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Tailored information dashboards: A systematic mapping of the literature

Andrea Vázquez-Ingelmo
GRIAL Research Group,
Department of Computer Science.
University of Salamanca
Salamanca, Spain
andreavazquez@usal.es

Francisco José García-Peñalvo
GRIAL Research Group,
Department of Computer Science.
University of Salamanca
Salamanca, Spain
fgarcia@usal.es

Roberto Therón
GRIAL, VisUSAL Research Group, Department of Computer Science.
University of Salamanca
Salamanca, Spain
theron@usal.es

ABSTRACT

Information dashboards are extremely useful tools to exploit knowledge. Dashboards enable users to reach insights and to identify patterns within data at-a-glance. However, dashboards present a series of characteristics and configurations that could not be optimal for every user, thus requiring the modification or variation of its features to fulfill specific user requirements. This variation process is usually referred to as customization, personalization or adaptation, depending on how this variation process is achieved. Given the great number of users and the exponential growth of data sources, tailoring an information dashboard is not a trivial task, as several solutions and configurations could arise. To analyze and understand the current state-of-the-art regarding tailored information dashboards, a systematic mapping has been performed. This mapping focus on answering questions regarding how existing dashboard solutions in the literature manage the customization, personalization and/or adaptation of its elements to produce tailored displays.

KEYWORDS

Dashboards, Information dashboards, Information visualization, Systematic mapping, Literature review, Customization, Personalization, Adaptation

1 INTRODUCTION

The exponential growth of data sources and the relevance that data has nowadays for a majority of essential activities and tasks has consolidated information dashboards as extremely useful tools to reach insights about large datasets and support decision-making. Information dashboards are composed of a series of graphical components and interaction methods that allow visual analysis of datasets to ease the recognition of interesting patterns or relationships among the presented variables.

However, information dashboards face several challenges. Their spread of use among different contexts and the increase of data sophistication turn their design process a complex task. What is more, dashboards are employed by many different users with different profiles, making difficult the suitability of a general dashboard solution, given the variety of potential user requirements. In recent studies, these challenges have been highlighted. Alper et al. conducted a systematic review of several dashboard solutions to characterize them and identify different types of dashboards [1]. The study proved that dashboard solutions are very diverse in terms of design, components, indicators, interaction patterns and, especially, goals. This nature causes the need for creating domain-specific solutions and even user specific solutions, consuming significant time and resources and being very difficult to adapt and reuse them in different contexts. To address these issues, there are user-friendly tools that enable users to create and customize their dashboard without requiring programming skills, like Tableau (https://www.tableau.com/) or Grafana (https://grafana.com/).

But, regarding dashboards, there is an additional issue; users can lack visualization literacy making the *customization* process of a dashboard a tedious and even arbitrary task that could lead to ineffective dashboards as a result [2].

That is why an adaptive dashboard solution could reduce the cost of creating new dashboards and improve the user experience by providing *personalized* views based on different factors (user knowledge, context, domain, etc.).

It is necessary, nevertheless, to distinguish between the terms "customized" and "personalized". Customization refers to a user-initiated process to tailor their interfaces, functionalities, contents, etc. to fulfill their requirements, while personalization refers to a system-initiated process that uses information to tailor the aforementioned elements without an explicit user intervention [3]. However, “personalized” and “customized” are often misunderstood as interchangeable terms, being necessary to emphasize their differences.

Given the large amount of content customization and/or personalization possibilities, and the potential misconception of those terms, this paper aims to investigate the existing literature regarding the customization, adaptation and/or personalization of information dashboards, focusing on mapping [4] the collected studies to understand the existing solutions and research lines of this area.

The remainder of this paper is organized as follows. Section 2 outlines the research method followed to perform the systematic mapping. Section 3 describes the data extraction process for analyzing the collected works. Section 4 presents the results of the systematic mapping, finishing with Section 5 where the results are discussed and Section 6, where the work's conclusions are shared.

2 RESEARCH METHOD

This study is based on the guidelines suggested by Kitchenham and Charters [5] for systematic literature studies and the guidelines suggested by Petersen [6] for mapping studies. The mapping process is organized in a series of phases; first, the planning phase, where the main goals and research questions to be answered are defined. Second, the conducting phase, where the search strategy is generated and the selection, assessment and data extraction of the studies are performed. The final stage is the reporting phase, where the results are disseminated.

2.1 Research questions

The research goal of this systematic mapping is to analyze proposed solutions regarding information dashboards' adaptation, personalization or any kind of variation regarding their contents (personalization, customization and adaptation processes will be referred to as "variability processes" to enclose them under the same term).

To do so, this systematic mapping aims to answer the following mapping questions:

- **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?

2.2 Inclusion and exclusion criteria

To discard irrelevant works (in terms of the scope of this paper) from the search results, a set of inclusion criteria (IC) and a set of exclusion criteria (EC) were defined:

- **IC1.** The paper described a dashboard solution (proposal, architecture, software design, model, tool, etc.) **AND**
- **IC2.** The solution was applied to information dashboards (omitting any other kind of "dashboard") **AND**
- **IC3.** The solution supported or addressed 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 were written in English or Spanish **AND**
- **IC6.** The papers were 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 following items refer to the exclusion criteria applied:

- **EC1.** The paper did not describe a dashboard solution (proposal, architecture, software design, model, tool, etc.) **OR**
- **EC2.** The solution was not applied to information dashboards **OR**
- **EC3.** The solution did not support or addressed 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 were not written in English or Spanish **OR**
- **EC6.** The papers were 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

2.3 Search strategy

The first step taken to extract relevant works for this paper was the selection of the employed electronic databases. In this case, four electronic databases were selected: Scopus, Web of Science (WoS), IEEE Xplore and SpringerLink. These databases were chosen according to a set of requirements:

- It is a reference database in the research scope.
- It is a relevant database in the research context of this mapping study.
- It allows using similar search strings to the rest of the selected databases as well as using Boolean operators.

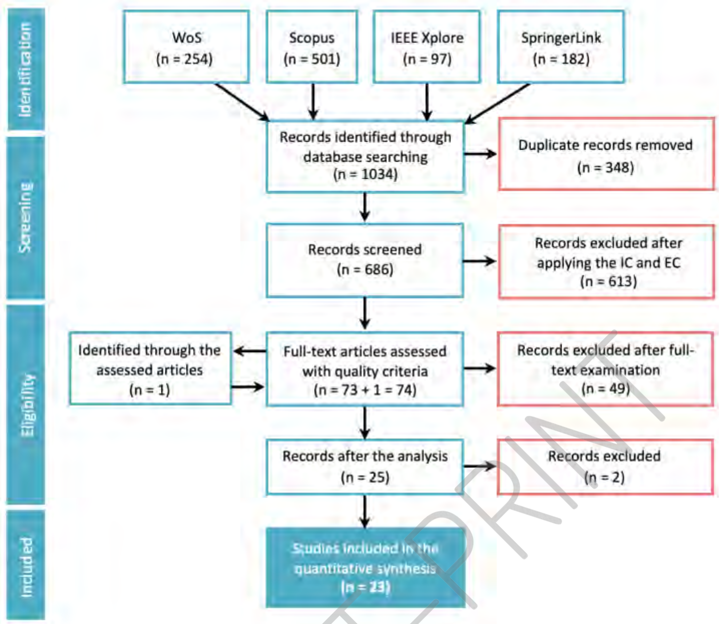

Figure 1: PRISMA flow. Adapted from [7].

Regarding the search terms, it was necessary to enclose any term related to customization, personalization, adaptation, context-awareness, etc. That is why, in addition to the terms above, concepts like flexible and configurable were included.

To include system-initiated processes that can address personalization, terms related to generation, template-based, composition or subject-driven processes were also incorporated. Finally, any work focused on dealing with heterogeneous, diverse, or dynamic stakeholders, users, requirements, tasks, etc. were also included as these circumstances could ask for customization or personalization.

The conjunction of these terms with the "dashboard" concept aims to collect any study addressing variability within the information dashboards' domain. The term "meta-dashboard" was also incorporated to retrieve works seeking to define abstract dashboards that can be used to generate different types of concrete dashboards.

2.4 Search strings

The search strings for each chosen source were defined from the search terms connected by boolean AND / OR / NEAR operators. Moreover, the wildcard (*) was used in Scopus and Web of Science (WoS) to include both 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 a specified number of words at most. This operator is very useful for this research, as the terms "customizable", "personalized", "adaptive", etc. should only refer to the dashboard term. However, it is necessary to explicitly select the number of words that can separate the target terms.

Specifically, 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 executing the same search with different proximity values (5, 7, 10 and 12). Examining 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).

The base structure of the search string (which was adapted to the specific syntax of the electronic databases afterward) was the following:

((meta-dashboard*) **OR**

((dashboard*) NEAR/10 (custom* OR personal* OR adapt* OR flexib* OR config* OR driven OR generat* OR compos* OR template* OR context-aware OR select*)) **OR**

((dashboard*) AND ((heterogeneous OR different OR diverse OR dynamic) NEAR/0 ("requirement*" OR "stakeholder*" OR "user*" OR "need*" OR "task*" OR "necess*")))) **AND NOT**

(car OR vehicle OR automo*)

Some terms belonging to the automotive field were excluded to avoid the retrieval of car dashboards' studies, which are out of the scope of this research.

In the case of SpringerLink, the NEAR operator is not supported, so the AND operator was used. To limit the results, only the records that contained the term "dashboard" in their titles were retrieved.

3 DATA EXTRACTION

To describe the iterative data extraction process followed, the PRISMA statement [7] is used (Figure 1). To accomplish the first stage, the results obtained after applying the search strings were downloaded in CSV (comma-separated values) format, stored in a repository in GitHub [8], and organized in a spreadsheet in Google Sheets (http://bit.ly/2L8GRfY). Next, the title, the abstract and the keywords of each paper were analyzed, and the inclusion and exclusion criteria were applied. Finally, each candidate paper was fully read to decide if it fulfills a quality criterion (i.e., a set of characteristics to ensure that a paper fits in the context of this research). During the analysis, a series of quantitative questions were answered to perform subsequently the analysis.

After the full reading of the works, other relevant papers were identified through their references. Concretely, one paper was added and read in depth too. All the information regarding this stage was organized in a fourth sheet ("Third phase") of the spreadsheet (http://bit.ly/2L8GRfY).

To sum up, 1034 papers were collected once the search strings were applied, of which 254 from WoS, 501 from Scopus, 97 from IEEE Xplore and 182 from SpringerLink.

- After removing duplicates, there were 686 papers maintained.
- Once the criteria were applied to title, abstract and keywords, 73 papers moved into the next phase (10.79% of the unique papers retrieved).
- One paper was added after reading the selected ones, leaving 74 papers for the quality criteria application.
- After applying the quality criteria, 25 papers were selected and thoroughly analyzed. After the analysis, 2 papers were excluded as they did not comply with the IC7 criteria item.
- Finally, a total of 23 papers were analyzed (3.35% of the unique papers retrieved and 31.08% of the full-text assessed papers).

4 SYSTEMATIC MAPPING RESULTS

This section presents the mapping results of the collected records through the search above strategy. A Jupyter notebook (http://jupyter.org) was created to support the analysis process of the raw data [8]. The notebook is based on the work developed by Cruz-Benito http://bit.ly/2tS9JgF.

4.1 MQ1. How many studies were published over the years?

The number of selected papers per year were counted as can be seen in Figure 2.

The results cover from 2011 to 2018, with a work placed in 2007 [9]. A few records were published in 2011 [10; 11], 2012 [12], 2013 [13], 2014 [14-16] and 2016 [17; 18]. However, the majority of records are distributed between 2017 [19-24] and 2018 [25-31], six and seven papers respectively.

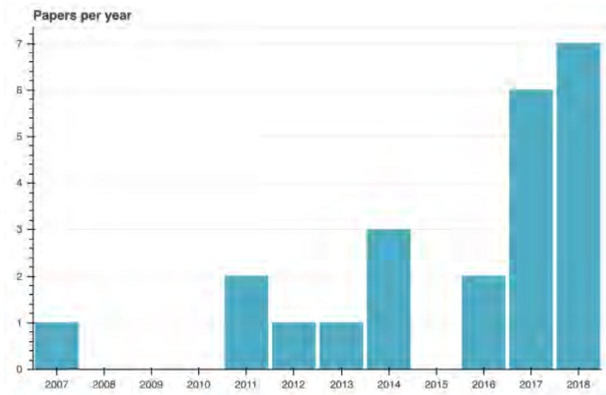

Figure 2: Distribution of papers per year.

4.2 MQ2. Who are the most active authors in the area?

Works published by each author were counted to answer this question. Only one author has more than one record. Kintz presents a model-driven solution for generating dashboards [12; 21], in one case it presents the semantic description language and in the other one it presents an extension to take into account user roles in the dashboards generation process. The rest of the authors appear only once in this mapping study. Table 1 shows all of the authors and their number of papers in the scope of this literature mapping. There are some authors that also had more than one paper related to tailored dashboards, however, they were omitted because of the exclusion criteria EC7, so the most recent and complete paper about their study made it to the final phase.

Table 1. Authors' addressing variability on dashboards.

Author	Total
Kintz M.	2
Arjun S.; Barros R.; Bederson B.B.; Belo O.; Bezerianos A.; Borges M. R. S.; Bose J.; Cardoso A.; Chowdhary P.; Collet P.; Correia H.; Danaisawat K.; Dantas V.; de Walle R .V.; Elias M.; Elmqvist N.; Filonik D.; Foth M.; Furtado V.; García-Peñalvo F. J.; George S.; Hruška T.; Huys C.; Hynek J.; Ines D.; Janssens O.; Jean-Marie G.; Ji M.; Karstens E.; Khunkornsiri T.; Kochanowski M.; Koetter F.; Kukolj S.; Kumar K.; Lavoue E.; Logre I.; Madeth M.; Magnoni L.; Majstorović B.; Mayer B.; McGuinness D. L.; Medland R.; Michel C.; Mihaila G.; Miotto G. L.; Mosser S.; Nascimento B. S.; Noonpakdee W.; Palpanas T.; Pastushenko O.; Petasis G.; Phothichai A.; Pinel F.; Pinheiro P.; Radovanović S.; Rittenbruch M.; Riveill M.; Rodrigues P.; Santos H.; Sebastien I.; Serge G.; Sloper J. E.; Soni S. K.; Sousa Pinto J.; Therón R.; Triantafillou A.; Van Hoecke S.; Vázquez-Ingelmo, A.; Verborgh R.; Vieira Teixeira C. J.; Vivacqua A. S.; Weinreich R.; Yalcin M. A.	1

4.3 MQ3. What type of papers has been published?

Each consulted electronic database provides the metadata to answer this mapping question. According to the inclusion and exclusion criteria, only papers involved in a peer review process (either in journals, conferences, books or workshops) are included. The complete list of types regarding the analyzed records can be consulted in Table 2.

Table 2. Papers grouped by type of publication

Type	Total	Papers
Article	4	[26] [29] [22] [9]
Conference paper	19	[13] [19] [17] [25] [20] [12] [21] [16] [27] [18] [11] [23] [28] [30] [14] [15] [10] [24] [31]

4.4 MQ4. To which contexts have been the variability processes applied?

Dashboards can be used in any domain; the only requirement is to have enough data to visualize. Regarding customizable and/or personalized dashboards, it can be seen that Business Intelligence (BI) is the most common application domain (Figure 3), followed by the Internet of Things (IoT), Learning Analytics (LA), services monitoring and social science domains.

Table 3. Papers grouped by target domain

Domain	Total	Papers
Business Intelligence	8	[9] [10] [12] [14] [21] [23] [25]
IoT	2	[16] [18]
Learning Analytics	2	[22] [24]
Services monitoring	2	[20] [26]
Disaster situations	1	[30]
Economics	1	[31]
Emergency management	1	[17]
Energy monitoring	1	[13]
Generic	1	[29]
Interface evaluation	1	[28]
Microservices monitoring	1	[19]
Physics	1	[11]
Sensor monitoring	1	[15]
Social sciences	1	[27]

4.5 MQ5. Which are the factors that condition the dashboards' variability process?

One of the first steps to perform a variability process is to determine the factors that will condition the dashboards' variation, i.e., the inputs of the customization and/or personalization stage. The majority of the included papers make use of the user preferences as input to modify the dashboard appearance and functionality (Table 4).

Table 4. Papers grouped by variability factors

Factor	Total	Papers
User preferences	15	[13] [19] [17] [25] [20] [26] [27] [11] [23] [28] [29] [15] [22] [10] [18]
Data structure	4	[23] [29] [24] [31]
Business process	3	[12] [9] [21]
User role	2	[21] [9]
Design guidelines	2	[25] [28]
Usage profiles	1	[14]
Data sources	2	[16] [18]
Goals	2	[12] [21]
User description	1	[24]
Analysis scenario	1	[24]
User abilities	1	[30]

4.6 MQ6. What is the target of the variability process?

Variability processes have a target that will change or be modified after the variation has been accomplished. In the case of dashboards, several elements could be the target of the variation: visualization types, layout, displayed data, visual design (i.e., color palettes, font sizes, etc.) and even interaction (pan, zoom, etc.) or functionalities (filters, exportation, etc.).

Table 5 lists the different variability targets identified in the included papers.

Table 5. Papers grouped by variability target

Target	Total	Papers

Displayed data	22	[13] [19] [17] [25] [20] [12] [26] [21] [16] [27] [18] [11] [23] [28] [9] [29] [14] [15] [22] [10] [24] [31]
Visualization types	21	[13] [19] [17] [25] [20] [12] [26] [16] [27] [18] [11] [23] [28] [9] [29] [14] [15] [22] [10] [24] [31]
Layout	20	[13] [19] [17] [25] [20] [12] [26] [16] [27] [18] [11] [23] [28] [9] [29] [14] [15] [22] [10] [24]
Functionalities	1	[27]
Visual design	2	[30] [26]
Interaction	2	[30] [12]

4.7 MQ7. At which development stage is the variability achieved?

The modification of dashboard features can be performed at different stages. In this case, four stages were identified: compile-time, run-time, pre-configuration time (i.e. a phase before the creation of the dashboard in which its configuration is defined by the end-user or any other stakeholder) and user-configuration time (i.e. at run-time, but the user is in charge of the configuration of its dashboard).

Pre-configuration and user-configuration seem to be the most preferred stages to customize or personalize the dashboards (Table 6).

Table 6. Papers grouped by variability methods

Stage	Total	Papers
Pre-configuration	9	[9] [12] [15] [21] [23] [25] [26] [27] [28]
User-configuration	8	[10] [11] [13] [17] [19] [20] [22] [31]
Run-time	6	[14] [16] [18] [24] [29] [30]
Compile-time	1	[16]

4.8 MQ8. Which methods have been used for enabling variability?

This mapping question aims at analyzing the methods, techniques, paradigms, etc. used for enabling customization and/or personalization within the dashboards' domain.

A set of methods have been identified through the included papers. The most repeated method consists of configuration wizards, to allow users to tailor their dashboards. Some solutions give extra support to these wizards with visual mapping to ease the selection of proper visualizations given the data structure to be visualized [11; 17; 29; 31]. Other common methods found involve configuration files, agents, software product lines (SPL) and model-driven development. The complete list of methods can be consulted in Table 7.

Table 7. Papers grouped by variability methods

Method	Total	Papers
Configuration wizard	8	[13] [19] [17] [11] [29] [22] [10] [31]
Visual mapping	4	[17] [11] [29] [31]
Configuration files	3	[20] [26] [28]
Model-driven	3	[12] [21] [9]
Agents	2	[16] [14]
SPL	2	[27] [15]
Pre-defined templates	2	[25] [9]
Semantic reasoner	1	[18]
Inclusive user modeling	1	[30]
Context-aware generator	1	[24]
Indicator ontology	1	[23]
Knowledge graphs	1	[23]

4.9 MQ9. How many studies have tested their proposed solutions in real environments?

The last mapping question is regarding the performed tests on the included dashboard solutions.

The majority (13) of the solutions have been tested in real-world scenarios, involving real data and real users, while 6 of the solutions have not been tested with real users or real data (Table 8). There are four solutions that have been partially tested in a real-world scenario, i.e., they have been tested with real data but not with real users, or vice versa.

Table 8. Papers grouped by testing maturity

Tested?	Total	Papers
Yes	13	[10] [11] [13] [15] [16] [17] [18] [21] [24] [25] [29] [30] [31]
No	6	[12] [14] [19] [20] [23] [26]
Partially	4	[9] [22] [27] [28]

5 DISCUSSION

In total, there are 23 papers that present dashboard solutions with tailoring features. However, as the systematic mapping results showed, these solutions are quite miscellaneous.

In [13], 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). This kind of "manual approach" is also used in [10; 19; 22], in which the customizability capacity is based on the possibility of arrange the components of the dashboard through explicit interaction, and even the capacity of crafting custom indicators, as presented in [22]. The same "customizability principles" are present in other papers, with the difference of involving automatized approaches through configuration files [20; 26; 28], models [15; 27] or pre-defined templates [25].

Other solutions involve personalization; in [12], 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 that input goals. The aforementioned work is extended in [21], where user-roles are taken into account to add more information to the dashboard personalization process. A similar solution is presented in [9], which also takes into account user-roles and business' KPIs to generate a dashboard that fits the business goals. Finally, in [30], 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.

There are also solutions that can adapt themselves at run-time based on environmental changes. Belo et. al [14] present an adaptive dashboard that restructures itself given user profiles and behaviors extracted from the dashboards' analytical sessions. Another adaptive solution presented in [24] uses a dashboard generator fed with user, data and visualization models, thus generating information dashboards based on these models.

In [16], 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. On the other hand, Van Hoecke et al. [18] use a semantic reasoner to personalize indicators from available data sources.. Santos et al. [23] also proposes personalized dashboards based on knowledge graphs and indicator ontologies, but the solution allows the users to modify the dashboard recommendation to its own preferences.

Finally, there are four solutions that can assist and help the users to build their dashboards according to a series of factors. The papers identified in this category [11; 17; 29; 31] help users to identify the best visualization types for the data to be visualized while building and designing their dashboards.

Taking into account the factors that affect the variation of the dashboards' features and the development stage at which the tailoring process is performed, a high-level classification of the selected papers is presented in Table 9.

Customizable dashboards take as input explicit user requirements regarding their dashboards, while personalized dashboards use implicit user data (usage profiles, goals, business processes, etc.) at the moment of the dashboard creation to tailor its features. Adaptive solutions, on the other hand, use implicit user data to adapt the dashboards' components at run-time, taking into account that user requirements can evolve.

Finally, two more kinds of tailored solutions have been identified. Hybrid solutions are personalized solutions with customization support (i.e., the user can manually change the dashboard's personalized features), while customizable solutions with system support help users to configure their dashboards with (personalized) recommendations that can be optionally selected.

Table 9. Dashboard solutions classified by type of tailoring

Type	Total	Papers
Customizable	10	[13] [19] [25] [20] [26] [27] [28] [15] [22] [11]
Customizable w/ system support	4	[17] [10] [29] [31]
Personalized	4	[12] [21] [9] [30]
Hybrid	3	[16] [18] [23]
Adaptive	2	[14] [24]

Tailoring information dashboards has been identified as a relevant field and process, given the potential number of different requirements and user profiles that can employ these tools to support their decision-making processes.

Customizable solutions are the most common solutions, both in research and commercial areas. However, customizable solutions, although they do not require programming skills, still induce cognitive workload on users, because they need to determine their requirements and build their dashboards accordingly. Adaptive, hybrid and personalized solutions would potentially benefit users that don't have a clear set of requirements.

As shown in the first mapping question (MQ1), tailoring information dashboards is a current topic with very recent works addressing this issue. Regarding the different domains in which the dashboard solutions have been applied, Business Intelligence is the most common domain, given the relevance of dashboards for supporting business decision-making processes. However, dashboards are using in very diverse contexts, ranging from learning analytics to economics and energy monitoring. Using dashboard models to create generic solutions that can be adapted to any context would be highly useful, as mentioned in [27].

The majority of works take advantage of user-configuration and pre-configuration methods (through configuration wizards and configuration files) to tailor their solutions. These methods allow to easily build dashboards focusing on user preferences and decreasing the development time of specific solutions.

However, there is still room for automation, which is why other solutions use implicit user data, like usage profiles or business processes, to adapt the dashboards at run-time or personalize them before their delivery to the users.

Regarding the variability targets, only one work included the dashboards' functionalities [27], interaction possibilities [12; 30] and/or visual design [26]. Although the displayed data, visualization types, and layout of the dashboards are very relevant elements, these aforementioned features should not be ignored, as they also influence the user experience [1; 32].

The methods to achieve the variability of dashboard characteristics are very diverse. In general, configuration wizards support customizable solutions. Configuration files, model-driven development, and software product lines also enable variability by modeling the requirements in a structured format for a system to understand, and to generate concrete dashboards. Agents also provide support to manage evolving requirements and perform changes on the dashboards' configuration.

On the other hand, four solutions used visual mapping to assist the customization process. Visual mapping allows the selection of the best visualization type given a set of inputs (displayed data structure, user profiles, etc.), and can be very useful to recommend suitable configurations [33].

Finally, the majority of the solutions have been tested in real-world environments. On the other hand, 10 solutions have not completely validated their solutions. Users are the final beneficiaries of these tools, so they should be tested to verify their usefulness. However, having flexible solutions that don't require significant development time can ease the testing processes through A/B testing, for example [34].

This work aimed at identifying solutions to address tailoring on information dashboards. Performing a systematic review allows to identify valuable records in the literature in a replicable and traceable way. Information dashboards are increasingly being used in different domains, not only in business intelligence contexts, which has been the tendency in the past. But as stated in the introduction, dashboards need to be tailored to take into account individual requirements and needs, thus enhancing insight delivery. Knowing which solutions have been applied in the past within the context of tailoring dashboards helps to provide a basis for research opportunities.

Customizable dashboards are easier to implement, but the final user is still the responsible of building the dashboard. These users may not realize which configuration is the best for them, because they may not explicitly know what they want in their screens. Having customizable solutions with system support can mitigate this drawback, but in the end, the responsibility is still on the user. On the other hand, personalized solutions could be rigid if the requirements evolve over time. That is why adaptive or hybrid solutions seem to be better approaches, providing the user with a personalized solution with room for customization and supporting the requirements evolution.

There are different research opportunities found through the performance of this systematic mapping. The majority of the papers retrieved are between the 2016-2018 interval, meaning that tailored dashboards are a current concern. Only two solutions mention artificial intelligence approaches [14; 18]. , as an ideal solution might be an expert system that performs the same tasks that a visualization expert performs to design a dashboard based on client requirements. In the end, the user, domain and data requirements can be structured for a system to analyze and provide as an output a dashboard configuration.

The majority of the solutions are focused on a few factors to tailor dashboards (user preferences, goals, etc.), but these factors should be combined as they are all related. User preferences must be taken into account, but the data structure is crucial for delivering well designed visualizations, as well as the goals of the user; a visualization could fit into the user requirements and be compatible with the data structure, but it might not meet the user goals, thus having as a result an ineffective (or at least a not-that-effective) visualization.

6 CONCLUSIONS

There are several dashboard tools that allow customization, personalization and/or adaptation. A systematic mapping of the literature has been performed to understand the state-of-the-art of these solutions regarding their tailoring capabilities.

Dashboards are powerful tools that enable users to reach insights about certain topics, but the great number of potential end-users imply a great number of user profiles and requirements. Managing these requirements is not a trivial task, and several methods can be applied to address this issue.

The presented mapping of the literature aims at answering questions regarding tailored dashboards: their application context, targets and factors that the tailoring process, etc., providing a basis for identifying research opportunities in the area of tailored dashboards.

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