AI or Humans: Who Designs Better Dashboard Layouts? An Initial Study

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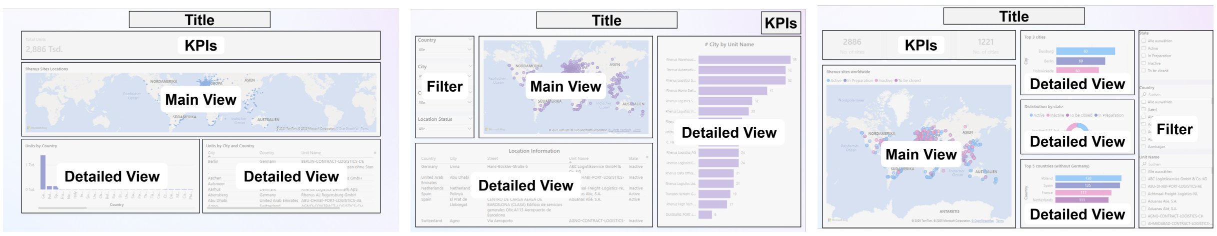

Figure 1: Spatial Layouts of AI-generated and Human-created dashboards.

Abstract

Well-designed dashboards composed of multiple visual components effectively deliver complex information. The layout significantly impacts dashboard efficiency. However, determining the optimal layout is challenging and time-consuming for designers. Previous work has provided numerous guidelines for creating and evaluating the quality of dashboard layouts that we systematize. Nevertheless, it remains unclear how to achieve high layout quality in practice. Artificial intelligence has the potential to assist humans in creating dashboards. This raises the question: Are dashboards generated by AI better than those generated by humans using guidelines? We compared the quality of AI-generated dashboards to those designed by humans, both with and without prior knowledge of actionable design guidelines. Our indicative results show that AI can create simple layouts quickly and with high quality. However, AI struggles with the nuanced task of connecting visual components in a meaningful and consistent way. Humans perform better at making these connections and refining layouts. In practice, our findings suggest that AI can significantly assist with the initial creation of dashboard layouts, but human involvement is essential for ensuring a cohesive and meaningful design.

Index Terms: AI Dashboards, Visual Component Mapping, Visual Arrangement, Visual Perception, Expert Evaluation, Spatial Layout Guidelines.

1 Introduction

High-quality dashboards have become crucial tools across domains such as meteorology, business, economics, healthcare, biology, transportation etc. [30]. They serve as primary interface through which decision-makers access and interpret complex data.

A dashboard's quality inherently encompasses multiple factors such as clarity, accuracy, efficiency, usability, and interactivity [3,25,29,33]. Among these dimensions, the spatial layout - how visual interface components are arranged - is a critical and yet often overlooked factor influencing dashboard effectiveness [5, 24].

With the emergence of generative AI systems, particularly large language models (LLMs), automated dashboard generation has become increasingly feasible [13]. Tools such as Microsoft's Copilot [18] and Tableau [28] integrate earlier research on visualization recommendation and multi-view composition [8,14,16,22,31], along with guidelines for effective human-AI collaboration [4]. These systems promise to streamline dashboard development, but their ability to produce layouts that adhere to human-centered design expectations remains underexplored [13,22,26,33].

This raises three important questions. First, do AI-generated dashboards adhere to established spatial layout guidelines? Second, to what extent do designers apply these guidelines when creating dashboards? Third, how do the resulting dashboards compare to their AI-generated counterparts?

To investigate these questions, this work conducts a controlled expert study, following established evaluation methodologies in visualization research [7,11]. We systematically compare dashboards created by experienced human developers (with and without access to layout guidelines) against dashboards generated by AI systems. The AI-generated dashboards were produced without distributing the collected layout guidelines because providing them would undermine the evaluation of the AI's ability to apply human-centered design principles independently. The goal of this study is to evaluate the extent to which current AI systems adhere to spatial design standards and to demonstrate the importance of explicit guidelines for human-centered dashboard development.

This work has threefold contributions. First, we summarized existing actionable design guidelines for dashboard spatial layouts into a new structure. Second, an expert study was conducted to compare AI-generated and human-created dashboard layouts. Finally, we developed a set of lessons learned for better dashboard design practices for AI and humans.

2 Dashboard Design Guidelines for Spatial Layout

An effective dashboard design relies not only on the information presented, but also on how that information is organized spatially [11]. A well-structured layout improves comprehension, directs user attention, and promotes analytical thinking.

Research has shown that spatial layout significantly impacts how users perceive, understand and act upon data presented in dashboards [5,12,24]. However, despite the importance of layout, existing dashboards often rely on intuitive design decisions rather than systematically applying structured frameworks or guidelines [2,33]. While broader information visualization research offers a variety of design principles [11, 17], relatively few studies deliver concrete, actionable guidelines for spatial arrangement. Actionable implies it can be used directly to take steps or make decisions [1, 14, 20].

This work proposes a new structure of actionable guidelines by combining existing visualization literature frameworks [2, 5, 8, 14, 25, 32]. We searched for and collected guidelines that we then organized into five thematic groups. The guidelines

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emphasize clarity, consistency, and meaningful arrangement, and they are organized from simple to complex. We provide a general description and actionable requirements for evaluating each guideline. This collection does not evaluate potential conflicts between the layout guideline and the data content.

G1. Simple Layout: The layout design must be simple, and the structure and organization must be clear [8, 32].

- G1R1: The dashboard should present less than five views and adopt a simple layout. [8]
- G1R2: The views should be positioned within a grid, with the edges aligned and equal spacing between the views [8], e.g., , , .

G2. Hierarchy and Reading Order: There must be a clear and logical reading order within the dashboard [5, 25].

- G2R1: The dashboard should use a stratified layout like top-down or bottom-up ordering [5, 25].

G3. Common Positions: Common positions denote the spatial locations where users conventionally expect the presence of views or interface components and must be used for certain view types [8].

- G3R1: Diagrams should be positioned in the center of the display [8].
- G3R2: Panels should not be positioned in the center of the display [8].
- G3R3: Text views should be positioned on top of other view types [15].
- G3R4: Views with more fields should be positioned on the bottom of views with fewer fields [15].
- G3R5: Components that serve as data input for others should be positioned close to the related components [14].

G4. Structured Layout: The layout must express the relations between views [5].

- G4R1: The layout should be schematic , and/ or
- G4R2: The layout should group views by type or task , and/ or
- G4R3: The layout should be structured as a table , and/ or
- G4R4: The layout should be stratified and show important information on top [5].

G5. Visual and Data Similarities: Views that are highly similar in terms of data or visuals, or are linked together, must be juxtaposed, and aligned [2, 14].

- G5R1: Two views should be positioned to the left or right of each other, if they are of the same type, and they use the same fields on the Y-axis [15].
- G5R2: Two views should be brushing each other, if they share more than 50% of the same data fields, and they use the same color for the same data fields [15].

3 User Study - Dashboard Creation

In the first part of the experiment, participants were instructed to design a dashboard layout. We then compared these layouts to AI-created layouts using Copilot. [10]. Because Copilot is directly integrated with Power BI [9, 10], it was used to minimize any potential overhead associated with switching service providers. Power BI version 2.139.1678.0, released in January 2025, was used for all experiments conducted in this study [19].

3.1 Datasets

To obtain results that are generalizable, we used two exemplar datasets space, time and variables, facets common to many datasets. The datasets were from two domains:

- **Sites Dataset** – Provided by Rhenus SE & Co. KG, contains geolocations of the company's branches with 2.886 data points. Accompanied by the dimensions of operational status (active/inactive), geographic coordinates (longitude/latitude), and addresses. In addition, a variable for ”effective date” is stored, indicating when the data was collected.
- **Meteorology Dataset** – Derived from ACTRIS Cloud Remote Sensing data, classifying nominal categories of cloud particles in a height-time plot with $1,759,400$ data points. The three dimensions of the dataset represent height, time, and particle definition. Other important variables include the altitude, longitude, and latitude of the recorded data.

3.2 Methodology

A **pilot study** with two participants was conducted prior to the main study. Each participant used a separate dataset and was provided with guidelines. The results of the pilot study indicated that the guidelines were understandable and precise and that one hour was sufficient time.

The **main study** involved six participants, who were divided into three groups of two. Each group of two participants was given a Power BI file containing one of two dataset models and a color scheme.

The **task** to be performed was chosen as general as possible. It was a common, domain-independent, widely employed task to create a dashboard to explore a new dataset. In particular, for our datasets, it was specified in a domain language as follows:

- **Sites Dataset** – ”Please create a dashboard page that displays the location of the Rhenus-sites and the units based in each country and location. Present this information from multiple perspectives.”
- **Meteorology Dataset** – ”Please create a dashboard page that displays the height and time at which the particles were measured by the classification of particles. Present this information from multiple perspectives.”

3.3 Dashboard Creation

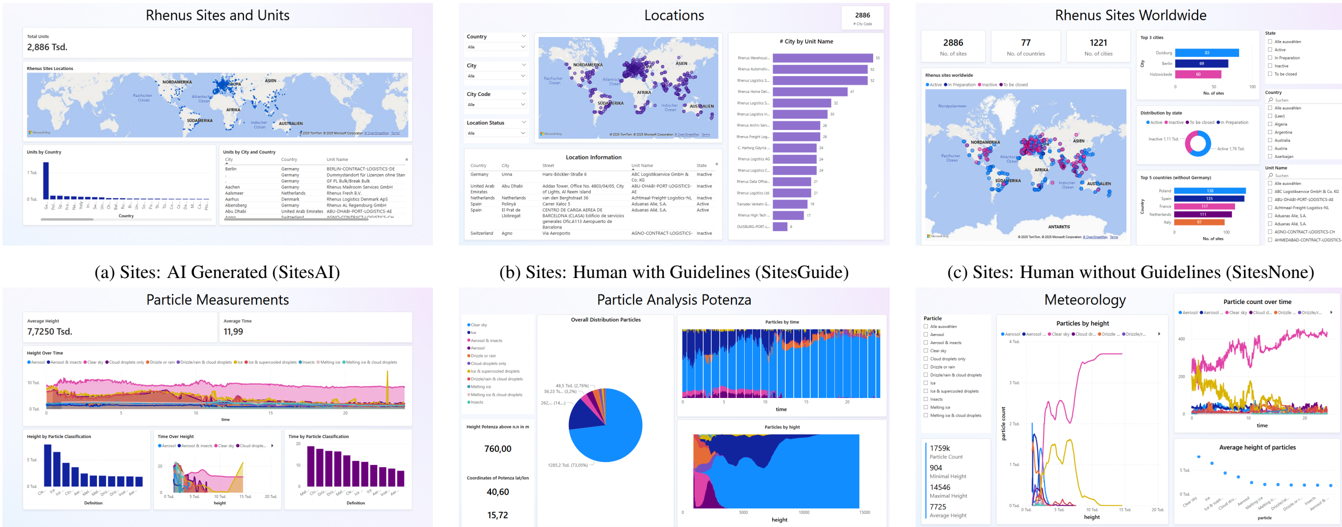
The first group used an AI chatbot to create the dashboard. After entering the task into the chatbot, an immediate result was not produced. Instead, the chatbot asked if they wanted to focus on a particular aspect of the dashboard. In both cases, the response was ”no focus.” This group consisted of visualization experts with no prior knowledge of the data. Their primary task was to provide prompts to the AI bot.

The second and third groups each consisted of two professional developers, each with an average of about three years of data experience. One group was given the spatial guidelines outlined in Sec. 2, and the other was not.

The results of all three groups are presented in Fig. 2 and are evaluated in the next section. Dashboards (a)-(c) belong to the Sites Dataset, and (d)-(f) to the Meteorology Dataset. Further, Dashboards (a) and (d) are AI-generated, whereas (b) and (e) are human-created using the guidelines, and (c) and (f) are human-created without guidelines. To prevent bias on AI and support an objective assessment of spatial structure in the following evaluation, the dashboards were visually standardized by removing or modifying colors, titles, and stylistic elements not related to spatial layout.

4 Dashboard Evaluation

The second part of the experiment included an expert evaluation designed to compare the quality of AI-generated dashboard layouts to those created by human experts. This evaluation consisted of two components: a questionnaire and a semi-structured interview. A pilot study was first conducted with one expert to validate the



(a) Sites: AI Generated (SitesAI) (b) Sites: Human with Guidelines (SitesGuide) (c) Sites: Human without Guidelines (SitesNone)

(d) Meteorology: AI Generated (MetAI) (e) Meteorology: Human with Guidelines (MetGuide) (f) Meteorology: Human without Guidelines (MetNone)

Figure 2: Six dashboards from the datasets Sites ((a)-(c)) and Meteorology ((d)-(e)). Pictures (a) & (c) show the dashboards created by AI, (b) & (e) by humans with the help of guidelines and (c) & (f) by humans without knowledge of the guidelines.

evaluation process. Participants were given the same task as the experts who created the layouts but were instructed to disregard factors such as dataset complexity, color scheme, and content quality.

The **questionnaire** was derived directly from the five core spatial layout guidelines **(G1-G5)** described in Sec. 2. For each dashboard, experts rated whether each requirement **(G1R1-G5R5)** was met using checkboxes (YES, NO, N/A) and free text fields for brief justifications. This format, adapted from previous studies such as [7, 11, 15, 23, 25], allowed for both structured data collection and open feedback (the full questionnaire is provided in the supplementary material).

The second part of the evaluation consisted of a **guided interview** in which the experts discussed their responses with the study facilitator. The interview sought clarification and deeper reasoning behind the questionnaire responses. Special attention was given to controversial or consistently agreed upon responses to surface patterns of evaluation and interpretation. A 5-point Likert scale [6, 27] was used in the post-interview reflections to capture overall impressions of each dashboard.

Six independent experts, none of whom had participated in the earlier dashboard creation sessions, took part. This ensured a clean separation between design and evaluation. Participants were selected to provide a balance of academic and industry perspectives, including five experts in data science/engineering, and one expert in visualization research.

Each expert was presented with all six dashboards created in the first part of the experiment (Fig. 2). To ensure objectivity, all dashboards were anonymized and presented in a unique order. There was no possibility of interaction because only pictures were shown.

Experts received the dashboards and questionnaire in advance and were asked to complete the questionnaire independently prior to the interview. The following interviews focused on the responses to the questionnaire. Each interview session lasted approximately 45 minutes to one hour, resulting in an extensive discussion of the dashboard layouts.

5 Results

This section will demonstrate how AI performs in comparison to humans. The study's results have been divided into two categories: quantitative results from the questionnaire and qualitative results from the interviews.

5.1 Quantitative Results

Overall, the three dashboard categories "AI Generated", "Human with Guidelines", and "Human without Guidelines" there is a visible difference.

Figure 3 shows the adherence to guidelines **(G1-G5)** for the three analyzed groups: AI, human with and without guidelines.

Adherence to guidelines (i.e. %YES) is calculated as %-YES $= \frac{YES}{YES+NO}$. The count of "Yes" is defined by the frequency with which each dashboard adhered to the established requirements (across guidelines), as determined by expert evaluation.

In detail, AI outperforms on Guideline **G1. Simple Layout** and **G2. Hierarchy and Reading Order**, while humans with guidelines performed best in following guideline **G5. Visual and Data Similarities** (see Figure 3). It is evident that **G3. Common Positions** guideline (76% YES) was most prevalent when compared to the other guidelines as examined by the experts. The guideline with the most disagreement was **G4. Structured Layout** with only 47% YES. It is unclear to whether the guidelines were ineffective or if the datasets were too complicated.

Notably, AI dashboards were created significantly faster – around 10 seconds compared to 45 minutes for humans.

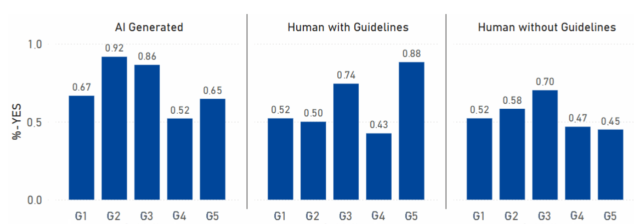


Figure 3: "%-YES" Values for Guidelines over participant groups.

The comparative analysis of dashboard response in Fig. 4 revealed that dashboard SitesAI (2a) (78%), SitesGuide (2b) (63%) and MetAI (2d) (60%) received the highest %-YES respectively. It indicates that experts performed better on gerneral datasets that are more familiar to them than on domain specific dataset.

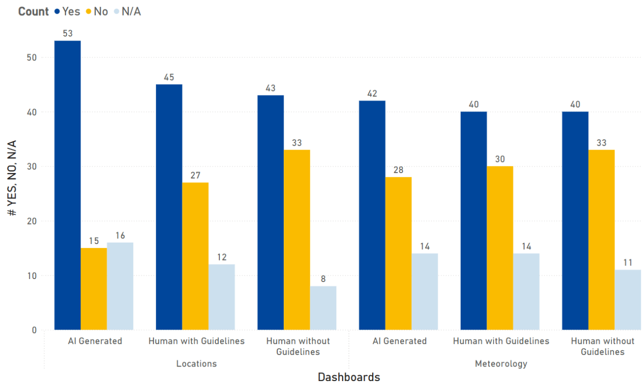


Figure 4: Result of Questionnaire per Dashboard.

5.2 Qualitative Results

After the quantitative results, a qualitative interview was carried out where six experts were asked to provide their opinions on all six dashboards based on their answers in the questionnaire [21,34]. The reviews are discussed below and have been summarized as our lessons learned, supporting future research:

- **Result 1 - Top-Down Reading Order (G2R1)**: The experts found that a staggered layout according to reading order promotes hierarchical attention and encourages users to view more of the content.
- **Result 2 - Panel Positions (G3R2)**: The insights revealed a clear preference among the experts for placing the panels in the top left corner of the layout. They recommended enclosing these panels within a defined shape — either a row or a column — and placing them next to the evaluation view to improve usability and coherence.
- **Result 3 - Overlap Title (G3R3)**: One critical observation from the expert feedback is the recommendation to not include view counts directly next to titles. The experts noted that this combination is obtrusive because the title and the view metric are unrelated. Presenting a numerical value without sufficient context can be confusing or misleading to users.
- **Result 4 - Grouped Cards (G4R2)**: Although the cards were structurally grouped, placing them in separate boxes created the misleading impression that they were part of separate groups. In contrast, another version of the visualization used a unified container and visual markings to more clearly group related information, effectively distinguishing and consolidating all information under one panel. This reduced the information overload on the page.
- **Result 5 - Charts Arrangement (G5R1)**: Placing charts side by side implies that they are comparable. Experts emphasize that if the charts are not intended for direct comparison, visual cues, such as different styling or layout adjustments, are necessary to avoid misleading interpretations. However, if comparison is the intention, the charts should be placed side by side without any offset.

5.3 Summary of Results

Quantitative data from questionnaires and qualitative insights from interviews revealed that, in terms of layout efficiency, AI dashboards generally outperformed human-created ones. However, closer inspection revealed that human participants designed better layouts for familiar datasets, such as Sites, while AI performed better with the Meteorology dataset. People can design layouts that align with their personal preferences when they quickly comprehend a familiar dataset.

6 Discussion and Future Research Directions

Our study provides indicative results for comparing AI- and human-generated dashboard layouts and the role of guidelines. The small scale of the study, with respect to both the number of dashboards and the number of experts, gives it an exploratory character. Nevertheless, it offers interesting insights, ideas, and avenues for future research. We describe these insights in this section.

Despite the small sample size, qualitative feedback emphasized AI's strengths in reading flow, common positioning, and simple layout. These characteristics can be interpreted as "programmable." However, human dashboards with guidelines performed better in areas requiring nuanced interpretation, such as visual and data similarity.

The small sample size of experts in this study is indicative. Future studies should include a more diverse group of participants, such as end users. These studies should also be repeated using newer AI models that reflect recent advancements since the initial evaluation in September 2024. Additionally, larger datasets should be examined, and realistic user tasks should be created to better evaluate the usability of the dashboards.

The AI-generated dashboards in this study did not use explicit design guidance on purpose. Future research could explore how AI performs when given clear guidelines through prompt engineering or constraint-based logic. Incorporating expert feedback into iterative refinement could also help bridge the gap between AI-generated and expert-level dashboards.

There are avenues for future work beyond the spatial characteristics of dashboards. Evaluating other aspects, such as color, interaction design, readability, and task relevance, provides a more comprehensive view of dashboard quality. With these additions, it would be useful to provide more narrative context for dashboard creation and assign tasks to measure results.

Thus, the present study should be viewed as a proposal for more thorough future research in this rapidly developing field.

7 Conclusion

This study evaluated AI- and human-created dashboard layouts based on spatial layout guidelines. In conclusion, the findings indicate that artificial intelligence can be used to generate a first draft of a spatial dashboard layout. While AI demonstrates competence in structured tasks and the management of complex datasets, it exhibits deficiencies in visualization literacy. Yet AI-assistance could still significantly reduce the time required for visualization experts and analysts. However, for more advanced interpretation and refinement of the spatial layout, human expertise remains indispensable.

Acknowledgments

The authors thank Rhenus SE & Co. KG and the Finnish Meteorological Institute for providing the dataset, and express their gratitude to all participants for their valuable contributions. This work was partially supported by the Key Profile Area "Intelligent Methods for Earth System Sciences" by the University of Cologne and the BMBF WarmWorld Project.

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