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Information Dashboards and Tailoring Capabilities - A Systematic Literature Review

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ABSTRACT The design and development of information dashboards are not trivial. Several factors must be accounted; from the data to be displayed to the audience that will use the dashboard. However, the increase in popularity of these tools has extended their use in several and very different contexts among very different user profiles. This popularization has increased the necessity of building tailored displays focused on specific requirements, goals, user roles, situations, domains, etc. Requirements are more sophisticated and varying; thus, dashboards need to match them to enhance knowledge generation and support more complex decision-making processes. This sophistication has led to the proposal of new approaches to address personal requirements and foster individualization regarding dashboards without involving high quantities of resources and long development processes. The goal of this work is to present a systematic review of the literature to analyze and classify the existing dashboard solutions that support tailoring capabilities and the methodologies used to achieve them. The methodology follows the guidelines proposed by Kitchenham and other authors in the field of software engineering. As results, 23 papers about tailored dashboards were retrieved. Three main approaches were identified regarding tailored solutions: customization, personalization, and adaptation. However, there is a wide variety of employed paradigms and features to develop tailored dashboards. The present systematic literature review analyzes challenges and issues regarding the existing solutions. It also identifies new research paths to enhance tailoring capabilities and thus, to improve user experience and insight delivery when it comes to visual analysis.

INDEX TERMS SLR, systematic literature review, tailoring, custom, personalized, adaptive, information dashboards.

I. INTRODUCTION

Information dashboards are nowadays key tools for understanding and extracting knowledge from large datasets, but they can take many forms. Information dashboards can be employed for different goals, to analyze different datasets (framed within different domains), to explain concepts, to generate knowledge, to confirm hypotheses, etc., [1]. The spread of dashboards and their use in different contexts makes their definition a complex task.

Although identifying what is and what is not an information dashboard can be confusing in some cases, an information dashboard can be defined as a set of (visual) resources that enable its audience to understand and/or reach insights regarding the data being displayed [1]–[3].

Their capabilities not only try to cover the exploitation of datasets but also to provide a proper user experience to ease knowledge discovery. However, user experience, as the name suggests, depends on each user, there is no ''one size fits all'' in this domain. Although a ''one size'' dashboard, valid and useful for every possible user profile would be ideal, it is utopic; not every user is driven by the same goals, not every

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user is interested in the same data, not every user has the same visualization literacy, and so on. These aspects include not only personal preferences, but also social factors, like biases, beliefs, or past experiences [4], [5].

The support that technology provides to our everyday life has led to an exponential growth of data, making it necessary and crucial to take advantage of information to perform informed decision-making processes. Data are more accessible, and thus, not only specific profiles are in charge of visual analyses. Some users might need solutions that not only let them configure or develop dashboards given their requirements, but also that assist them in choosing a proper configuration if they don't have enough experience with visual analyses or enough visual literacy. Users should be provided with tailored dashboards that fulfill their requirements and foster insight delivery to enhance the outcomes of the decisions made.

Given these facts, it is essential to take into account final users when developing information dashboards, to improve the user experience and subsequently provide a dashboard that promotes knowledge generation. The user-centered design paradigm tries to address these issues by focusing on the user needs and requirements during all the development phases [6]. Involving the end-user into the design processes supports the development of better systems, which are useful for them and match their needs.

While necessary, this paradigm still lacks individualism when providing a solution, as not every potential user of the system can be involved in a development process. These potential users can present very different characteristics, mental schemas, and goals and therefore can demand very different features, especially in the dashboards domain that is faced in this work, given its complexity, so each person should be taken into account. However, is it efficient to develop an individual dashboard for each user? Should several quantities of resources be involved for the benefit of individualism? There exist any other approaches for designing and for building information dashboards for several and different user profiles?

Personalization and customization approaches try to address these individualization issues by tailoring products through different mechanisms. These mechanisms aim at supporting developers to configure products by reusing components and consequently, by decreasing the development time (even by assisting users in configuring their own products driven by their own needs). In the case of dashboards, there exist user-friendly tools that enable users to create and customize their dashboards without requiring any programming skills, like Tableau[1] or Grafana[2]. This kind of approaches give freedom to the users to configure their tools, but in such a complex domain that is visual analytics, some users might not exactly know which configuration is the best to accomplish their goals [7].

It is clear that dashboards are valuable but sophisticated tools, and their potential benefits when supporting decision-making processes has increased their popularity in several fields (business intelligence, learning analytics, services monitoring, etc.) and activities. Sarikaya *et al.* shown in a recent survey the relevance of researching on these tools and the relevance of users' goals, their characteristics, and context for designing useful dashboards [1]. However, before tackling how a tailored dashboard can be efficiently delivered to a specific user, it is necessary to understand and explore existing research lines and solutions regarding this domain. Laying a foundation on tailored dashboards can help to design better solutions based on case studies found in literature, analyzing their strengths and weaknesses.

A systematic literature review of existing tailoring methods regarding information dashboards has been carried out to clarify this matter. Through this review, the authors aim at providing a comprehensive view of this domain's solutions, to examine new research paths and opportunities for delivering effective tailored dashboards, and to learn about the trends and methods regarding the problem of finding a suitable dashboard configuration given a concrete user. Also, this systematic literature review can help to identify caveats or research opportunities to improve tailoring processes and to obtain more practical, usable, and individualized dashboards subsequently.

The term "tailored dashboard" is used throughout this work to enclose any dashboard solution that can vary its appearance and functionalities to match the users', data's and context's requirements, be them explicit requirements or implicit requirements. A general term is necessary, because using "customizable," "personalized" or "adaptive" indistinctly to refer to these solutions, could lead to misconceptions around these last terms, which, in the end, have different nuances.

As it will be exposed, tailored dashboards can be categorized taking into account a series of factors like the stage at which the tailoring process is performed, the driver of the tailoring process, the targets of the tailoring process, etc. This categorization shows that although the outcomes are "the same" (tailored dashboards), the methods to provide them can differ from each other (customization, personalization, adaptation, etc.).

The rest of this work is organized as follows. Section two (Methodology) describes the methodology, and the steps followed to perform the review. Section three (Review Planning) details the SLR planning phase. Section four (Review Process) presents the review and data extraction steps. Section five (Results) presents the results obtained from the analysis of the selected works to answer the research questions. Section six (Discussion) discusses the results, followed by section seven (Threats to Validity), in which the threats to the validity of the review are outlined. Finally, section eight

[1] https://www.tableau.com/
[2] https://grafana.com/

(Conclusions) includes some conclusions and future research lines.

II. METHODOLOGY

A systematic process has been followed to conduct the present literature review; specifically, the systematic literature review (SLR) methodology by Kitchenham [8] and Kitchenham and Charters [9]. The SLR has been complemented with a systematic mapping of the literature following the methodology proposed in [10]. The mapping results can be consulted in [11]. In this section, the protocol followed in carrying out the SLR is described, providing all the necessary information to trace the subsequent results. Following the [8], [9] guidelines, the SLR is composed of three main phases: planning, conducting, and reporting the study. These phases are detailed through the following sections.

Before planning the present SLR, a preliminary search was made to verify that no recent SLRs about tailored dashboards were carried out. If that were the case, there would not be any necessity to conduct a new one. This verification was performed by searching through different electronic databases (Scopus, Web of Science (WoS), IEEE Xplore and Springer) terms related to the methodology (''SLR'', ''systematic literature review'', etc.) and the target of the review (''tailored'', ''customizable'', ''personalized'', etc., along with the term ''dashboards''). The outcomes of these queries confirmed that currently, there are no previous systematic literature reviews about the thematic addressed in this work, justifying the execution of this SLR.

III. REVIEW PLANNING

The review planning process involves the identification and definition of different aspects to lay the foundations of the review execution, such as posing the questions to be answered, detailing the protocol followed, and any other relevant information to make the review traceable. These different aspects are described in this section.

A. RESEARCH QUESTIONS

First, a series of research questions have been raised. These questions can be classified into three main blocks: technical aspects (RQ1-RQ4), artificial intelligence (AI) application (RQ5), evaluation of the solutions (RQ6).

- **RQ1.** How have existing dashboard solutions tackled the necessity of tailoring capabilities?
- **RQ2.** Which methods have been applied to support tailoring capabilities within the dashboards' domain?
- **RQ3.** How the proposed solutions manage the dashboard's requirements?
- **RQ4.** Can the proposed solutions be transferred to different domains?
- **RQ5.** Has any artificial intelligence approach been applied to the dashboards' tailoring processes and, if applicable, how these approaches have been involved in the dashboards' tailoring processes?
- **RQ6.** How mature are tailored dashboards regarding their evaluation?

The first RQs block aims at answering questions regarding how tailoring capabilities have been materialized in tangible dashboard solutions (methods, requirements management, domain transferability). The goal of answering RQ5 is to identify research opportunities in terms of the application of AI mechanisms to support the dashboards' tailoring processes automatically. The last question's purpose is to understand if the solutions found have been tested with end-users and if the tailoring capabilities have been useful for enhancing insight delivery and knowledge generation.

As mentioned before, the SLR has been complemented with a literature mapping to perform a quantitative analysis of the domain and to obtain a broad view of the research area. The following mapping questions (MQs) were posed, but the outcomes of the mapping are out of the scope of this paper and can be consulted at [11]:

- **MQ1.** How many studies were published over the years?
- **MQ2.** Who are the most active authors in the area?
- **MQ3.** What type of papers are published?
- **MQ4.** To which contexts have been the variability processes applied? (BI, learning analytics, etc.)
- **MQ5.** Which are the factors that condition the dashboards' variability process?
- **MQ6.** What is the target of the variability process? (visual components, KPIs, interaction, the dashboard as a whole, etc.)
- **MQ7.** At which development stage is the variability achieved?
- **MQ8.** Which methods have been used for enabling variability?
- **MQ9.** How many studies have tested their proposed solutions in real environments?

The systematic mapping performed at [11] employs the same approach as in the present SLR. However, the mapping provides an overview of the research area by identifying and classifying the available evidence, while the following SLR results involve the analysis and interpretation of the evidence found [12] to answer the specific research questions posed at the beginning of this subsection.

Given the previous research questions, the PICOC method proposed by Petticrew and Roberts [13] has been followed to define the review scope.

- **Population (P):** Software solutions
- **Intervention (I):** Provide support to tailor (information) dashboards
- **Comparison (C):** No comparison intervention in this study, as the primary goal of the present SLR is to analyze existing approaches regarding tailoring capabilities and gain knowledge about them.
- **Outcomes (O):** Information dashboard proposals
- **Context (C):** Environments related to data visualization and (or) decision making (in the academia, industry, etc.)

B. INCLUSION AND EXCLUSION CRITERIA

Once the scope of the review has been established, a series of inclusion (IC) and exclusion criteria (EC) are defined to select relevant works for answering the identified research questions. If a work does not meet the whole set of inclusion criteria or does meet any exclusion criterion, it will be excluded from the review.

- **IC1.**The paper describes a dashboard solution (proposal, architecture, software design, model, tool, etc.) AND
- **IC2.** The solution is applied to information dashboards AND
- **IC3.** The solution supports or addresses tailoring capabilities (customization, personalization, adaptation, variation) regarding information dashboards AND
- **IC4.** The tailoring capabilities of the dashboard are related to its design, components or KPIs AND
- **IC5.** The papers are written in English or Spanish AND
- **IC6.** The papers are published in peer-reviewed Journals, Books or Conferences AND
- **IC7.** The publication is the most recent or complete of the set of related publications regarding the same study

The exclusion criteria are derived from the inclusion criteria as their opposite.

- **EC1.**The paper does not describe a dashboard solution (proposal, architecture, software design, model, tool, etc.) OR
- **EC2.** The solution is not applied to information dashboards OR
- **EC3.** The solution does not support or address tailoring capabilities (customization, personalization, adaptation, variation) regarding information dashboards OR
- **EC4.** The tailoring capabilities of the dashboard are not related to its design, components or KPIs OR
- **EC5.** The papers are not written in English or Spanish OR
- **EC6.** The papers are not published in peer-reviewed Journals, Books or Conferences OR
- **EC7.** The publication is not the most recent or complete of the set of related publications regarding the same study

The IC5 includes the Spanish language, because the main research terms, as it will be seen in the next subsection, are compatible with their Spanish equivalent terms (dashboard* along with custom*, personal*, adapt*, flexib* and config*). As a consequence, works written in Spanish could be retrieved through the search string and could be potentially included in the review given the authors' comprehension of this language.

C. SEARCH STRATEGY

It is necessary to identify the most important databases regarding the research context in which the queries will be performed to obtain relevant outcomes from the search. In this case, four electronic databases were selected: Scopus, Web of Science (WoS), IEEE Xplore, and SpringerLink. These databases were chosen according to the following criteria:

- It is a reference database in the research scope
- It is a relevant database in the research context of this literature review
- It allows using similar search strings to the rest of the selected databases as well as using Boolean operators to enhance the outcomes of the retrieval process

Regarding the search concepts employed to build the search query, the following terms were included:

- The "meta-dashboard" concept to search for solutions that employ a meta-modeling approach to extract common and abstract features from dashboards that can be applied for tailoring processes.
- Related terms to tailoring capabilities: tailored, customized, personalized, adaptive, flexible, configurable, context-aware, etc., along with the word "dashboard," which is the main target of the review.
- Other terms like "selection," "composition," or "generation" to search for generative solutions that provide dashboards as a result of a generation, composition or selection process of suitable visualizations and features.
- The term "template" to retrieve works that use dashboard templates that can be configured to fit specific requirements (this term can also be related to generative processes)
- The term "driven" to enclose works that use context-driven, data-driven, user-driven, etc., approaches, thus being necessary to take into account these factors to develop the dashboards
- Additional terms related to heterogeneous requirements and diverse necessities to retrieve works that do not mention directly any of the above terms, but do implicitly refer to them by calling upon the heterogeneity of dashboards requirements and the involved user profiles, thus potentially addressing these issues by tailoring mechanisms.

Finally, given the fact that the word "dashboard" is also employed for referring to cars' control panels, words related to the automotive area ("car," "vehicle," "automotive") were excluded to avoid irrelevant papers outside the scope of information dashboards.

D. QUERY STRINGS

The search strings for each chosen source were built using relevant search terms derived from the PICOC methodology outcomes, connected by Boolean AND / OR / NEAR operators. Moreover, the wildcard (*) was used to enclose both the singular and plural of each term.

The NEAR operator enables the user to retrieve works where the terms joined by this operator are separated by an interval of words explicitly specified. This operator is handy in the context of the present research, as the terms "customizable," "personalized," "adaptive," etc. should only refer to the dashboard term, to avoid works that are not explicitly focused on the tailoring capabilities of dashboards. However, the drawback of using this operator is the necessity to explicitly define the maximum number of words that can separate the target terms.

In this case, the chosen number was 10 (i.e., the ''dashboard'' term and the rest of the terms will be within 10 number of words of each other). This number was selected after performing a ''simulation'' by executing the same search with different proximity values (5, 7, 10, and 12). Examining the titles, abstracts and keywords of the additional records found after incrementing this value, it was concluded that the ten value would retrieve relevant works without adding noise (i.e., irrelevant works), meaning that the terms affected by the NEAR operator are potentially in the same sentence, given average sentence length guidelines and evidence [14], [15].

Once the NEAR operator value was selected, the specific query strings for each chosen database were specified using their query syntax.

1) SCOPUS

TITLE-ABS-KEY ((meta-dashboard) OR ((dashboard*) W/10 (custom* OR personal* OR adapt* OR flexib* OR config* OR tailor* OR context-aware OR generat* OR compos* OR select* OR template* OR driven)) OR ((dashboard*) AND ((heterogeneous OR different OR diverse OR dynamic) W/0 (requirement* OR stakeholder* OR user* OR need* OR task* OR necess*)))) AND NOT TITLE-ABS-KEY (car OR vehicle OR automo*) AND NOT DOCTYPE(cr)*

2) WEB OF SCIENCE

TS=((meta-dashboard) OR ((dashboard*) NEAR/10 (custom* OR personal* OR adapt* OR flexib* OR config* OR tailor* OR context-aware OR generat* OR compos* OR select* OR template* OR driven)) OR ((dashboard*) AND ((heterogeneous OR different OR diverse OR dynamic) NEAR/0 (requirement* OR stakeholder* OR user* OR need* OR task* OR necess*)))) NOT TS= (car OR vehicle OR automo*)*

3) IEEE XPLORE

(((meta-dashboard) OR ((dashboard) NEAR/10 (custom OR personal* OR adapt* OR flexib* OR tailor OR tailored OR configurable OR context-aware OR generation OR generated OR generative OR composed OR composition OR selection OR selecting OR template OR driven)) OR ((dashboard) AND ((heterogeneous OR different OR diverse OR dynamic) NEAR/0 (requirement OR stakeholder OR user OR need OR task OR necessities)))) AND NOT (car OR vehicle OR automo*))*

4) SPRINGERLINK

((meta-dashboard) OR ((dashboard*) NEAR/10 (custom* OR personal* OR adapt* OR flexib* OR config* OR tailor* OR context-aware OR generat* OR compos* OR select* OR template* OR driven)) OR ((dashboard∗) AND ((heterogeneous OR different OR diverse OR dynamic) NEAR/0 (requirement* OR stakeholder* OR user* OR need* OR task* OR necess*))))*

In case of SpringerLink, this query string was complemented with an additional restriction, given SpringerLink policy of searching the query terms along with the papers' full-text (which includes huge amounts of noise to the review process). Through the advanced search tool, the query results were limited to those that have the term ''dashboard*'' in their titles, additionally to the search string terms in their full-texts to ensure that the main focus of the retrieved works is information dashboards.

E. QUALITY CRITERIA

Although the inclusion and exclusion criteria are useful for including in the review relevant works in terms of the scope of the literature review, they don't address the quality of the retrieved papers regarding their capacity to answer the posed research questions. A new set of criteria has been defined to check the works' quality before including them into the final literature review. Each criterion can be scored with three values: 1 (the paper meets the criterion), 0.5 (the paper partially meets the criterion) and 0 (the paper does not meet the criterion).

1. The research goals of the work are focused on addressing the variability, adaptability, customization or personalization of an information dashboard to improve individual user experience (UX)
   - *Partial: not every research goal tries to address UX through tailoring capabilities*
2. A software solution that supports the variability of the dashboard components is presented
   - *Partial: the software supports customization of the dashboard but is not the focus*
3. A model, framework, architecture or any software engineering artifact that address the variation of the dashboard components and interaction methods are properly exposed
   - *Partial: a model, framework, architecture or any software engineering artifact is exposed but not detailed, i.e., the nature of the referred elements is mentioned, but their internal structures and details are not further explained.*
4. The employed methods or paradigms to achieve tailoring capabilities are properly described
   - *Partial: the employed methods or paradigms to achieve tailoring capabilities are partially described, i.e., the methodology is mentioned, but how the methodology has been particularly used within the application context is not detailed.*
5. The context or domain of application of the dashboard is described
   - *Partial: the context or domain of application is mentioned but not detailed.*

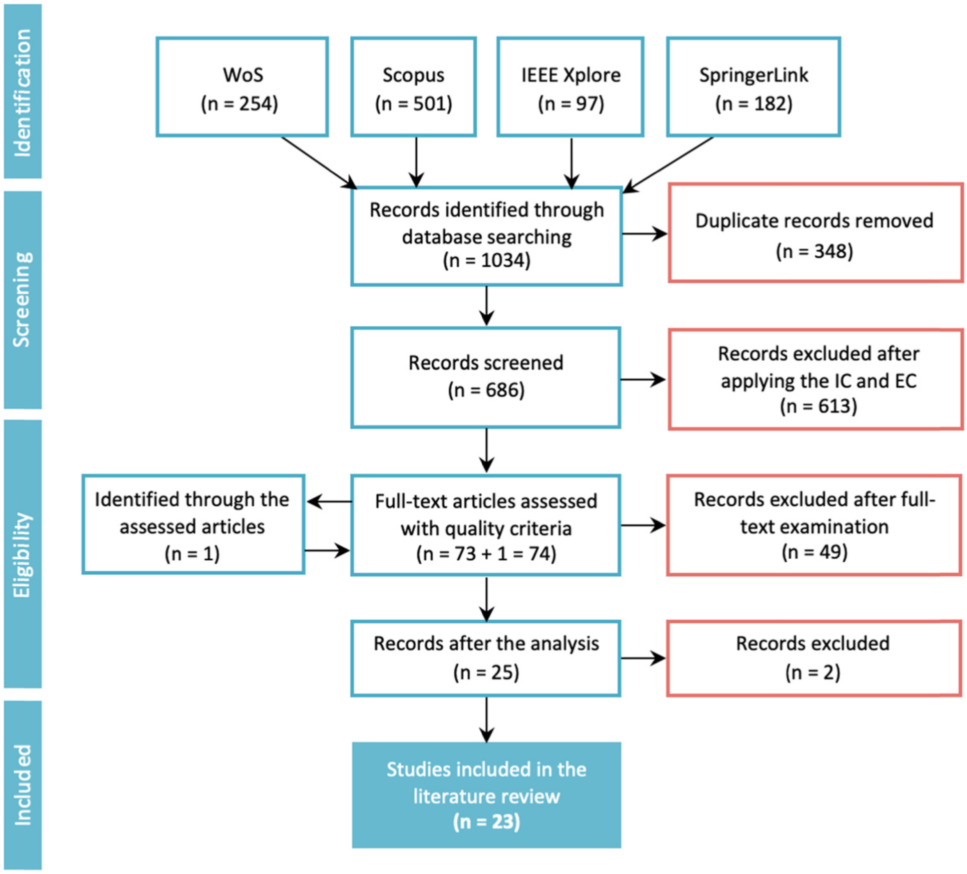

FIGURE 1. **Phases and outcomes of the review process using the PRISMA flow diagram.**

6. The proposed solution has been tested with real users
   - *Partial: real users have used it and tested its functionality, but no further testing has been performed*
7. Issues or limitations regarding the proposed solution are identified
   - *Partial: issues or limitations are mentioned but not detailed*

Each paper can obtain a maximum of 7 points regarding its quality following this methodology. This 0-to-7 score was transformed into a 0-to-10 scale, and the seven value was chosen as the threshold for including a paper into the final synthesis. If in a 0-to-10 scale, a paper obtains a score of fewer than seven points, it will be dismissed from the review as it did not meet a minimum quality to answer the stated research questions.

The chosen threshold ensures that the works have obtained the maximum score in some criteria, without neglecting the rest of the quality statements. With this threshold, a paper is limited to a maximum of two criteria with a 0 score to reach the next phase, ensuring that the majority of the criteria is always fully or partially met.

IV. REVIEW PROCESS

The data gathering process to conduct the present SLR has been divided into different phases in which various activities are carried out. The PRISMA flow diagram [16] has been employed to detail the actions performed during the data extraction (Figure 1).

Once the search was performed (on January 22, 2019), the paper selection process was carried out through the following process:

1. The raw results (i.e., the records obtained from each selected database) were gathered in a GIT repository[3] [17] and arranged into a spreadsheet[4]. A total of 1034 papers were retrieved: 254 from Web of Science, 501 from Scopus, 97 from IEEE Xplore and 183 from SpringerLink.
2. After organizing the records, duplicate works were removed. Specifically, 348 records were removed, retaining 686 works (66.34% of the raw records) for the next phase.

[3]https://github.com/AndVazquez/slr-tailored-dashboards
[4] http://bit.ly/2wRCU5w

3. The maintained papers were analyzed by reading their titles, abstracts, and keywords and by applying the inclusion and exclusion criteria. A total of 613 papers were discarded as they didn't meet the criteria, retaining 73 papers (10.79% of the unique papers retrieved) for the next phase.
4. The selected 73 papers were read in detail and further analyzed. The papers were scored regarding their quality to answer the research questions using the quality assessment checklist described in the previous section. One paper was added after checking the references of the assessed works, leaving 74 records for this quality assessment phase.
5. After applying the quality criteria, a total of 23 papers (3.35% of the unique papers retrieved and 31.08% of the full-text assessed papers) were selected for the present review.

Two records were finally discarded. The reason for this exclusion was that the two works were previous versions of other studies found within the retrieved records. The decision was to keep the more complete and/or more recent work.

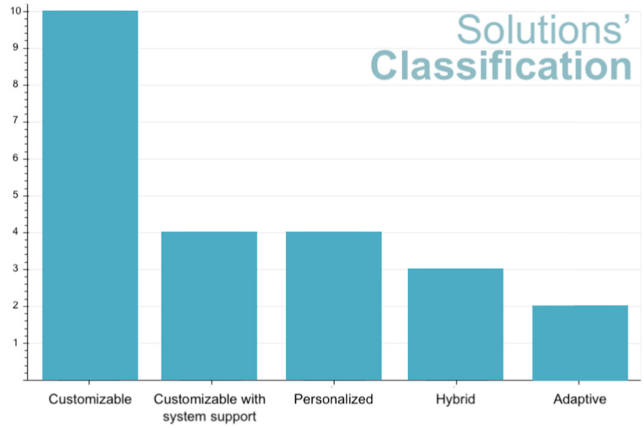

FIGURE 2. Classification of the retrieved solutions in terms of their tailoring method. Source: [11], elaborated by the authors.

V. RESULTS

A. HOW HAVE EXISTING DASHBOARD SOLUTIONS TACKLED THE NECESSITY OF TAILORING CAPABILITIES?

The first research question tries to answer, which are the trends when it comes to tailoring an information dashboard. As stated in the introduction of this work, some terms are misleading or not being appropriately used, given their formal meaning. ''Custom'' and 'personalized'' are often used as interchangeable terms with the same connotations. It is important to make distinctions among these terms, as they have entirely different meanings regarding their mechanisms.

The selected works were categorized in terms of their tailoring process. Each paper was analyzed to answer the questions that would frame the tailoring process employed (i.e., at which stage is the tailoring process performed? Who performs the tailoring process?). As shown in Figure 2, the majority of the selected works are framed in the category of ''customizable,'' meaning that the tailoring process of the dashboard is driven by explicit user requirements [18]–[27].

Most customizable solutions identified involve manual approaches (which will be detailed in RQ2), meaning that users need to perform a set of explicit actions to tailor their dashboard according to their needs.

In [18], a customizable dashboard display for monitoring mobile energy is presented; users can build their dashboards by selecting pre-defined widgets and data streams from different sources (sensors, government agencies, social media, and generic services). Manual approaches like those above are also used in [19], [26], [27], in which the customizability capacity is based on the possibility of arranging the components of the dashboard through end-user interaction, and even the ability to craft custom indicators, as described in [26].

However, not only manual user interactions are employed for arranging the tool, some of these customizable dashboards involve generative or automatized approaches through the specification of configuration files [21], [22], [24], models [23], [25] or pre-defined templates [20]. Although technically the tailoring process is indeed made by the system (not involving direct user actions to modify the dashboard appearance), which is a characteristic of personalization approaches, the data contained within the configuration files or model instances does involve explicit user requirements, so the dashboard is tailored according to the users by means of their requirements. In the end, these generative approaches add an abstraction layer which helps users to configure their dashboards without requiring programming skills. For these reasons, these solutions are also classified as customizable dashboards.

Despite the previous distinction about customizable dashboards, personalized solutions have also been identified. In this case, personalized solutions infer a suitable configuration based on implicit data about users, tasks, or goals [28]–[31]. In [28], the methodology takes as input a model of the business process and goals to describe and generate a dashboard, so the authors use implicit data (goals) to build a concrete dashboard that would help to reach the input goals. User-roles are also added to this methodology in [29], to include more information to the dashboard personalization process. A similar solution is presented in [30], which also takes into account user-roles and business' KPIs to generate a dashboard that fits the business goals. Finally, in [31], the focus is on personalizing the display taking into account the user abilities through an initial questionnaire that ask users if they have eye diseases or any tremor in hands, making the dashboard accessible if necessary. Once generated, these dashboards cannot be adapted at run-time, being essential to re-generate them.

Adaptive solutions, on the other side, can adapt themselves at run-time based on environmental changes. Belo *et al.* [32] present an adaptive dashboard that restructures itself given user-profiles and behaviors extracted from the dashboards' analytical sessions (i.e., through the analysis of the user queries). Another adaptive solution presented in [33] uses a dashboard generator fed with user, data and visualization models, thus generating information dashboards according to different contexts, and, in theory (as the proof of concept is not fully adaptive at the time of publishing the paper), adapting themselves given their users' interaction history.

Other two kinds of tailored solutions have been identified, as they cannot be framed on the last categories (customizable, personalized, or adaptive). On the one hand, solutions identified as "hybrid" are mainly personalized or adaptive dashboards that allow the user to have the last word regarding the dashboard configuration, or need user actions to complete the tailoring process. In [34], a device cloud platform dashboard is built based on the data model of the remote devices being monitored, but users can also customize it manually. Van Hoecke *et al.* [35] use a semantic reasoner to personalize indicators from available data sources, but the dashboard construction is still a user task. Santos *et al.* [36] also proposes personalized dashboards based on knowledge graphs and indicator ontologies, but allow the users to modify the dashboard recommendation to her or his preferences.

On the other hand, there are customizable solutions that can assist and help the users to build their dashboards according to a series of factors. The four papers identified in this category [37]–[40] use visual mapping to help users to determine the best visualization types for the data to be visualized while building and designing their dashboards. These solutions are mainly customizable dashboards with mechanisms that help users with the selection of a suitable dashboard configuration.

Classifying these tools regarding their tailoring capabilities is complex, as the selected papers present too many different solutions implemented through various methods with different goals, so this classification of tailored dashboards should be seen as a spectrum, allowing the existence of dashboards that mix features of different approaches. However, framing them in distinct categories, allow better understanding regarding existing solutions as well as regarding the current state of the present field.

B. WHICH METHODS HAVE BEEN APPLIED TO SUPPORT TAILORING CAPABILITIES WITHIN THE DASHBOARDS' DOMAIN?

This research question is tightly related to RQ1. In the end, the selected tailoring process narrows the potential methods to accomplish it. As shown in the first research question, the most common type of tailored dashboards are customizable dashboards, within the scope of this systematic literature review. Regarding these mechanisms, the preferred method for customizing dashboards is the use of configuration wizards that supports the users' decisions when building her or his customized dashboards without requiring programming skills. For example, [18], [19], [26], [27] use graphical user interfaces that ease the selection of widgets and the data to be displayed, following the workflow shown in Figure 3.

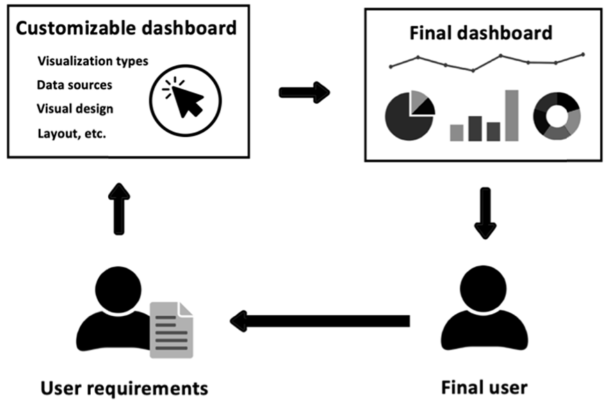

FIGURE 3. Customizable dashboard workflow.

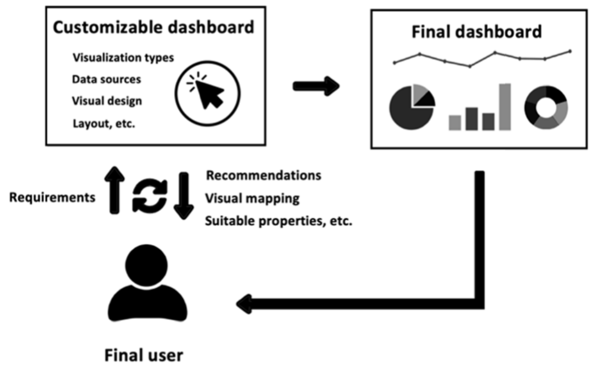

FIGURE 4. Customizable dashboard with system assistance workflow.

Configuration wizards are also the preferred method for customizable dashboards with system assistance, in conjunction with visual mapping methods that ease the selection of visualization types given the data types or structure [37]–[40]. Visual mapping is a transformation that matches data properties with visual marks or visual elements to obtain a suitable visualization for the selected data [41]. Figure 4 shows a generic workflow of how this approach work; users configure their dashboards based on their needs, and the system provides feedback to support the customization process and to obtain more effective dashboards potentially.

Another common method to customize dashboards is to configure them by using structured configuration files [21], [22], [24], which also allow users to tailor their dashboards with a higher level of abstraction (through JSON files, XML files, etc.) through richer and more domain-specific syntaxes than programming languages. Figure 5 shows the workflow of these configuration processes using configuration files, where a series of parameters are set to render a concrete and functional dashboard.

Some works also take advantage of the Software Product Line (SPL) paradigm [23], [25] or Model-Driven Development (MDD) [28]–[30]. In the case of SPL approaches applied to dashboards, they are based on the conception that dashboards are sets of components with optional, alternative,

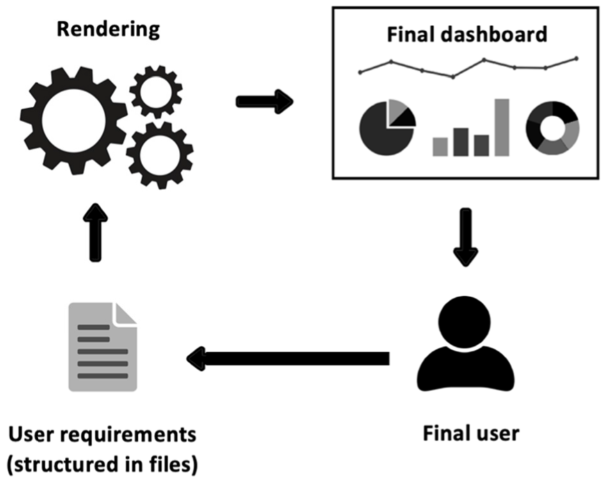

FIGURE 5. Dashboard configuration process involving files.

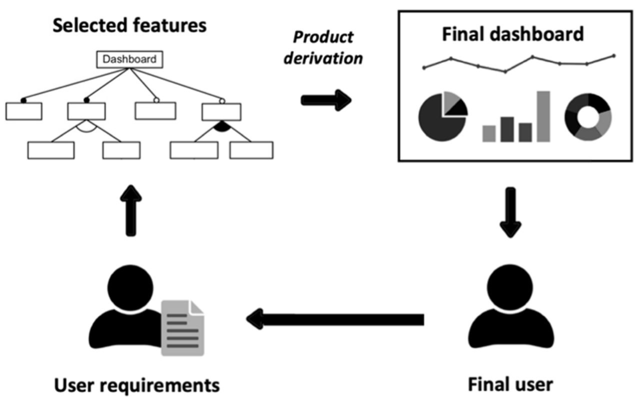

FIGURE 6. The software product line paradigm applied to dashboards.

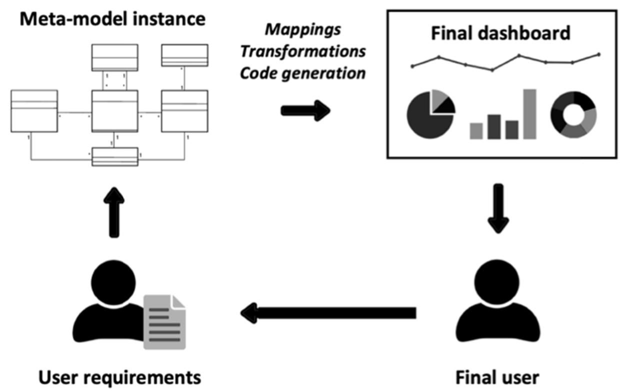

FIGURE 7. The MDD workflow applied to dashboard development.

or mandatory features. These paradigms are used to finally generate a dashboard that fits the previously defined feature model, as shown in Figure 6. Regarding the solution presented in [23], it is worth to mention that an extended version of this work can be found at [42]. This last work did not appear within the selected papers because it was published after the execution of the present SLR, but in subsequent updates, it would replace the previous paper, keeping the most complete and recent version of the study.

In the case of MDD approaches, the logic is similar; code generators are fed with a series of models that describe the dashboard at high-level, for example, as described in [28]. With a set of transformations and mappings, high-level models are transformed into concrete dashboards, through specific description files [28] or by using pre-defined or custom-made templates [30]. Figure 7 illustrates this approach.

In [30], the authors point out the necessity of having pre-defined templates in conjunction with the models, to materialize and generate the dashboards. The approach of using pre-defined templates is also present in [20], where authors propose a framework for creating different templates with different KPIs and goals for small and medium enterprises.

A similar MDD approach is followed in [33], although authors don't explicitly indicate that they followed this paradigm. In this case, to generate the dashboard, a context-aware generator with user, data and visualization models as inputs is in charge of generating the dashboard instances, but the internal features of the dashboard generator are not detailed.

Regarding adaptive solutions, agents are a common method for managing changing requirements [32], [34]. In [34], device cloud platform dashboards are adjusted through cloud agents that adapt themselves to the devices' data models, thus generating remote user interfaces based on the characteristics of the monitored devices. In [32], an analytical system is guided by agents that are present in five communities (gatherers, conciliators, providers, visualizers, and restructurers) to log user interactions with the system and reconfigure the dashboard accordingly.

Other methods found in the selected papers enclose inclusive user modeling for adapting the dashboard interface to the user abilities [31], semantic reasoners for selecting appropriate data sources and compositions [35] and knowledge graphs and ontologies to adapt the dashboards to the target data domain [36].

C. HOW THE PROPOSED SOLUTIONS MANAGE THE DASHBOARD'S REQUIREMENTS?

As introduced before, the necessity of tailored dashboards lies in a large number of existing user profiles that could potentially use these tools. Generic or "one size fits all" dashboards are relatively easier to implement than a specific dashboard for each end-user, because the latter approach is not scalable at all, as the number of users could increment and their requirements evolve. However, "one size fits all" dashboards lack of flexibility, and would only be effective and efficient for specific user profiles [43], because data that is relevant for one user could be irrelevant for another user, and vice versa, and could play different roles in their decision-making processes.

These are the reasons why tailored dashboards should be considered; to fulfill the requirements and necessities of each user profile simultaneously. But managing this high volume of requirements at once (that can even evolve) is not a trivial task.

That is why this question is to be answered; to learn how these solutions manage the requirements associated with each user and how they provide a tailored dashboard accordingly.

The second research question shown that configuration wizards are popular methods to manage these requirements by giving the user the responsibility of building their own dashboard based on their necessities. These solutions allow users to customize their displays while using their dashboards freely, thus performing the tailoring process at user-configuration time (i.e., at run-time, but with the intervention of the user through explicit actions). All solutions found that use a configuration wizard approach [18], [19], [26], [27], [37]–[40] manage individual user requirements by implementing authentication and account management services, associating each user to his/her dashboard configuration persistently. Even some solutions let users build visualizations without logging in to the system [40], in case the users do not need or do not want to save their own configuration for the future. This user management approach is also applied to other solutions found, like in [31], where a user creates an account and fills a questionnaire about her or his abilities to finally access her or his personalized view based on the previous information.

However, these works do no further discuss the storage method nor the possibility of storing different versions of a user dashboard over time, which could be very useful to collect the evolution of the preferences or user behavior.

On the other hand, 10 of the selected works take advantage of structured files or models to hold individual dashboard requirements that finally serve as inputs of generators that provide the configured dashboard instance meeting the original specifications. In this category fall those solutions based on configuration files [21], [22], [24], context models [33], software product lines [23], [25] or model-driven development [28]–[30]. In this case, user requirements are managed ''outside'' the dashboard systems, before their exploitation, and stored within individual files or models.

In the case of [20], no requirement management is explicitly performed, as the pre-defined templates enclose general requirements collected from the gathering and analysis phase, and subsequently, users select the template that fits better their needs. This management method allows better requirement traceability, as requirements are parsed and mapped from the specification to the concrete system features. Also, it allows an easier version control of each file or model, keeping the evolution of individual dashboard requirements.

Also, in the agent-based solution found [34], the system's cloud agent adapts to each device data-model and adds additional cloud agent information markers which act as a user interface description language. These markers are initially provided by the devices' data model but can be modified through the solution's web application. As the paper exposes, the devices' data models are held in XML format, so the requirements management is made through these device models, and therefore falling in the same category as these previous works based in models and structured files.

The other agent-based solution presented in [32] stores and modifies settings according to the users' behavior and their events, thus needing also authentication and account management services to work correctly, as discussed at the beginning of this research question. In this case system's agents are the drivers of the dashboard modifications.

The remaining solutions proposed, on the one hand, a semantic reasoner to infer potentially interesting compositions of data streams in the context of the Internet of Things (IoT) [35]. This solution personalizes the presented information by composing semantically annotated data and visualization services. However, as specified in the research question RQ1, the solution is classified as hybrid, as the paper states that ''sensor and data compositions need to be dynamically visualized, thereby limiting the user input to selecting the preferred visualization method from a system-generated list of meaningful options, taking into account the preferences and characteristics of the current user profile'' [35].

So the dashboard is personalized given the available sensor data (the dashboards' requirements are managed through reasoning processes and knowledge bases), but in the end, users need to select the widgets that will compose their dashboard, although this aspect of the system is no further discussed in the paper.

On the other hand, Santos *et al.* presented in [36] a knowledge graph and indicator ontology approach to automatically generate dashboards in the context of smart cities. The proposed dashboard generator takes as input serialized knowledge graphs and offers different dashboard configurations accordingly. The application allows the customization of the automatically proposed dashboard, given the user freedom to change the configuration before generating it. The dashboard information requirements are managed through knowledge graphs, but the user requirements management when manually customizing the dashboard is not further discussed.

D. CAN THE PROPOSED SOLUTIONS BE TRANSFERRED TO DIFFERENT DOMAINS?

Dashboards are used to exploit datasets that are usually large, but also these datasets come from different domains. This research question tries to answer the flexibility of the solution found regarding their transfer capabilities to another domain. In other words, can the solutions fully support the visualization of data from other domains without significant changes in the original code?

When a solution is focused on a particular data domain, it could be challenging to reuse that same solution for other data domains if the source code is coupled to the original goals, allowing tailoring capabilities, but only within the domain's frontiers.

Some solutions based on configuration wizards, like [38], [39], support the exploitation of datasets from different domains by allowing the users to upload or specify their concrete data sources. These solutions are robust as they can be reutilized for different goals depending on the data domain. The rest of solutions using configuration wizards allow freedom when configuring the dashboards, but only within the original domain (environmental performance [18], micro-services monitoring [19], emergency situations [37], learning analytics [26], physics [27] or economics [40]).

On the other hand, although the solution presented in [22] can be adapted to different monitoring scenarios, it cannot be transferred to other data domains as it relies on API endpoints to monitor resources. In the case of [21], the configuration files allow the specification of the data sources, which can be local as well as remote, and their associated elements, meaning that the solution can be applied to other data domains besides web analytics (which is the domain of the presented prototype). The dashboard generator detailed in [24] also allows the specification of the dataset to be represented, but this approach is mainly employed to develop studies regarding usability guidelines, so the data domain's transferability is not significantly relevant in this case.

Other solutions that take part in the configuration files approach, as discussed in the second research question, are the ones using MDD or SPL approaches. These solutions, which are based on meta-modeling [28]–[30], take advantage of high-abstraction levels and commonalities among the potential products [23], [25] to address the generation of different dashboards. Meta-modelling and domain engineering allow the abstraction of the dashboards' features, improving reusability of core assets and thus, making it possible to transfer the solutions to other data domains without significant efforts.

The dashboard presented in [31] is also tightly coupled to its original domain, as the adaptation of the dashboard is focused on the user physical abilities. The same is true for [20]; although alternative templates can be chosen to visualize different data aspects, they are always related to business intelligence (sales, human resources, overall equipment effectiveness, etc.). The template approach can be taken, of course, to address other data domains, but, new templates should be developed for each target domain to accomplish this "domain transfer." In the case of [36], the solution employs a knowledge graph and indicator ontologies to generate personalized dashboards; the ontologies used are related to the Smart City context, so, to transfer this methodology to other domains, ontologies related to them should be employed.

Some of the works are focused on sensor monitoring [35] and device clouds [34]. The methodologies employed in the papers mentioned above (semantic reasoners and multi-agent systems, respectively) could be reused for other domains, but in the end, the dashboard solutions would need to be built from zero to adapt them to new domains.

The remaining works, on the one hand, use agents to restructure dynamically a dashboard based on user behavior. This adaptive process is not coupled to the data domain, as there are a specific community of agents (called gatherers) that are responsible for collecting the data from different sources [32], suggesting that their task is to gather data no matter its domain. Finally, in [33], a dashboard generator fed with the user, visualization, and analysis scenario models is presented in the context of learning analytics. The user and visualization models are more generic and focused on the users' preferences, experience, goals, visualization purposes, etc., allowing their reuse on other data domains. However, the analysis scenario model is more coupled to the learning analytics domain, mentioning learning objectives, pedagogical context, fields of education, etc., so it could not be reused for domains outside the learning analytics context.

As a clarification, it is worth to state that every methodology employed in the selected papers could be applied to develop dashboards in different data domains. However, the purpose of this research question is to identify the most flexible and powerful solutions regarding their abstraction and, therefore, their potential reuse to other domains in an automatized manner (i.e., avoiding to develop the same solution for new domains manually).

E. HAS ANY ARTIFICIAL INTELLIGENCE APPROACH BEEN APPLIED TO THE DASHBOARDS' TAILORING PROCESSES AND, IF APPLICABLE, HOW THESE APPROACHES HAVE BEEN INVOLVED IN THE DASHBOARDS' TAILORING PROCESSES?

Again, dashboards deal with lots of data and requirements, and even generative approaches based on configuration files or generators still need from manual configuration through high-level languages or domain-specific languages. A similar issue arises from configuration wizards; in the end, users need, through actions, to specify requirements that are not always clear for themselves.

Using methods that involve artificial intelligence (AI) algorithms to manage the dashboards requirements could lead to more accurate dashboard configurations and decrease the consumed resources during the requirement elicitation phases, as requirements could be automatically inferred by the AI algorithm. With AI, systems can use algorithms to learn patterns from data and apply inference to predict future values. This approach would be potentially beneficial in the domain of tailored dashboards because user preferences could be inferred from behavioral data, context, or any other factor.

Only a few works have applied or mentioned AI when presenting their dashboard solutions. In [32], the Apriori algorithm [44] is used to compute association rules, which is a technique from the data mining field. This solution takes advantage of "pairs of events that have happened in sequence" that fed the Apriori algorithm to obtain a set of if-then rules that will be used to restructure the dashboard in terms of the presented data and visualization types employed. In a study referencing those mentioned above [45], the same authors specify that their solution also supports the restructuration of the dashboards through other methods, like Markov chains or top-k queries, but they don't detail these processes.

Also, in [35], a semantic EYE reasoner is employed to discover potentially interesting data compositions through a knowledge base and semantically annotated visualization and data services. The use of semantic reasoners allows the inference of consequences from facts, enabling in this case, "the detection of complex events that previously would have remained undetected" [35]. However, no details about the implementation of the reasoner are addressed in this work.

Other papers mention the possibility of introducing AI techniques, like [24], to rate the generated dashboards through classification algorithms, but authors state that is out of the scope of the paper and refer to [46] as an inspiration. There is also a work that mentions inference [33] to provide a suitable dashboard given the context, user description, and analysis scenario, although no further details are given nor the inference method named

F. HOW MATURE ARE TAILORED DASHBOARDS REGARDING THEIR EVALUATION?

The proposed dashboard solutions are functional regarding their tailoring capabilities, but the maturity of these dashboards regarding their usability is essential to demonstrate if tailoring the dashboards is beneficial for the final users.

In [18], focus groups, pre- and post-study interviews were employed to test the perceived usability and impact of the customizable dashboards. Five experts were in charge of testing the prototype, and subsequently, 13 participants tested the final prototype. Issues regarding the solution involved the configuration process, the interface, and the diversity of available widgets to include in each dashboard, meaning that users needed more components to satisfy their concrete requirements.

In the case of [19], a combined survey and interview was performed to obtain requirements regarding micro-service monitoring. A total of 15 participants were involved, and the gathered information was used to define the main requirements of the customizable dashboard, but no further usability testing was performed regarding the finally implemented dashboard solution.

In [37], it is mentioned that "first evaluations with users from the domain have already shown that this solution could successfully address the problem of information overload," but no details about the evaluation methods nor detailed results are given.

The pre-defined templates-based solution presented in [20] was evaluated during 6-9 months in 40 different small and medium enterprises (SMEs) and evaluated the implemented dashboards' capabilities through [47], obtaining good results regarding dashboard layout, design, presentation, alerting, analysis, KPIs, etc. Also, "25% of SMEs suggested to change some types of graph or chart and changing some layouts and colors", possibly needing more customizable elements.

The two model-driven solutions regarding semantic approaches [28], [29] also mentioned user testing and claiming that the feedback shown the relevance of the semantic description language to adapt their dashboards easily. On the other hand, in [29], two users were considered for the assessment to test the role-based dashboard generation and provided their KPIs requirements; however, no further details about this evaluations were given.

In [34], the unique evaluation mentioned that addresses user experience shows that it takes less time for a user to find device commands through the custom user interfaces described in that work. However, no details about the evaluation sample nor methodologies are provided.

The dashboard solution focused on novices presented in [38] is complemented with a detailed usability study to validate their approach and to examine how novice users create dashboards. Fifteen users (7 novice users and 8 BI dashboards experts) participated in the study at a usability lab, where they were interviewed, recorded and asked to complete a series of tasks with the dashboard solution following the think-aloud protocol. The findings shown that novices ranked better the dashboard regarding utility, functionality, ease of use, and overall satisfaction, and expressed the intuitiveness of the dashboard. Experts, on the other hand, requested extra functionalities. The authors then provide a series of additional guidelines when designing visualization systems for novice users based on the results, which can be found in [38].

In [39], an insight-based evaluation is employed to test the validity of the presented model. Six participants not skilled in visual data exploration were asked to do an unguided exploration of a dataset. Participants were asked to complete a survey focusing on insight-based metrics [48] complemented with a demographic survey. The study shown that "non-default, less familiar settings for expressive richness are more likely to lead to incorrect statements."

The solution described in [26] performed a usability test through the SUS questionnaire [49] and other open questions. Twelve participants were asked to complete a series of tasks using the DDART system (7 users performed the experiment remotely and 5 with the presence of a researcher). The general usability using the SUS scale was 53.93 for the remote group and 54.50 for the assisted group. They also tested the ease of use of the dashboard by analyzing the success ratio, average time, efficiency and average invalid operations ratio when crafting indicators to gain insights about the difficulty of this feature; results shown that the assisted group performed better than the remote group.

Finally, the dashboard presented in [40] was also tested to obtain information about the usefulness of the solution through users' feedback. In this case, more than 60 users tested the solution through half-open scenarios, where users can ask questions and directions are given only under their demand. Satisfaction scores were collected regarding usability, information output, and functionalities like search, detail view of the results, visualizations, and maps; obtaining high percentages of satisfied users.

The solutions presented in [21]–[25], [27], [30]–[33], [35], [36], did not mention any formal testing regarding end-users' perceptions about the dashboard solutions, mentioning these evaluations as future work. Some of these proposed tools were tested in real-world scenarios to prove their applicability or functionalities, but this research question is focused on user perceptions and experiences on the solutions

VI. DISCUSSION

A variety of works have been retrieved regarding tailoring capabilities within the dashboards' context. Through this literature review, it has been possible to answer questions about the capacities and approaches taken to build tailored dashboards through the existing solutions found in the literature.

It is clear that dashboards can be extremely powerful tools if leveraged; they can support decision-making processes, motivate, persuade, and even make data memorable if properly designed [50]. However, as introduced, a large number of potential users and their large number of individual requirements makes ''one size fits all'' approaches only effective for some profiles, primarily because one size does not fit all for tasks involving cognitive processes; users are influenced by their experiences, their biases, their individual preferences, etc., [43]. Different people could see the same dashboard with the same data and reach different insights as they could be driven by different goals. This cannot be overlooked because people could be missing relevant data for their decision-making processes if the dashboard is not correctly configured for them. What also comes into play are users' abilities: a colorful dashboard could be a pleasant, aesthetic and effective dashboard for one person, but could be a nightmare for a person with eye diseases [51], [52].

For all these reasons, dashboards should include mechanisms to allow tailor-made solutions for individual users without requiring large amounts of resources (making a dashboard from scratch for every potential user is not an efficient option). The existing literature has been analyzed to find how these tailoring processes have been addressed before and to understand the current research context in this area.

Accurately, 23 solutions that addressed the necessity of customizing, personalizing, adapting, etc. dashboards were retrieved. The retrieved solutions address this challenge through very different approaches. The first three research questions had the goal of identifying the technical features of the retrieved solutions. These research questions allowed to distinguish between tailored dashboards by classifying them through technical dimensions. While some solutions let users customize their displays manually [18]–[27] or with assistance [37]–[40], other personalized dashboards through implicit requirements like goals, roles, target data, etc., [28]–[31], in some cases letting users customize the personalized display on demand [34]–[36], the remaining adapted the dashboards in real-time based on user behavior [32], [33].

Customizable solutions address individual requirements by directly asking the user to design their own dashboard without requiring programming skills; by either using graphical user interfaces [18], [19], [26], [27], [37]–[40] or high-level configuration files [21]–[25], [28]–[30] that can abstract the technical and complex details of the dashboard implementation. This approach partially delegates the dashboard design and composition responsibility to the users, which lead to a decrease in development time. But these solutions come with a significant disadvantage: users do not always know what is good for them [7], so they can build ineffective dashboard solutions unwillingly.

This issue can be addressed through assisted customization processes, as found in [37]–[40]. These approaches give freedom to the users regarding their dashboards composition, but also help them with design decisions and charts selection through methods like visual mapping. Another approach is to personalize dashboards by extracting dashboard requirements implicitly from the users [28]–[31].

Hybrid solutions also seem to address these caveats by taking into account that users do not always know what the best for them or their goals is, thus requiring to add a degree of personalization that can materialize implicit requirements. But forcing users to stick to a ''personalized'' solution that makes them uncomfortable is counterproductive, so customizability options should be available if a user feels that she needs to change something. Also, it is interesting to take into account an adaptive dimension to consider the users' behavior evolution because what could seem the best configuration at some point of time could become ineffective over time, as users are involved in new experiences that could change their goals and even improve their visualization literacy and knowledge.

However, relevant questions regarding self-adaptive solutions involve how often should be the dashboard updated to display a new configuration or when it is considered that a requirement has evolved enough and, therefore, the dashboard needs a new configuration. Works addressing adaptive solutions have almost no allusions regarding this concern [32], [33]. In [33], authors state that the adaptation is made on-demand on their proof of concept dashboard, but they don't mention this issue. In [32], [45], the authors suggest that the restructuring period is previously set in each restructurer agents' agendas, but they don't identify or test the implications of these restructuration periods. Adaptation time or adaptation triggers are relevant factors to address when using this approach, because continually changing the user interface could annoy users [53] and be counterproductive, despite the potential benefits of the adaptation.

One of the limitations of the retrieved solutions is that they are very specific to the domain to which they were designed for, as exposed in RQ4. An ideal solution would be valid for every data domain and context, but the vast number of varying features these tools can have increased the complexity of creating a suitable dashboard for every domain and context. There are interesting approaches that tackle tailored dashboards from an abstract point of view, proposing generic solutions that are instantiated to fit into concrete requirements. For instance, model-driven development [28]–[30] and domain engineering paradigms [23], [25] aim at extracting commonalities and shared properties from instances of dashboard systems to foster reusability and decrease the development time. Dealing with domain transferability seems to be easier when a generic point of view of the problem has been established, as it can be seen in [23], [25], [28]–[30], where instantiated dashboards can be adapted to fit into other requirements, domains and contexts without modifying high-level, abstract models.

The answer to RQ5 revealed that artificial intelligence (AI) mechanisms are not leveraged, which could be useful to infer user requirements. Only one work exposed the application of a data mining technique to their dashboard proposal. However, although potentially beneficial, AI approaches present challenges, like the gathering process of significant data to build models. It is crucial to implement collecting mechanisms to store user behavior and their implicit/explicit preferences. But before implementing these mechanisms, relevant users' aspects and factors that can influence their user experience must be identified and backed up by previous studies about perception, to avoid an arbitrary selection of factors that could skew the AI models' outcomes.

Regarding this application, solutions based in structured files to describe a dashboard's features, like in [21]–[25], [28]–[30], [33], provide a good basis for implementing AI solutions because AI algorithms are easier to handle if their inputs are already structured. AI models could be useful to detect patterns or clusters of users regarding dashboard configurations [54]. Artificial intelligence is currently identified as a potentially beneficial method to recommend suitable settings of single information visualizations given different factors, like the target data, user behavior, etc., [55], [56]; but dashboards, where several information visualizations can be displayed and can even hold linked views, are not mentioned in these works.

Finally, there is a lack of user testing regarding the developed solutions. As exposed in RQ6, the solutions were tested regarding their functionality, but few works also included testing regarding user experience and insight delivery. Formal testing is essential in this kind of solutions because it can expose the actual usefulness of tailoring capabilities in terms of usability and knowledge generation, thus helping to improve the tailoring mechanisms and enhance decision-making processes.

This systematic literature review exposed a wide range of available approaches to tackle tailored dashboards. Choosing a proper approach depends, of course, on the application context, the audience, the data, and the available resources for the development of tailored dashboards. Experts could demand fine-grained features, but they can build their own dashboards without assistance given their visualization literacy. Novices could require system support for composing a dashboard, or even a personalized display already designed to match their requirements. Some users could request contextual information about the presented data if their knowledge about the data domain is limited. And so on. What is clear after conducting the present SLR is that one size does not fit all when talking about dashboards, but pursuing generic solutions that can be derived to match different contexts might be a proper path to follow.

VII. THREATS TO VALIDITY

This kind of reviews can be influenced by a series of limitations. One of these limitations is the authors' bias regarding the whole data extraction. As exposed in previous sections, quality criteria were employed to reduce the effects of bias in the inclusion phase of the SLR. The three authors were involved in the review planning to identify and avoid any early issues regarding the study design. Moreover, the first author was the primary reviewer, while the last two authors reproduced each SLR phase to ensure the validity of the results taking into account different perspectives.

Also, different resources with the outcomes of each step are provided to make the whole process reproducible.

Although following a systematic, well-defined protocol, it is not guaranteed that all the relevant works about this field are retrieved. Regarding the search medium, the most relevant electronic databases in the field of computer science were included. The exclusion of Google Scholar from this review is justified by the necessity of considering only databases that index quality contrasted contents. Also, to include the maximum quantity of representative terms about the tailored dashboards, synonyms, and related terms were identified, and the results of preliminary search strings were evaluated to analyze if the retrieved data were relevant for the scope of this literature review. Through this iterative process, the query string was refined to ensure useful and precise data extraction.

One of the main limitations regarding the field in which this SLR is framed is that several dashboard solutions are commercial solutions. Thus no public research works regarding their technical features or the methodologies used are available. Despite this issue, enough relevant works for answering the considered research questions were retrieved.

Lastly, to ensure that the whole process is traceable and reproducible, all the materials, partial results, checklists, etc., have been made available through public repositories.

VIII. CONCLUSION

A systematic literature review (SLR) has been conducted to analyze previous works that address tailoring capabilities and mechanisms regarding information dashboards. This SLR addresses relevant aspects regarding these solutions, such as the applied methodologies, dashboard requirements management, domain transferability, artificial intelligence applications, and user experience testing, to identify current issues and challenges, as well as new research paths to enhance tailoring capabilities and consequently, knowledge generation through individualized dashboards.

By performing an SLR, research questions about these dashboard solutions have been answered, providing a comprehensive view of this research field's current state. During the review process, 1034 papers were retrieved from 4 different electronic databases. The number of papers was reduced to 23 after applying an inclusion and exclusion criteria, and a quality assessment to keep only relevant works for the scope of the research. The analysis of the selected papers exposed that tailored dashboards have been tackled through diverse methodologies and mechanisms that enable support for different dashboard configurations without consuming loads of resources and without requiring long development processes as compared with the design and implementation of individual dashboards from scratch.

This SLR provides a foundation in terms of existing approaches for tailoring information dashboards. Information dashboards have become key tools when dealing with data, and there are a lot of challenges regarding their development and design; one of these challenges is their adaptation to different contexts, domains and users [1]. This review can support researchers and developers in choosing a proper mechanism to develop tailored dashboards. Also, the identified challenges can open new research paths. Moreover, the obtained results can be applied to improve dashboard solutions lacking flexibility.

Future work will involve the application of the gained knowledge to propose new tailored dashboard solutions that address the challenges and issues found through this review. Based on the presented analysis, one of the most promising research avenues is the application of AI paradigms to automatize the design and development of dashboards. This application will not only involve the selection and development of tailoring mechanisms but also the study and classification of users to make these automatic tailoring processes useful and effective.

REFERENCES

[1] A. Sarikaya, M. Correll, L. Bartram, M. Tory, and D. Fisher, "What do we talk about when we talk about dashboards?" *IEEE Trans. Vis. Comput. Graph.*, vol. 25, no. 1, pp. 682–692, Jan. 2019.

[2] S. Few, *Information Dashboard Design*. Sebastopol, CA, USA: O'Reilly Media, 2006.

[3] S. Wexler, J. Shaffer, and A. Cotgreave, *The Big Book of Dashboards: Visualizing Your Data Using Real-World Business Scenarios*. Hoboken, NJ, USA: Wiley, 2017.

[4] J. Hullman, E. Adar, and P. Shah, "The impact of social information on visual judgments," in *Proc. ACM SIGCHI Conf. Hum. Factors Comput. Syst.*, 2011, pp. 1461–1470.

[5] Y.-S. Kim, K. Reinecke, and J. Hullman, "Data through others 'eyes: The impact of visualizing others' expectations on visualization interpretation," *IEEE Trans. Vis. Comput. Graphics*, vol. 24, no. 1, pp. 760–769, Jan. 2018.

[6] D. A. Norman and S. W. Draper, *User Centered System Design: New Perspectives on Human-computer Interaction*. Boca Raton, FL, USA: CRC Press, 1986.

[7] L. Padilla. (2018). *How do we Know When a Visualization is Good? Perspectives From a Cognitive Scientist*. [Online]. Available: https://medium.com/multiple-views-visualization-research-explained/how-do-we-know-when-a-visualization-is-good-c894b5194b62

[8] B. Kitchenham, "Procedures for performing systematic reviews," Dept. Comput. Sci., Keele Univ., Keele, U.K., Tech. Rep. 0400011T.1, 2004, pp. 1–26, vol. 33.

[9] B. Kitchenham and S. Charters, "Guidelines for performing systematic literature reviews in software engineering," School Comput. Sci. Math., Keele Univ., Keele, U.K., Tech. Rep. EBSE-2007-01, 2007. [Online]. Available: https://goo.gl/L1VHcw.

[10] B. A. Kitchenham, D. Budgen, and O. P. Brereton, "Using mapping studies as the basis for further research—A participant-observer case study," *Inf. Softw. Technol.*, vol. 53, no. 6, pp. 638–651, 2011.

[11] A. Vázquez-Ingelmo, F. J. García-Peñalvo, and R. Therón, "Tailored information dashboards: A systematic mapping of the literature," presented at the Interacción, Donostia, Spain, 2019.

[12] B. Napoleão, K. R. Felizardo, É. F. de Souza, and N. L. Vijaykumar, "Practical similarities and differences between systematic literature reviews and systematic mappings: A tertiary study," in *Proc. SEKE*, 2017, pp. 85–90.

[13] M. Petticrew and H. Roberts, *Systematic Reviews in the Social Sciences: A Practical Guide*. Hoboken, NJ, USA: Wiley, 2008.

[14] M. Cutts, *Oxford Guide to Plain English*. Oxford, U.K.: OUP Oxford, 2013.

[15] R. R. Prasath, "Learning age and gender using co-occurrence of non-dictionary words from stylistic variations," in *Proc. Int. Conf. Rough Sets Current Trends Comput.* Berlin, Germany: Springer, 2010, pp. 544–550.

[16] D. Moher, A. Liberati, J. Tetzlaff, D. G. Altman, and T. P. Group, "Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement," *PLoS Med.*, vol. 6, no. 7, 2009, Art. no. e1000097.

[17] A. V. Ingelmo. (2019). *Resources for the Paper, Information Dashboards and Tailoring Capabilities—A Systematic Literature Review*. [Online]. Available: https://zenodo.org/record/3246043-.XTl15ZMzZ24

[18] D. Filonik, R. Medland, M. Foth, and M. Rittenbruch, "A customisable dashboard display for environmental performance visualisations," in *Persuasive Technology*. Berlin, Germany: Springer, 2013, pp. 51–62.

[19] B. Mayer and R. Weinreich, "A dashboard for microservice monitoring and management," in *Proc. IEEE Int. Conf. Softw. Archit. Workshops (ICSAW)*, Gothenburg, Sweden, Apr. 2017, pp. 66–69.

[20] W. Noonpakdee, T. Khunkornsiri, A. Phothichai, and K. Danaisawat, "A framework for analyzing and developing dashboard templates for small and medium enterprises," in *Proc. IEEE 5th Int. Conf. Ind. Eng. Appl. (ICIEA)*, Apr. 2018, pp. 479–483.

[21] K. Kumar, J. Bose, and S. K. Soni, "A generic visualization framework based on a data driven approach for the analytics data," in *Proc. 14th IEEE India Council Int. Conf. (INDICON)*, Dec. 2017, pp. 1–6.

[22] A. Cardoso, C. J. V. Teixeira, and J. S. Pinto, "Architecture for highly configurable dashboards for operations monitoring and support," *Stud. Inform. Control*, vol. 27, no. 3, pp. 319–330, 2018.

[23] A. Vázquez-Ingelmo, F. J. García-Peñalvo, and R. Therón, "Domain engineering for generating dashboards to analyze employment and employability in the academic context," presented at the 6th Int. Conf. Technol. Ecosyst. Enhancing Multiculturality, Salamanca, Spain, 2018.

[24] O. Pastushenko, J. Hynek, and T. Hruška, "Generation of test samples for construction of dashboard design guidelines: Impact of color on layout balance," in *Proc. World Conf. Inf. Syst. Technol.* Cham, Switzerland: Springer, 2018, pp. 980–990.

[25] I. Logre, S. Mosser, P. Collet, and M. Riveill, "Sensor data visualisation: A composition-based approach to support domain variability," in *Proc. Eur. Conf. Model. Found. Appl.* Cham, Switzerland: Springer, 2014, pp. 101–116.

[26] C. Michel, E. Lavoué, S. George, and M. Ji, "Supporting awareness and self-regulation in project-based learning through personalized dashboards," *Int. J. Technol. Enhanced Learn.*, vol. 9, nos. 2–3, pp. 204–226, 2017.

[27] G. L. Miotto, L. Magnoni, and J. E. Sloper, "The TDAQ Analytics Dashboard: A real-time Web application for the ATLAS TDAQ control infrastructure," *J. Phys., Conf. Ser.*, vol. 331, no. 2, 2011, Art. no. 022019.

[28] M. Kintz, "A semantic dashboard description language for a process-oriented dashboard design methodology," in *Proc. 2nd Int. Workshop Model-Based Interact. Ubiquitous Syst. (MODIQUITOUS)*, Copenhagen, Denmark, vol. 947, 2012, pp. 31–36.

[29] M. Kintz, M. Kochanowski, and F. Koetter, "Creating user-specific business process monitoring dashboards with a model-driven approach," in *Proc. MODELSWARD*, 2017, pp. 353–361.

[30] T. Palpanas, P. Chowdhary, G. Mihaila, and F. Pinel, "Integrated model-driven dashboard development," *Inf. Syst. Frontiers*, vol. 9, nos. 2–3, pp. 195–208, 2007.

[31] S. Arjun, "Personalizing data visualization and interaction," in *Proc. ACM Adjunct Publication 26th Conf. User Modeling, Adaptation Personalization*, 2018, pp. 199–202.
[32] O. Belo, P. Rodrigues, R. Barros, and H. Correia, "Restructuring dynamically analytical dashboards based on usage profiles," in *Proc. Int. Symp. Methodol. Intell. Syst.* Cham, Switzerland: Springer, 2014, pp. 445–455.
[33] I. Dabbebi, S. Iksal, J.-M. Gilliot, M. May, and S. Garlatti, "Towards adaptive dashboards for learning analytic: An approach for conceptual design and implementation," in *Proc. 9th Int. Conf. Comput. Supported Edu. (CSEDU)*, Porto, Portugal, vol. 1, 2017, pp. 120–131.
[34] S. Radovanović, B. Majstorović, S. Kukolj, and M. Z. Bjelica, "Device cloud platform with customizable remote user interfaces," in *Proc. IEEE 4th Int. Conf. Consum. Electron. Berlin (ICCE-Berlin)*, Sep. 2014, pp. 202–204.
[35] S. Van Hoecke, C. Huys, O. Janssens, R. Verborgh, and R. Van de Walle, "Dynamic monitoring dashboards through composition of Web and visualization services," in *Internet of Things. IoT Infrastructures*. Cham, Switzerland: Springer, 2015, pp. 465–474.
[36] H. Santos, V. Dantas, V. Furtado, P. Pinheiro, and D. L. McGuinness, "From data to city indicators: A knowledge graph for supporting automatic generation of dashboards," in *Proc. Eur. Semantic Web Conf.* Cham, Switzerland: Springer, 2017, pp. 94–108.
[37] B. S. Nascimento, A. S. Vivacqua, and M. R. S. Borges, "A flexible architecture for selection and visualization of information in emergency situations," in *Proc. IEEE Int. Conf. Syst., Man, Cybern. (SMC)*, Oct. 2016, pp. 3317–3322.
[38] M. Elias and A. Bezerianos, "Exploration views: Understanding dashboard creation and customization for visualization novices," in *Proc. IFIP Conf. Hum.-Comput. Interact.* Berlin, Germany: Springer, 2011, pp. 274–291.
[39] M. A. Yalçın, N. Elmqvist, and B. B. Bederson, "Keshif: Rapid and expressive tabular data exploration for novices," *IEEE Trans. Vis. Comput. Graphics*, vol. 24, no. 8, pp. 2339–2352, Aug. 2018.
[40] G. Petasis, A. Triantafillou, and E. Karstens, "YourDataStories: Transparency and corruption fighting through data interlinking and visual exploration," in *Proc. Int. Conf. Internet Sci.* Cham, Switzerland: Springer, 2017, pp. 95–108.
[41] E. H.-H. Chi, "A taxonomy of visualization techniques using the data state reference model," in *Proc. IEEE Symp. Inf. Vis. (INFOVIS)*, Oct. 2000, pp. 69–75.
[42] A. Vázquez-Ingelmo, F. J. García-Peñalvo, and R. Therón, "Taking advantage of the software product line paradigm to generate customized user interfaces for decision-making processes: A case study on university employability," *PeerJ Comput. Sci.*, vol. 5, p. e203, Jul. 2019.
[43] S. D. Teasley, "Student facing dashboards: One size fits all?" *Technol., Knowl. Learn.*, vol. 22, no. 3, pp. 377–384, 2017.
[44] R. Agrawal and R. Srikant, "Fast algorithms for mining association rules," in *Proc. 20th Int. Conf. Very Large Data Bases, VLDB*, vol. 1215, 1994, pp. 487–499.
[45] O. Belo, H. Correia, P. Rodrigues, and R. Barros, "A personalization system for data visualization platforms," in *Proc. IEEE 6th Int. Conf. Innov. Comput. Technol. (INTECH)*, Aug. 2016, pp. 162–167.
[46] K. Reinecke, T. Yeh, L. Miratrix, R. Mardiko, Y. Zhao, J. Liu, and K. Z. Gajos, "Predicting users' first impressions of website aesthetics with a quantification of perceived visual complexity and colorfulness," in *Proc. ACM SIGCHI Conf. Hum. Factors Comput. Syst.*, 2013, pp. 2049–2058.
[47] M. Dyczkowski, J. Korczak, and H. Dudycz, "Multi-criteria evaluation of the intelligent dashboard for SME managers based on scorecard framework," in *Proc. IEEE Federated Conf. Comput. Sci. Inf. Syst.*, Sep. 2014, pp. 1147–1155.
[48] P. Saraiya, C. North, and K. Duca, "An insight-based methodology for evaluating bioinformatics visualizations," *IEEE Trans. Vis. Comput. Graphics*, vol. 11, no. 4, pp. 443–456, Jul. 2005.
[49] J. Sauro, *A Practical Guide to the System Usability Scale: Background, Benchmarks & Best Practices*. Scotts Valley, CA, USA: Createspace Independent, 2011.
[50] S. Berinato, *Good Charts: The HBR Guide to Making Smarter, More Persuasive Data Visualizations*. Brighton, MA, USA: Harvard Business Review, 2016.
[51] S. Silva, B. S. Santos, and J. Madeira, "Using color in visualization: A survey," *Comput. Graph.*, vol. 35, no. 2, pp. 320–333, 2011.
[52] T. Zuk, L. Schlesier, P. Neumann, M. S. Hancock, and S. Carpendale, "Heuristics for information visualization evaluation," in *Proc. ACM AVI Workshop BEyond Time Errors, Novel Eval. Methods Inf. Vis.*, 2006, pp. 1–6.
[53] M. Zavyiboroda. (2018). *Why User Interface Changes Annoy People & How to Handle it*. [Online]. Available: https://speckyboy.com/annoying-ui-changes/
[54] J. Cruz-Benito, A. Vázquez-Ingelmo, J. C. Sánchez-Prieto, R. Therón, F. J. García-Peñalvo, and M. Martín-González, "Enabling adaptability in Web forms based on user characteristics detection through A/B testing and machine learning," *IEEE Access*, vol. 6, pp. 2251–2265, 2018.
[55] M. Vartak, S. Huang, T. Siddiqui, S. Madden, and A. Parameswaran, "Towards visualization recommendation systems," *ACM SIGMOD Rec.*, vol. 45, no. 4, pp. 34–39, 2017.
[56] P. Kaur and M. Owonibi, "A review on visualization recommendation strategies," in *Proc. 12th Int. Joint Conf. Comput. Vis., Imag. Comput. Graph. Theory Appl. (VISIGRAPP)*, vol. 3, 2017, pp. 266–273.

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