scale, TAM - Technology Acceptance Model, UAT - User Acceptance Testing, UC - User control. ***Compared against***: ExistSol - Existing solution, MultiVers - Multiple versions of the same technology.

evaluation. The most commonly used tool was the System Usability Scale (SUS) [79], an instrument that measures self-report usability of a product or system, and which was used by 5 studies. The Technology Acceptance Model [80], was used in its complete form in one study, and two studies used the Perceived Usefulness and the Perceived Ease-of-Use dimensions of TAM. The Health Information Technology Usability Evaluation Scale (Health-ITUES), that measures usability in IT tools [81], and the Quality of Work Life questionnaire [82], that measures the perception of the work environment, were used in 2 studies.

Half of the selected papers compared their solution with the system currently in use [22], [23], [44], [45], [49], [52], [53], [57]–[59], [63]–[66], [70], attempting to show benefits over it. This was appropriate to understand, for example, whether the proposed solution decreased task times and improved clinician workflow. Some papers investigated how their solution changed the hospital workflow, before and after implementation [37], [49], while others tested both solutions concurrently. Five studies compared different versions of their prototype [54], [55], [57], [68], [69], which suggests this approach is not very widely used in this context.

G. Lessons learned from studies

This section distills the lessons learned from the studies in the review. Considering the importance of learning from the experiences of the dashboard designers, we analysed the papers for their results, conclusions, and recommendations, which led to the following eight lessons.

Ensure dashboard design enables information retrieval and appropriate workflow fit. A salient theme from the studies was the importance of speeding up information retrieval by optimizing the dashboard design and its integration into the clinical workflow. Nelson et al. suggested automating low-level cognitive tasks, such as retrieving, organizing, and sorting out graphical data, to overcome this issue [63]. Hakone et al. argued for the importance of ensuring a system matched the workflow of the clinical setting, to decrease cognitive load [83]. Khan et al. [70] analyzed order to achieve that effect, whilst Koopman et al. [23] built a dashboard where some of the data was purposefully hidden, to be consistent with the workflow of the clinicians. In summary, dashboards can be

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used to expedite information retrieval and workflow, through automation, alignment with existing processes, ordering, or hiding specific information.

Adjust visualisation literacy for ensuring comprehension. Another insight from the analysed studies, was the importance of carefully choosing the visualisations used, taking into consideration the literacy of the end-users. Drawing on different experimental studies, authors concluded that using simple visualisations, such as bar charts, positively impacted the ability of users to understand dashboards [55], [56], [62]. This highlights the importance of choosing idioms with low literacy requirements, or in the case of using idioms of higher complexity, making sure the familiarity and knowledge of the users aren't an obstacle to their performance.

Consider building single page dashboards. Another factor to consider is the prevalence of single-page dashboards, a decision which was validated by Wegier et al. [55] in their claim that EHRs that require switching between different windows increase the cognitive load of the user. Another paper, stated that the decision to keep all the information of the dashboard on a single page remains undecided as to whether it improved quality of care and general outcomes [23], in which case it is a factor up for exploration.

Beware of alert fatigue. Some studies tested the role of alerts in decision-support systems, paying attention to their integration with other systems [24], [50]. Alert fatigue was brought up as an issue that can cause cognitive overload, and break the thought of consciousness of someone performing important tasks. Alerts can also interfere with each other, which should certainly be avoided [51]. Besides alerts, severity indicators [57], [61], which enable clinicians to distinguish between mild and severe conditions, were also mentioned as an important element of dashboard designs. The use of colour grading to distinguish patient risks was highlighted as indicative of a usable design choice [60], [60]. Goal ranges were pointed-out to be relevant elements, that should use the pre-attentive attributes of colour and position to be absorbed more easily [55]. Febreti et al. [69] also identified two distinct user behaviours in reaction to alerts, with 70% of users following a colour-based navigation and handling the red-level alerts first, and 25% following a layout-based navigation, where users tackled alerts on top of the interface first, and proceeded to moved down.

Consider mechanisms for data insertion. Another aspect of information retrieval is how clinicians add data to the system. Currently, only eight dashboards belong to the category of "Modify data or the world" [22], [43], [50], [51], [53], [57], [65], [70], meaning most dashboards were designed mostly as analytical tools, and not (truly) interactive systems.

Ensure training of clinicians. One study reported distinct results according to previous experience with a tool, with undecided results from users who did not have previous experience, and positive results from those who had [50]. Koopman et al. [23] also celebrated the ease with which their dashboard was embraced by the medical team, and attributed this factor to the 90-second video tutorial explaining its use. Thus the training and involvement of clinicians might support their performance in studies.

Assess the possibility of enabling clinicians to personalise their dashboard. The ability to personalise the dashboard was another discussed factor, whereby users were allowed to pick the data they saw. Some studies favoured this approach [56], [67], while others were unsure on about giving users that flexibility [69].

Iterate design based on user testing. User evaluation was one of the focal points of this review. Our analysis suggests that iterating the design and development of these platforms based on user feedback is of clear importance to meet user needs. The process often includes a preparatory research phase to gather user requirements, where studies reported using sketches as a form of design preparation, as well as focus groups and interviews. Following preparatory research, the process of design creation often happens in an iterative fashion, where prototype evaluations happen along the development of the product, using methods such as questionnaires, interviews, and usability tests.

Design for web browser compatibility. Foraker et al. [51] explained the importance of ensuring that the proposed system was compatible with the hospital's network, and with all browsers. Taking into consideration that the users might not choose the browser they will use, making sure prototypes work well in a variety of browsers might be important for having a successful tool.

IV. Discussion

This paper overviewed several key aspects to take into account when designing patient dashboards, including the used data types, visualisation techniques, dashboard literacy, interaction, design, and evaluation. In this section, we discuss the trends identified, highlight some outliers, and point to current challenges that should be further addressed.

From the features identified in this review, we can gather that the common traits that form the typical EHR dashboard. The dashboard aim is usually to accelerate diagnostic, with the goal of aiding clinicians to understand the patient status quickly and make correct decisions more efficiently. These are one-page interfaces representing vital signs, medication, or exams, with a chart showing a timeline or evolution of values over time, no possibility of construction/composition, with some filters or selections, with low literacy requirements, and with the purpose of visualising data (not updating it). The evaluations of patient dashboards are usually cross-sectional, with an average of 36 users participating in an interview/questionnaire/usability test, in a lab, and compared against an existing solution.

Comparing to other reviews of visualisation in EHR we find several differences. Rind et al. [26] reviewed EHRs, but focused mainly on design and did not consider the evaluation with users. West et al. [4] evaluated visualisation techniques, and user-evaluations, but they did not go into detail about how those categories unfold. They also did not explore data types, or other dashboard characteristics such as interactivity

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and literacy. Rostamzadeh et al. [27] evaluated EHRs based on tasks, analytics, visualisations, and interactions. However, they did not consider end-user evaluations, and also did not focus on the data types considered, and how that affects the choice of evaluation techniques used.

The review from Rostmazdeh et al. [27] also identified an overwhelming prevalence of time-based visualisations in EHR systems. Their results also show a small representation of hierarchical-based visualisations as also occurs with our dataset, indicating either a lack of need to represent hierarchies in clinical datasets, an attempt to keep the literacy of the dashboards as Basic to facilitate use, or an underexplored representation technique in this field. The same applies to highlighted numbers and clusters as a form of visualisation.

In general, qualitative data was less present than quantitative and was usually stored in tables, lists or unstructured note sections. Although this is the case, it is important to point out that qualitative data has been recognized as a very important information source [43], [47], and a significant proportion, of medical documentation. It might be the case that EHRs are focusing more on the quantitative side of data because of their intention to summarize and display it in the most efficient possible way. In fact, most visualisations are used to accelerate diagnostic, which means speed is one of the characteristics that is prioritised, this is reflected in the use of alerts, colour coding, and threshold warnings as common mechanisms used to achieve diagnostic efficiency; and in the evaluation phase, where timing tasks is one of the preferred methods. In contrast, some systems in this review, such as *Doccurate* [47] pay particular attention to the integration of text data, even stating that text is the preferred way of communication because of the detailed richness it provides compared to other forms of data, although it has a problem with being scalable.

On the other hand, this redirects us to the issue of scalability, which was not directly addressed in most papers, although it is of major importance [65]. Line charts such as that of Figure 3, or timelines, work for the scale chosen for the axis. However, if there are no proper filtering or scaling mechanisms, the visualisation might only work with a certain amount of data. As an example, Zhang et al. [57] developed a radial visualisation, where scalability can be a problem since more data will mean each section of the diagram is less visible.

Regarding the evaluations, it is important to restate that there are few systems tested in a hospital environment, as has already been pointed out in other surveys regarding health technologies [84]. Systems following laboratory evaluations might have added difficulties in transferring their results from the lab to real world scenarios, which can cause unexpected issues and lead to technology abandonment. Fifteen of the dashboards are also not evaluated against variations of themselves, which would allow for a deeper understanding of how isolated design elements affect their usability.

Most dashboards in the review were not compared against current market solutions, which removed the opportunity to test whether they are an improvement to the state of the art. The same point could be made in an analysis of the data sources used in these patient dashboards. Some papers used data directly from clinics and hospitals, while others used fictional data, which can impact the usability of the system when installed outside of the lab. Dashboards were often evaluated through usability metrics, being that the System Usability Scale was very popular. Other common design evaluation tools were also frequently used, such as timing tasks, and error counting. It would be worth exploring the appropriateness of these methods in the health context since while they certainly give important information, they are often not tailored to completely fit the context at hand. Interviews and focus groups were also common methods that researchers used in order to fit the design to the expectations of the users.

It is also curious to see the shy appearance of papers from HCI and InfoVis. Regarding the HCI community, the review included only three papers from CHI, one paper from INTERACT, and one from HCI International. The InfoVis was represented with three papers from TVCG, one from EVA, and one from IEEE VAHC. It is possible that InfoVis venues focused on exploring more abstract forms of visualisation, which were not necessary to test in clinical contexts. It may also be the case that that was the case because papers from those venues have not focused on dashboards for specific clinical contexts. Another possibility is that they could have had a more experimental approach in the lab, and selected users without clinical experience to test their interfaces. If the InfoVis and HCI community aim to have an impact in clinical practice, one future work possibility is experimenting with these solutions in a real clinical environment.

V. Future Work Opportunities

One future opportunity is to explore more deeply the design guidelines that are specific for certain medical contexts. One example would be the different scenarios of between acute and chronic visualisations, since one seems to require a more long-term follow-up, while another refers to singular situations. However, many others can be explored, such as design guidelines that are disease-specific, such as kidney injury, or specialisation specific, such as pediatric care.

Another possible research focus would be to explore more types of visualisation techniques, and the pros and cons of certain representations in a clinical context. We saw how literacy might be a factor taken into account, but it is not clear why certain visualisation types are rarely seen, as is the case for hierarchy and correlation displays. Visual biases are also something that can be further explored in relation to visualisation types. As an example, it would be interesting to see some exploration on whether certain techniques are prone to transmit larger health risk perceptions compared to others.

The setting of the evaluations performed is also an aspect that calls for attention. Many are done in the lab, instead of a clinical environment, limiting the applicability of the results. Dashboards are also sometimes not compared with current solutions, or against different versions of themselves. These are all points that should be taken into account, and improved when proposing new EHR dashboard designs.

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The inclusion of textual data in patient dashboards is another hidden opportunity. Twenty-one dashboards do not enable the insertion of clinical notes and focus more on the display of quantitative data. However, qualitative data is also an important part of a clinician's routine, and it would be useful to find more discussions of the integration of qualitative data into these systems. Some papers have started in this direction [47], and propose solutions regarding text visualisations, and Natural-Language Processing techniques, however, further work should be done in this area.

The issue of scalability is also an important one, that requires further considerations. Although it is mentioned on a few articles, it still seems to be an issue with some designs. Often timelines are short in size, and it is a bit ambiguous how they would display increasing amounts of data. Whether it is through filtering mechanisms, or other solutions, it would be interesting for articles to show more transparency on this issue, since it is sometimes hard to evaluate whether they would work with large amounts of data, or only work with the data selected for the experiment.

Finally, another opportunity would be to revisit this survey in a few years, and investigate whether the increasing interest in Artificial Intelligence systems has changed the design paradigm or the requirements for an efficient EHR system.

VI. Conclusion

In this survey we analyze 30 papers on EHR visualisation dashboards, and evaluate their characteristics in order to condense them into a set of design guidelines that inform the future design of EHR dashboards. Dashboard design is not a new topic, however, it seems that the advancements in this area have yet to catch up to the needs of clinicians. We found that typical iterative design methods are used, with clinicians in the loop, so that the tools are designed around their needs. Nevertheless, since a few dashboard characteristics are tested at a time, there is still work missing to start designing dashboards that are efficient on various aspects. We analysed them in terms of clinical context, dashboard aim, design, and interactivity, visualisation techniques, types of data represented, end-user evaluation, and lessons learned. Overall, this work reviews the existing body of work and lessons to support design, and suggest future opportunities for what is yet to be explored.

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