Let's Get Personal: Exploring the Design of Personalized Visualizations

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ABSTRACT

Media outlets often publish visualizations that can be personalized based on users' demographics, such as location, race, and age. However, the design of such personalized visualizations remains underexplored. In this work, we contribute a design space analysis of 47 public-facing articles with personalized visualizations to understand how designers structure content, encourage exploration, and present insights. We find that articles often lack explicit exploration suggestions or instructions, data notices, and personalized visual insights. We then outline three trajectories for future research: (1) explore how users choose to personalize visualizations, (2) examine how exploration suggestions and examples impact user interaction, and (3) investigate how personalization influences user insights.

Index Terms: Human-centered computing—Visualization—Visualization application domains

1 Introduction

In a world where online news platforms and blogs compete with social media outlets for user engagement, there is a pressing need to generate content that connects with users. Personalization, particularly *feed personalization* (or tailoring content feeds to provide more relevant information), has been one of the many strategies employed to encourage user engagement [8]. More recently, however, news outlets have explored another form of personalization, *content personalization*, that tailors an article's content based on user information [1, 8, 17]. This personalization may include injecting text with local statistics for a user's location [17] or personalizing a visualization to show data related to a user's age. Not only would this personalization provide more relevant experiences, but some prior work argues that it may even increase engagement [1, 8].

However, such personalization raises questions around user impact, especially when it comes to personalized visualizations. After all, visualizations communicate in ways that plain text cannot [11], and user takeaways from visualizations in public media can impact decisions ranging from how readers vote [A24] to how they stay safe in a pandemic [A13]. Thus, it is vital to address the following question: *how do designers structure personalized visualizations, encourage exploration, and present insights?* To this end, we collect a corpus of 47 public-facing articles with personalized visualizations from different media outlets in-the-wild. We then conduct a qualitative design space analysis to understand trends around the structure and content of these visualizations. Based on our results, we propose three trajectories for future research: (F1) explore how users choose to personalize visualizations, (F2) examine how exploration suggestions and examples impact user interaction, and (F3) investigate how personalization influences user insights.

2 Related Work

While work on personalized visualizations is fairly nascent, we outline existing research that aims to better define the space. We then highlight the potential benefits and challenges of designing, developing, and deploying personalized visualizations for public-facing articles with a general audience. For this paper, **we define personalized visualizations as any visualizations in which users manually or automatically provide personal, demographic information (such as location, income, race, and gender) to "modify the base set of facts" [8] shown in the visualization or accompanying text**.

2.1 Defining Personalized Visualizations

While prior work has explored the design space and impact of interactive and narrative visualizations [4, 15], background on personalized visualizations is limited. In particular, the term *personalized visualizations* takes on several different definitions in prior work. Some papers equate personalized visualizations to adaptive visualizations, or visualizations that adapt to users' changing contexts, interests, goals, and cognitive abilities [12]. For example, Domik and Gatkauf proposed adapting graphs based on user models of color perception, memory, and ranking [5]; Green and Fisher explored how personality factors like locus of control, extraversion, and neuroticism impacted users' ability to complete interactive visualization tasks [9]; Steichen et al. used participants' eye gaze patterns to predict user attributes (such as cognitive ability and visual working memory) and adapt visualizations accordingly, in real time [16].

Adar et al. diverge from this definition by arguing that personalized visualizations are a form of content personalization that automatically alter the "facts that appear in an article's content based on properties of the reader" [1]. This definition requires users' information to be *automatically* inferred and/or applied without direct manipulation from the user. One example of this definition is The Pudding's article on geographic music bubbles, which uses readers' IP addresses to show the most popular song in their area [A14]. Gearing et al. further this definition by noting that content personalization must modify the "non-personalized facts" presented in the article [8]. While Adar et al. and Gearing et al.'s definitions highlight an emerging frontier in visualization research, they note that automated personalized visualizations are rare given the resources required to create them [1]. As such, our corpus also includes personalized visualizations that users can manipulate (e.g., manually entering your location to see popular songs in your area), as they are more widely available and made up 94% (44/47) of our corpus.

Beyond the definitions above, Qian et al. align personalization with preferences by building a personalized visualization recommendation system that learns visual and data preferences from target users and users with similar preferences [14]. Still others, like Oscar et al., utilize the term *personalized visualization* as a synonym for *personal visualizations*, or visualizations that reflect a users' own data [12]. Personal visualizations are often used for health, social media connections, and progress logs [10]. However, for this work we draw a distinction between personalized visualizations and personal visualizations, as the public-facing visualizations that we study do not reflect users' own data, but highlight data that might be relevant to the user based on their demographics.

2.2 Benefits & Challenges of Personalized Visualizations

While prior work lacks an overview of the design space of personalized visualizations, some researchers utilize findings around personalization in other contexts, such as education, to hypothesize potential benefits, which include increased reader engagement

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and support for behavioral change [1, 8]. Prior work has also explored readers' perceptions of personalized text-based articles across four dimensions: credibility, likability, quality, and representativeness [17]. Despite reading extra paragraphs customized to their location, area description (urban versus non-urban), and gender, there were few major differences in readers' perceptions of the two conditions [17]. However, the personalized article received more high ratings for sub-dimensions such as enjoyability, timeliness, and bias. Peck et al. add to this conversation by suggesting that data presented in a "personal, familiar manner" benefits a wide array of users. As such, personalized visualizations may help journalists to create engaging content that connects with diverse audiences [13].

On the other hand, personalizing visualizations raises questions about user impact and interaction. Prior work suggests that interaction and exploration are integral to the sensemaking process. In fact, Yi et al. state that "one of [the] most important factors to help users gain insight might be the degree of users' engagement" [18]. Despite its importance, prior work has found that users tend to underexplore news visualizations in comparison to designers' expectations, creating questions around the impact of personalization on exploration [4, 7]. Feng et al.'s prior research deepens these questions as they found that exploring different portions of a visualization can lead to a different set of findings among users [7].

Challenges around personalized visualizations are compounded by the required development effort. Several journalists that Adar et al. surveyed noted that while content personalization would be ideal, it "require[s] more resources than their organization could easily provide" [1]. To address these challenges, Adar et al. developed PersaLog to support journalists in creating personalized visualizations and converting non-personalized ones [1]. Other tools like Idyll can support personalized visualization design by reducing the work required to develop web-based, interactive articles [3]. While these tools may ease authoring challenges, they do not address journalists' other concerns around bias and reader perceptions of privacy [1].

3 Personalized Visualization Corpus

While this prior work provides a starting point for understanding different characteristics of personalized visualizations, little is known about how designers craft such visualizations [1, 8]. To this end, we analyze a corpus of 47 articles containing personalized visualizations with or without accompanying, textual narratives from public-facing news outlets and digital visualization publications.

3.1 Corpus Collection

To build our corpus, we selected articles from traditional news sources (e.g, the New York Times), digital visualization publications (e.g., The Pudding), and research centers (e.g., the APM Research Center). We selected these outlets because they are public-facing and often feature visualizations in their content. From these publications, we reviewed recent articles via their visualization lists or tags and gathered additional articles by searching article recommendations, similar authors, similar topics, and similar title structures (e.g., titles addressing the reader: "You"). This search resulted in a set of 58 articles with candidate personalized visualizations.

We then reviewed each article to eliminate ones that did not contain at least one personalized visualization per our earlier definition. Notably, user preferences, beliefs, and/or habits were not considered demographic information on their own, as such factors may fluctuate daily. We thus eliminated 11 articles that did not match our criteria, resulting in a corpus of 47 articles. The full article list is included in the supplemental material and Appendix A. While other good personalized visualizations may exist, this work collects and analyzes a sample of in-the-wild, public-facing examples missing from prior work [1, 8] as a basis for continued research.

3.2 Corpus Coding Process

To create our initial codebook, the first author took notes on a subset of 17 articles. These notes informed discussions between the first and last author who jointly developed codes to categorize the articles and personalized visualizations. This process resulted in 65 initial codes which were refined through two iterative phases to a first round codebook with 17 codes relevant to user exploration.

We then enlisted the help of 11 additional coders (4 researchers and 7 PhD students) and assigned two coders to each article. We provided a codebook, two coded example articles, and a coding guide to maintain consistency. Conflicts were resolved by the first author, who re-reviewed each article to determine the final code, and by the last author to address uncertainty and reach a consensus.

Grouping and dividing our first round codes, we then developed 29 higher-level codes to analyze our results across five categories: *article meta-information*, *guidance*, *properties*, *visual components*, and *insights*. While we only describe categories pertinent to our analysis below, the full codes for each article are included in the supplemental material along with the initial codes and first round codebook. In the following sections, the 10 codes analyzed in this paper are labeled A-J corresponding to the results in Figure 1.

Properties. This category describes the data used to personalize visualizations and how that personalization occurs. For each personalized visualization, we record the *types of data fields* (i.e., the form fields that trigger personalization), the *defaults* provided for each data field, the *entry mode* for the data field (that is, whether or not users have to manually enter values), and the *domain of the data field* (that is, all of the potential values for the field). We labeled each article's *granularity* based on the amount of data requested from the user: (i) low (asks for 1 piece of data to personalize the visualization), (ii) medium (asks for 2-3 pieces of data), or (iii) high (asks for 4 or more pieces of data). We also noted whether the article contained (A) *data notices* about how the user's data is handled.

Guidance. This category describes how articles encourage users' exploration of personalized visualizations. (B) *Personalization instructions* explicitly encourage the user to enter personally-relevant data, whereas (C) *exploration suggestions* highlight whether the author explicitly suggests specific values to the user for none, some, or all of the data fields. If there are exploration suggestions, we record the *location of exploration suggestions* (i.e., before, after, or on the personalized visualization) and the *type of exploration suggestions* (e.g., provided in the article itself or via a visualization component). We also note if the article includes *exploration examples* that show users how to interact with the visualization and implicitly suggest data values for user exploration. For exploration examples, we note the *type of exploration examples*: (D) *default values* for data fields, (E) *visual walkthroughs* or tutorial-like slideshows, (F) *in-text* examples, (G) *comparison data points* that are juxtaposed to personalized data points, and (H) *pre-defined data configurations*.

Insights. The final category describes the major takeaways from the article by recording the presence of (I) *personalized takeaways*. We also code (J) *personalized visual takeaways* (i.e., takeaways that are reinforced visually in the personalized visualization itself).

3.3 Corpus Design Space Analysis

The following sections describe the main results from our analysis. Figure 1c summarizes the final codes broken down by publication with letter references to specific codes mentioned in Section 3.2.

3.3.1 Simple location data dominates rather than instructions

Raising user interaction concerns, we first find that **57% (27/47) of the articles do not include any text instructing users to enter personally-relevant data (B)**, leaving the user to determine how to interact with the visualization. For example, FiveThirtyEight's *Gun Deaths in America* [A9] instructs users to explore the visualization,

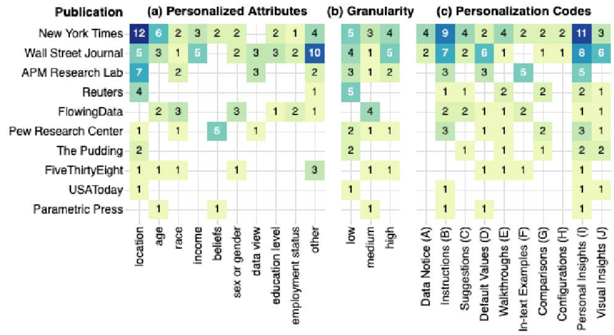

Figure 1: An overview of the personalized visualizations corpus based on the (a) personalized attributes contained in the article, (b) granularity, and (c) resulting codes for different publications. The full list of individual codes is included in the supplemental material. Attributes that only appeared in 1-3 articles are grouped together under "other."

but does not guide them to enter their *own* gender, age, and/or race. In contrast, the Wall Street Journal's *What's Your Pay Gap?* [A44] encourages users to enter their occupation to see the pay gap between men and women within their specific industry. Further, **87% (41/47) of the articles did not include a (A) *data notice* detailing how user data would be used.** While seemingly small, the lack of instructions and data notices may influence if users choose to interact with the visualization and how they tailor their interaction.

Considering the number and types of data fields used to personalize the content, we find that **low granularity articles dominate, constituting 47% (22/47) of our corpus** (Figure 1b). In comparison, medium and high granularity articles made up 26% (12/47) and 28% (13/47) respectively. Furthermore, location-based data was the most common attribute used to personalize visualizations. In fact, **70% (33/47) of the articles in our corpus asked for location-based data** (Figure 1a). However, it should be noted that location data fields have a variety of input domains. For example, the Pew Research Center's *Religious Restrictions Around the World* [A2] asks users to enter a specific country to personalize the visualizations while the New York Times' *Olympic Races in Your Neighborhood* [A26] allows users to enter different countries, states, cities, points of interests, and addresses as a location. An overview of the attributes used for personalization is included in Figure 1a, with location as the most popular followed by age, race, and income.

3.3.2 Limited exploration suggestions, but many examples

Looking beyond initial interactions, we also consider the role of user exploration. After all, prior work suggests that when users explore different parts of a visualization they walk away with different insights [6]; for articles in our corpus, personalization can emphasize different segments of a visualization and/or its data, which may lead to different reader experiences. Thus, encouraging users to enter multiple values may help them to develop more generalizable insights and a more complete understanding of the data, with their own data more contextualized. However, our analysis suggests that **authors underutilize explicit exploration suggestions** that actively encourage users to explore values that may not be personally-relevant to them. In our corpus, 79% (37/47) of the articles lacked (C) explicit exploration suggestions, which may contribute to underexploration and limited takeaways, as users must drive the analysis themselves.

Of the articles with explicit exploration suggestions, 50% (5/10) included suggestions *before* the visualization was shown, 40% (4/10) included suggestions *after* introducing the personalized visualization, and 10% (1/10) included suggestions directly *on* the visualization. This placement may impact how users engage with the content. For example, the New York Times article *Are You Rich? Where Does Your Net Worth Rank in America* [A35] includes an exploration suggestion that allows users to skip the personalization requirement and simply explore the net worth ranking for a household with a combined net worth of $150,000 and a head of house between the ages of 45 and 54. While such suggestions can help users develop generalized takeaways without requiring them to manually explore different property values, this approach also allows users to skip personalization entirely, potentially impacting their personalized takeaways. Conversely, FlowingData's *How You Will Die* [A47] includes an exploration suggestion after the visualization that encourages users to go back and re-explore how age impacts the likelihood and cause of death for people of the same sex and race, thus encouraging users to add generalized takeaways to the personalized ones first developed when viewing the article.

While most articles lacked specific exploration suggestions, **approximately 83% (39/47) of the articles included exploration examples**. These examples are more indirect than exploration suggestions, but may still encourage users to try different values and/or develop more generalizable takeaways. The most common type of exploration example was (D) *default values* (38% or 15/39). For example, the Wall Street Journal's *Which College Graduates Make the Most?* [A27] uses default values to initially show the earning-debt ratio of undergraduates who earn business administration-related degrees and those who graduate with degrees in other disciplines. As such, users may view information that is not specifically related to them *before* choosing to enter more personally-relevant data values.

The articles also heavily relied on (E) *visualization walkthroughs*, which accounted for 28% (11/39) of the exploration examples. Visualization walkthroughs display different segments of the visualization step-by-step. This approach provides an overview of the visualization while also exposing users to data and takeaways they may not otherwise see when personalizing the visualization. For example, The New York Times' *Quiz: Let Us Predict Whether You're a Democrat or a Republican* [A11] asks users multiple questions to predict their political leaning while also providing an interactive tree diagram for users to explore the different response paths and results.

3.3.3 Personalized insights often shown in text, not charts

Finally, we find that while 74% (35/47) of the articles included at least one personalized insight (I), **57% (20/35) of these articles contained insights that users could not directly extract from the personalized visualizations (J).** For example, Reuter's *COVID-19 Vaccination Tracker* [A5] allows users to search for a specific country and view a customized page with text and visualizations about the country's COVID-19 response. While the visualizations show the total number of infections and deaths since last year, the personalized text provides cumulative information since the pandemic began – an insight that cannot be extracted from the visualizations. While this difference could reflect the authors' aim to augment the visual information with additional details, redundancy in the text can help to reinforce messages represented by the visualizations [2]. As such, not visually complementing takeaways from the text may hinder users' ability to remember and discern important takeaways.

Potentially worse, **26% (12/47) of the articles did not provide any type of personalized insight to help users identify key takeaways that were relevant to them.** For example, the Wall Street Journal's *Home Values Rebound, But Not For Everyone* [A25] includes a personalized visualization for users to explore home value trends in United States metro areas. However, the only text related to this visualization is a label indicating the highlighted metro area; there are no tooltips, annotations, or text summarizing what the user can learn. Broadly, the lack of personalized insights may place the burden on users to decipher meaning from visualizations and lead to takeaways that do not align with the article, especially if users are quickly scrolling through content and not reading the text [4].

3.4 Main Takeaways from the Design Space Analysis

Our analysis revealed three key observations. First, **low granularity articles and location fields dominate** (Figure 1a-b). However, most articles **do not include (A) data notices or (B) instructions encouraging users to enter personally-relevant data**. Secondly, **articles rarely include (C) explicit exploration suggestions** that encourage users to explore values beyond their personal ones, but **most articles include exploration examples** that passively encourage exploration, especially via (D) default values and (E) visualization walkthroughs (e.g., tutorial-like guides). Finally, while the majority of the articles included (I) personalized takeaways, **users may not be able to directly observe takeaways from the visualization itself (J)**.

4 Discussion

Building on prior research, we use our analysis of in-the-wild personalized visualizations to identify **three trajectories for future work (F#)**: (F1) explore how users choose to personalize visualizations, (F2) examine how exploration suggestions and examples impact user interaction, and (F3) investigate how personalization influences user insights [1, 8].

4.1 Encouraging and Understanding Personalization

First, based on the lack of (B) personalization instructions in our corpus, **we recommend that researchers continue to study whether or not users choose to interact with personalized visualizations when reading articles (F1a)**. Prior work has shown that readers may "simply [scroll] through to the end of content" with a "superficial level of engagement," suggesting that getting users to initially interact with personalized visualizations may be a challenge [3].Thus, the field needs to better understand how different elements impact user interaction, and how interventions like (B) personalization instructions can prompt users to engage with the visualization.

We also recommend further research on the types of personal information users are willing to provide during interaction (F1b). Concerns around privacy have been a key theme of nascent prior work, with initial guidelines calling for a better understanding of users' privacy perspectives [1]. Practitioners echo these concerns, noting that asking for personal information may dissuade users from even engaging with the content [1]. Despite the emphasis placed on user privacy, we find that 87% (41/47) of the articles in our corpus do not include a (A) data notice indicating how user data will be handled. Furthermore, visualizations were personalized using different granularities (or amounts of data), and various types of data, with location being the most requested piece of information (Figure 1a-b).

While some personalized visualizations in our corpus sidestep privacy issues by providing flexibility around what information is required, we suggest that future work investigate how users approach privacy via interaction. For example, do users enter their personal information (e.g., *one's hometown*) or do they attempt to protect their privacy by entering nearly personal information (e.g., *a friend's hometown*) or random information (e.g., *a random town in the U.S.*)? Do they skip certain fields they deem too personal, and if so, what fields are often skipped? We also propose exploring the impact of interventions, like the (A) data notice featured on the Wall Street Journal's *How Do You Stack Up in Today's Job Market?* [A30], on users' perceptions and decisions around privacy.

4.2 Complementing Personalization with Exploration

Beyond the initial interactions, **we contend that researchers should also examine how interventions like exploration suggestions and examples impact user interaction (F2)**. Prior work has shown that exploring a visualization is vital for decision-making [18]. However, prior work has not studied if users explore personalized visualizations beyond their personal demographics, which may be important for visualizations that only show a segment of the data (as in the New York Times' *Are You Rich?* [A35]). The lack of work on exploration also raises concerns about bias, which could occur if users only consider data that is personalized to their experiences.

Given these concerns, we suggest that researchers consider interventions to encourage user exploration and contextualization of their personalized insights. While our corpus analysis shows that designers rely heavily on indirect exploration examples, are specific forms of exploration examples (i.e., (D) *default values*, (E) *visual walkthroughs*, etc.) better for cultivating exploration? How do exploration examples compare to the more underutilized, but explicit (C) exploration suggestions that we saw in our corpus? How does the granularity (or the amount of data) influence exploration? To this end, we hope to conduct future user studies on personalized visualizations that explore these questions in depth.

4.3 Conveying Personalized Insights

Lastly, **we encourage researchers to explore how personalization impacts user insights (F3)**. Personalized or not, one of the foundational goals of visualizations is to provide useful insights to the reader [18]. Yet, outside of hypothesized benefits [1, 8], it is unclear if personalization actually aids insight generation. Furthermore, our corpus shows that articles did not always provide (I) personalized insights to summarize the key takeaways and 57% (20/35) included personalized insights that could not be extracted visually.

As such, we propose that researchers examine the insights that users generate from interacting with personalized visualizations. Do users prioritize personalized insights over generalized insights? Are personalized insights more memorable than non-personalized ones? What happens when users' personalized insights diverge or align with the author's takeaways? While personalization may provide another tool for user engagement, we need to understand how design choices impact users' interpretations of insights.

5 Limitations

As discussed in Section 4, there are several research trajectories needed to understand the impact of personalization on users; this future work should also explore cultural differences around personalization. We collected articles from English-speaking publications with a predominately American base, as we did not have the language skill, and/or cultural knowledge to explore publications in other areas. Thus, these findings may not hold for non-English speaking and/or non-American bases, and future work should explore personalized visualizations within such populations. In addition, Segel and Heer have noted that subjectivity is an inherent part of analyzing a design space [15]. As such, our codes may not cover every characteristic of the visualizations in our corpus, but reflect the common trends we saw. Therefore, we invite other researchers to continue to chart this area to support practitioners and further the field.

6 Conclusion

This work contributes a design space analysis of personalized visualizations from a corpus of 47 public-facing articles in-the-wild. We find that exploration suggestions, personalization instructions, and personalized visual insights tend to be underused, raising questions for future work about how users explore and learn from personalized visualizations. These findings provide a foundation for our three proposed trajectories for future research that aim to better understand the effective design of personalized visualizations: (F1) explore how users choose to personalize visualizations, (F2) examine how exploration suggestions and examples impact user interaction, and (F3) investigate how personalization influences user insights.

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APPENDIX A

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