Information Visualization Redesign Project

1. *Theory (Exercise 3 Refined)*

Map chosen

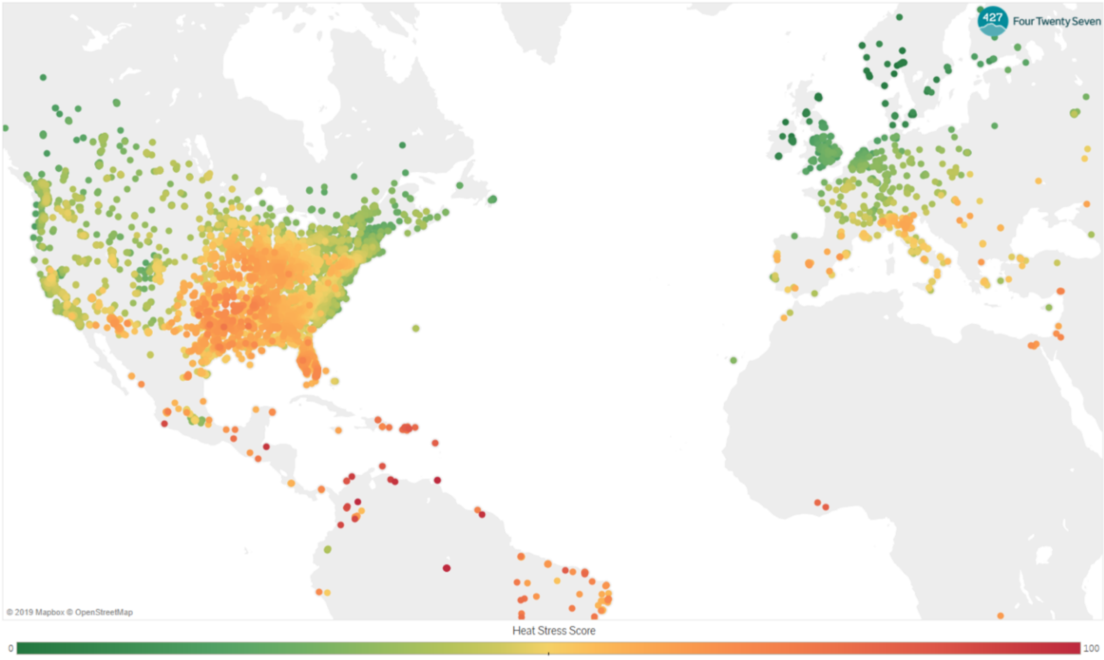

Figure 1. Original Map from AWS website

Deepseek's critique:

1. Clarity and Readability:
   - Strengths: The color gradient makes it easy to identify high-risk areas.
   - Weaknesses: Missing legend, unclear facility markers, and lack of context (e.g., score range, methodology).
   - Improvements: Add a clear legend, distinct markers for facilities, and a subtitle explaining the score.
2. Effectiveness in Communicating Insights:
   - Strengths: Shows geographic distribution of risk, useful for resilience planning.
   - Weaknesses: No interactivity, comparative data, or contextual layers (e.g., population density).
   - Improvements: Add time-series data, interactive features, and overlay contextual layers.
3. Aesthetic Appeal and Design Principles:

- Strengths: Minimalistic design with a single-color gradient.
- Weaknesses: The color palette may not be colorblind-friendly, generic base map, and have poor typography.
- Improvements: Use a colorblind-friendly palette, enhance typography, and use a more engaging base map.

4. Potential Improvements or Alternative Designs:
    - Create an interactive dashboard with filters and tooltips.
    - Overlay contextual layers (e.g., population density, infrastructure).
    - Use comparative visualizations (e.g., heat stress vs. flooding).
    - Develop a storytelling visualization to guide users through the data.

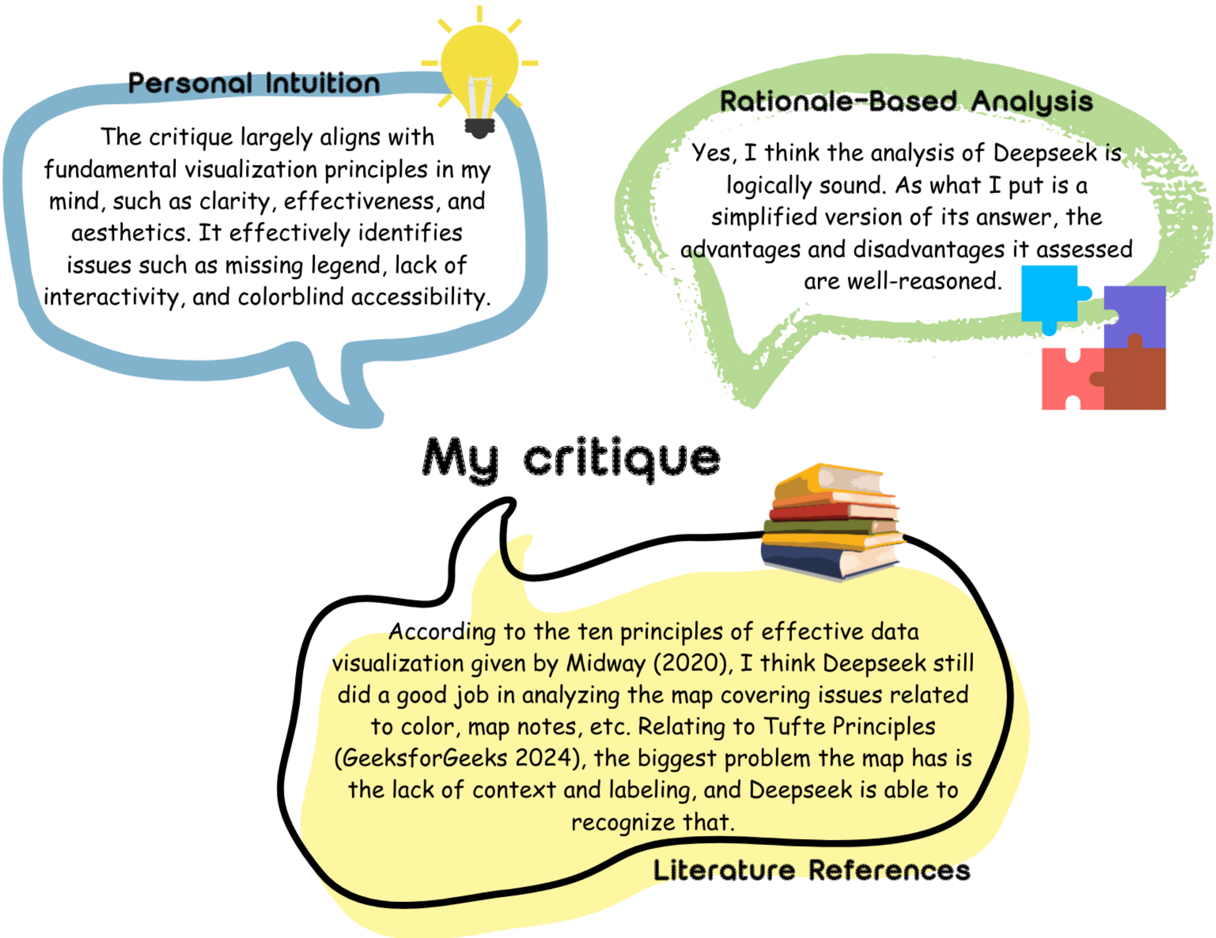

Figure 2. Critique of original map

Updated critique using the FAIR principle (GO FAIR 2017)***:***

1. Findable

Issue: The map lacks metadata (title, date of data, data source), making it hard to locate or search for the original dataset.
Critique: Without proper labels or identifiers (e.g., dataset ID or DOI), users can't trace it back to its original dataset or publication.

2. Accessible

Issue: The map is presented as a static image. There's no link, reference, or interactive element to access the underlying dataset.
Critique: Users cannot download or retrieve the raw heat stress score data behind the visualization.

3. Interoperable

Issue: No indication of standards used (e.g., geolocation format, units of measurement, encoding of scores).
Critique: Lack of standard formats or clear data structures limits integration with other climate or environmental datasets.

4. Reusable

Issue: There's no license, no methodology, or explanation of scoring (how is heat stress score calculated?).
Critique: Lack of contextual information reduces scientific transparency and hinders reuse for research or policymaking.

Critique Process

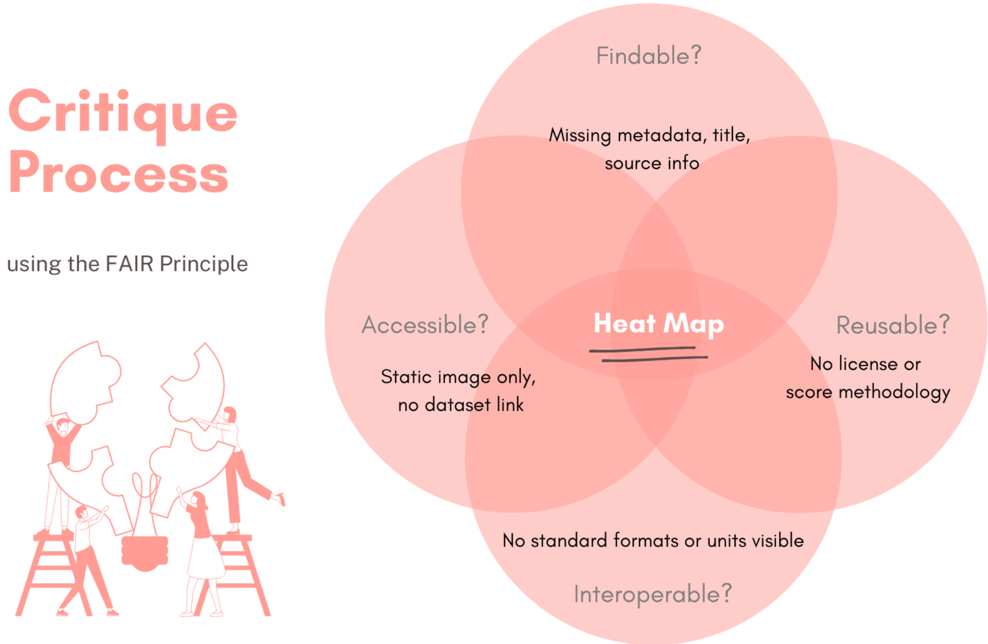

Figure 3. Critique Process

This critique process evaluates the map using the FAIR Data Principles: Findable, Accessible, Interoperable, and Reusable. We begin by checking if the data is Findable—are there clear labels, metadata, or source identifiers? Next, we assess Accessibility—can users obtain the raw dataset, or is it locked behind a static image? Third, we consider Interoperability—does the map follow standard data formats that allow integration with other datasets? Finally, we evaluate Reusability—is there enough context (e.g., methods, licenses) for others to repurpose the data confidently? The critique reveals that the map lacks transparency, data traceability, and openness—violating multiple FAIR principles. Enhancing metadata, accessibility, and documentation would greatly improve its scientific and policy value.

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2. *Research*

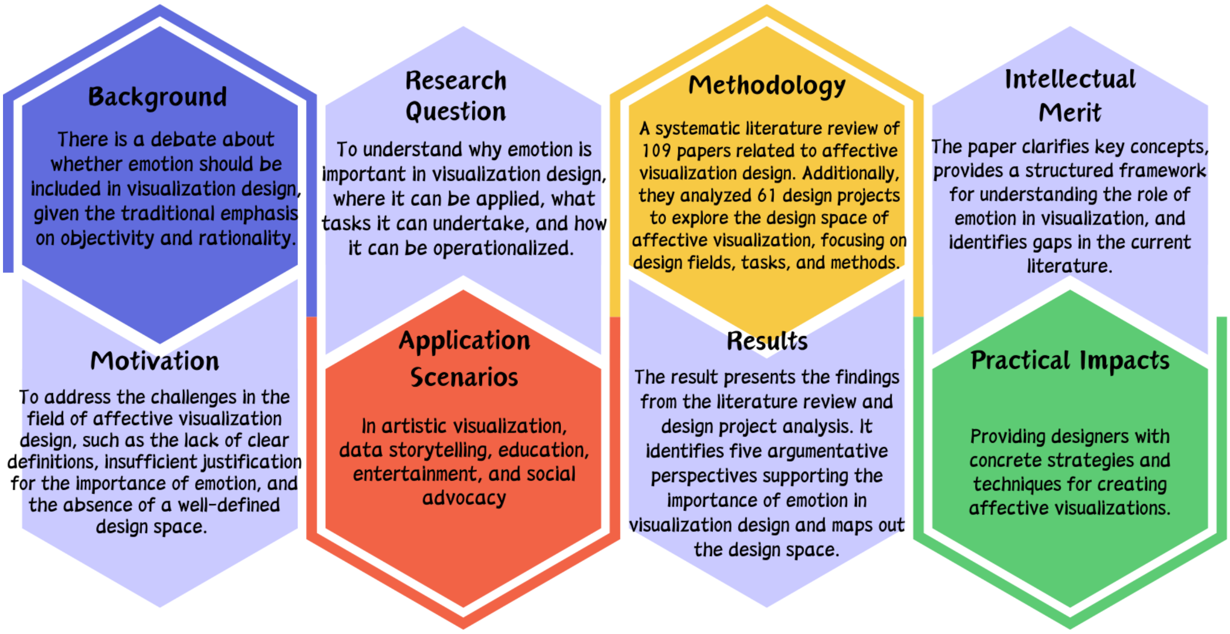

Figure 4. Summary of the article

Critique of the paper "Affective Visualization Design: Leveraging the Emotional Impact of Data"

The paper *"Affective Visualization Design: Leveraging the Emotional Impact of Data"* by Lan et al. (2023) addresses the emerging field of emotion-driven data visualization. By synthesizing existing literature and design practices, the authors aim to legitimize the role of emotion in visualization design, clarify its scope, and outline its design space.

The paper's primary strength lies in its systematic organization of a fragmented research area. By defining affective visualization design as "data visualizations designed to communicate and influence emotion" (p. 2), the authors establish a clear focus distinct from related threads, such as visualizing emotional data or emotion as a precondition. This clarity is critical for fostering interdisciplinary dialogue. The categorization of arguments into five perspectives—application, usefulness, rhetoric, sociology, and humanism (pp. 3–5)—provides a robust framework for justifying the integration of emotion in visualization.

The analysis of 61 design projects further enriches the field by mapping the where, what, *and* how of affective visualization. The identification of tasks such as inform, engage, *and* provoke (pp. 5–6) aligns with Segel and Heer's (2010) narrative visualization framework, extending it to emotional contexts. The inclusion of diverse genres—interactive interfaces, installations, and artifacts (p. 7)—demonstrates the expanding toolkit available to designers, reflecting trends in participatory and embodied visualization (Kuznetsov et al., 2011; Perovich et al., 2020).

The corpus collection methodology, combining snowball sampling and venue-based searches, ensures coverage of seminal works. However, reliance on papers from "well-recognized leading venues" (p. 3) risks overlooking niche or practitioner-driven contributions, a limitation the authors acknowledge (p. 9). While the dual-author coding process (Cohen's Kappa = 0.82) enhances reliability, the subjective interpretation of design intents—especially for in-the-wild projects—introduces potential bias. For example, the classification of U.S. Gun Death (Periscopic, 2013) as an advocacy task relies on secondary sources (designer interviews), which may not fully capture audience reception.

The paper's emphasis on designer intent overlooks user-centric evaluations. While the authors cite studies where affective techniques enhanced engagement (Lan et al., 2022, p. 4), gaps remain in understanding how diverse audiences emotionally interpret visualizations. For instance, Boy et al. (2017, cited in p. 5) found anthropomorphism had inconsistent effects on empathy, suggesting a need for context-specific validation. The ethical discussion, though brief, raises critical questions about emotion's potential to bias judgment (p. 9). However, the critique of empathy's limitations (Bloom, 2014) warrants deeper engagement with ethical frameworks, such as D'Ignazio and Klein's (2020) data feminism principles.

In conclusion, Lan et al. provide a foundational synthesis of affective visualization design, offering theoretical clarity and practical insights. While methodological constraints and ethical complexities persist, the paper successfully charts a path for future research, encouraging the visualization community to reconcile emotion with analytical rigor.

Bibliography

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3. *Practice*

3.1 Amazon Quick Sight

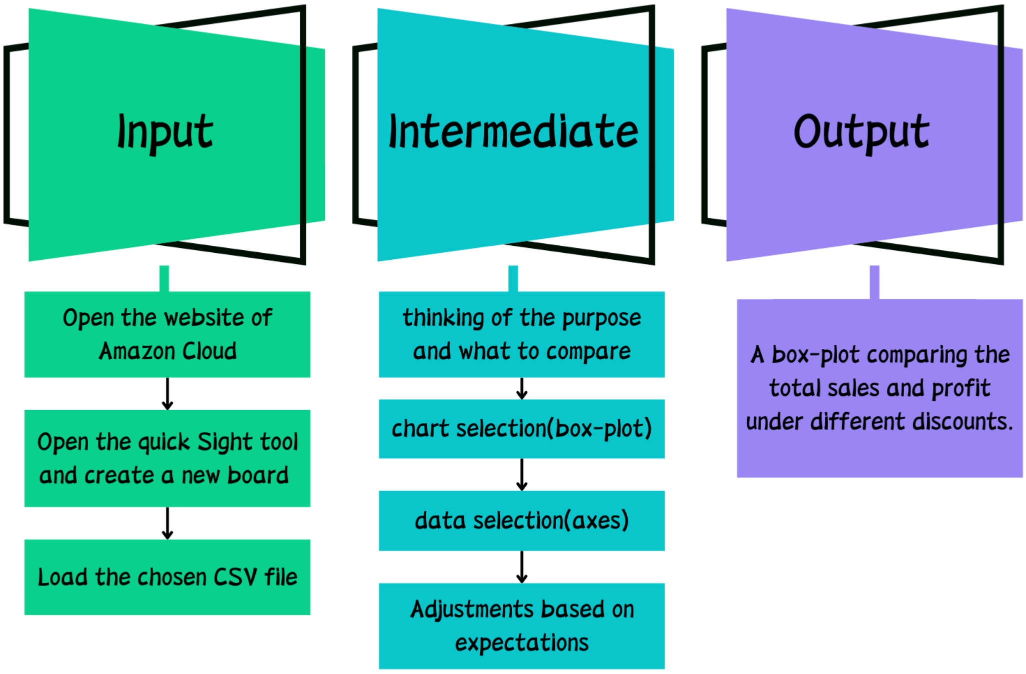

Figure 5. How to use Amazon Quicksight

Strength:

1. Quick: can handle and process large datasets in a very short period
2. AI-powered: Quick Sight uses AI to generate the graphs, fast and. accurate
3. Have a variety of plots to choose from so we can create different graphs. according to our needs.
4. Easy to use
5. Automatically has some UI designs. For example, I created a world map, when the user's mouse is hovered in one place, it can show the data embedded.

Weakness:

1. I tried to command the Q edit, which is an AI tool provided to alter the. color of the graph, but failed. The commands it could respond to are very limited.

2. The choices of the graphs are plenty but for more academic or. professional usage, it would not be enough.
3. I created three plots initially, but on the display board, I can't drag them. into a suitable place that can make a screenshot on one page.
4. While Quick Sight offers a series of visualization options, its ability to. emotionally design can be limited. According to the paper "Affective Visualization Design: Leveraging the Emotional Impact of Data" by Lan et al. (2023), Quick Sight may not support the complex emotional design techniques mentioned in the article, such as Kinetic Movement or Immersive Environment. These techniques may be necessary in certain scenarios, such as data art or social advocacy.

3.2 Reality Composer

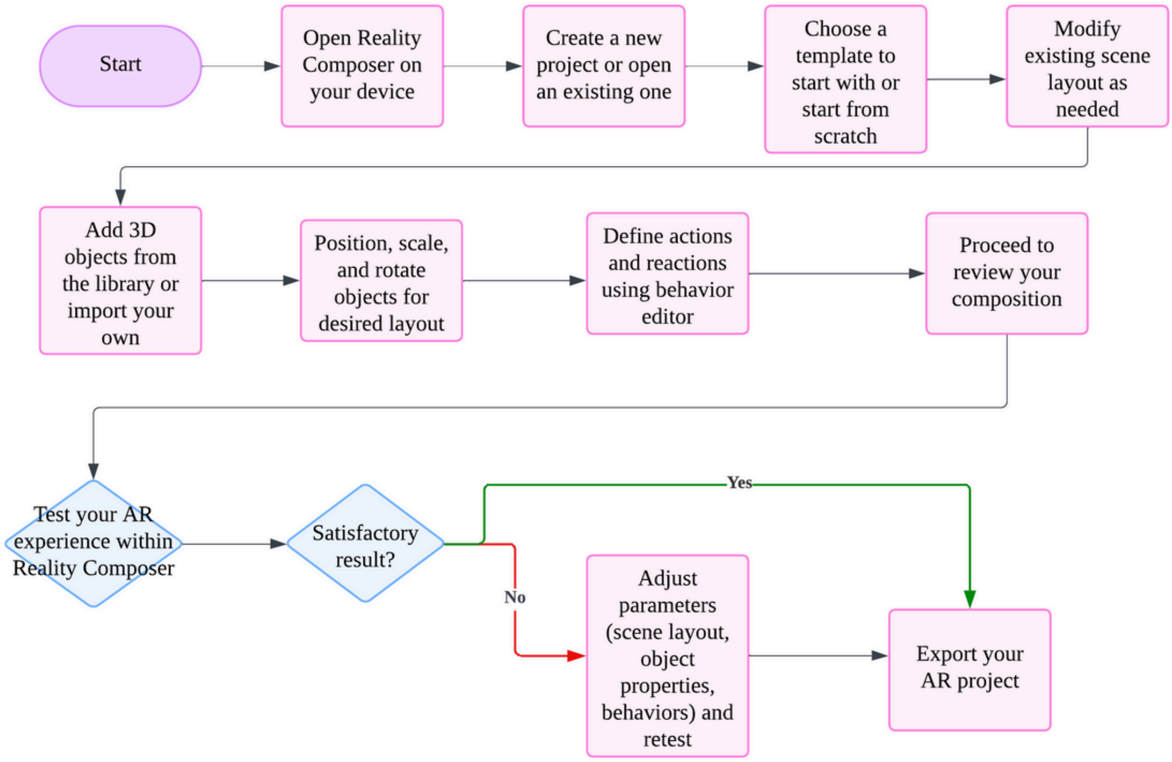

Figure 6. Using Process of Reality Composer

Exploring the tool, I made a bowling ball game using the app. Working in a 3D space is a brand new experience for me, and it inspired me to think about design, spatial relationships, and user engagement. Unlike 2D design, where elements are fixed on a plane, 3D environments demand careful consideration of depth, scale, and perspective. Ensuring that objects are positioned in a way that is both visually appealing and functionally effective can be very challenging to a green hand like me. Also, due to the limits of the app, the simulations of the collision are not quite similar to the real world, which I think how this app could improve in the future. Despite some challenges in aesthetic communication, 3D environments could have various advantages. Reality Composer enables interactive elements, such as animations and physics-based behaviors, which can enhance user engagement and emotional connection. Additionally, with Reality Composer's AR capabilities, virtual objects can seamlessly blend into real-world spaces, allowing for more intuitive and natural interactions with digital content. Mastering these elements leads to richer, more engaging experiences that transform how we interact with digital content in the physical world.

3.3 Comparative Reflection

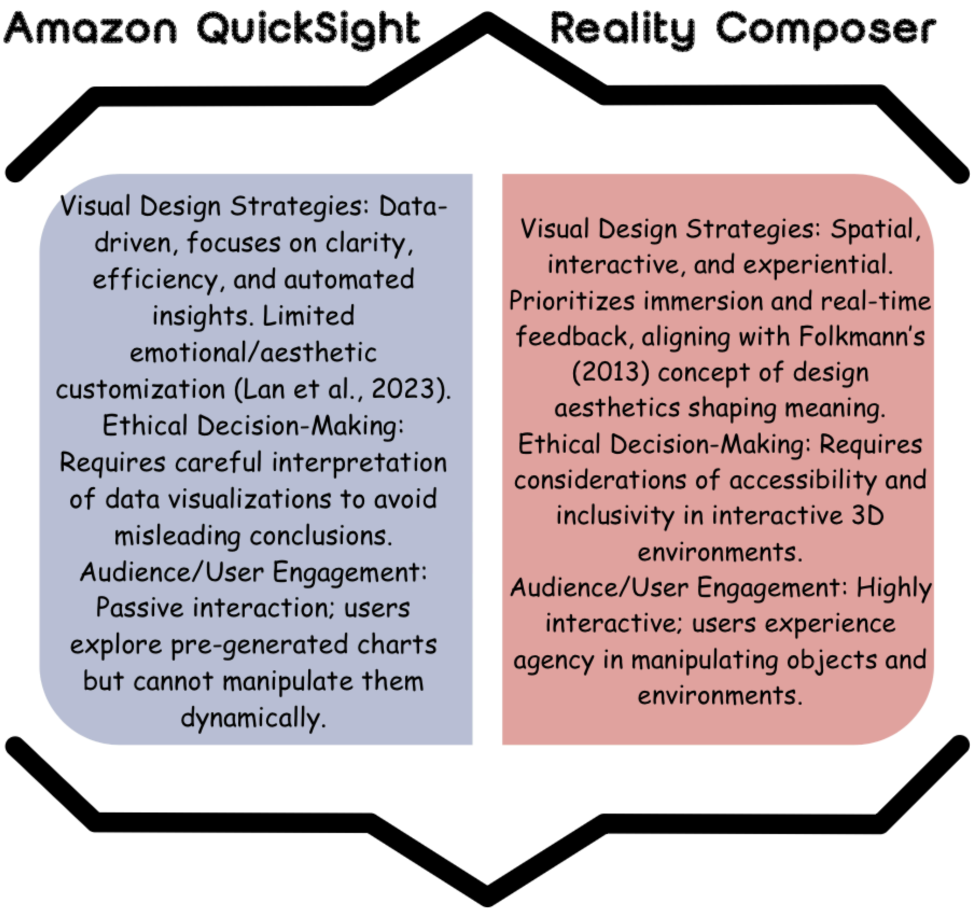

Figure 7. Comparison of Amazon Quick Sight and Reality Composer

The two tools serve different purposes: QuickSight emphasizes efficiency in data visualization, while Reality Composer enhances interactive design aesthetics. Quick Sight aligns with modernist design principles—function over form—limiting emotional engagement (Folkmann, 2013). Reality Composer, however, embodies spatial aesthetics, supporting immersive experiences and dynamic user engagement. Ethically, both require responsible design—Quick Sight for data integrity and Reality Composer for inclusive interaction. While Quick Sight risks misleading users with biased visualizations, Reality Composer must consider usability in 3D accessibility. In engagement, Reality Composer fosters active user participation, whereas Quick Sight primarily enables data exploration. This difference underscores the shift from static representation to dynamic interaction, a core principle in contemporary design aesthetics.

4. *Innovation*

Title: Interactive global average temperature map

Sources: The cleaned dataset is from Kaggle (https://www.kaggle.com/datasets/berkeleyearth/climate-change-earth-surface-temperature-data) and the raw data comes from the *Berkeley Earth data page.*

Inspiration Sources:

1. Tool: R studio
2. The Fair Principle

   We follow the FAIR data principles — Findable, Accessible, Interoperable, and Reusable — to ensure that the data we use and the outputs we generate can be easily located, accessed, shared, and integrated by others. These principles guide our efforts in making the dataset and the visualization transparent, well-documented, and reusable.
3. Affective Visualization Design

   This project is also inspired by the article *Affective Visualization Design: Leveraging the Emotional Impact of Data* (Lan et al., 2023). The research highlights how visualizations can evoke emotional responses and deepen the viewer's connection with the data. Our goal is to go beyond simply showing numbers — we aim to engage users emotionally by presenting the data in a way that encourages reflection on climate trends and their broader implications.

Advancements:

1. **Dynamic Time Exploration** – Animated timeline (1743-1987) with play/pause controls
2. **Granular Data** – Country-level temperatures (°C) instead of a single abstract score
3. **Full Climate Context** – Shows both extreme heat and cold (-10°C to 20°C)
4. **Interactive Features** – Scrubbable timeline and precise temperature readings

GitHub Site: https://github.com/YuxingZhang727/data-visualization/blob/main/README.md

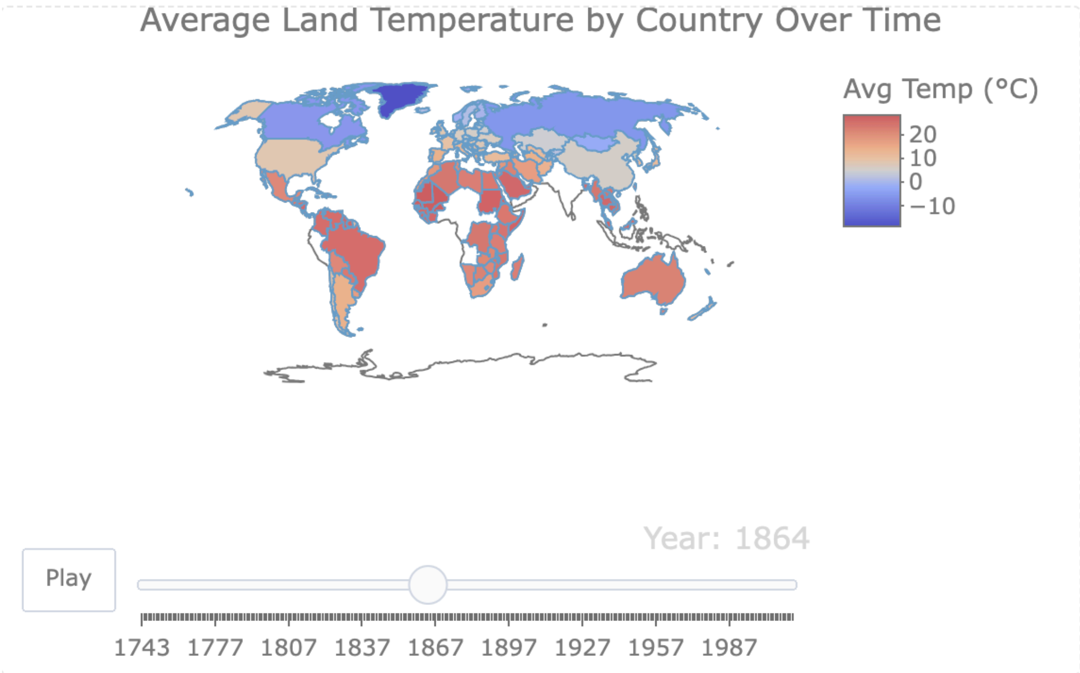

Figure 8. Redesigned map

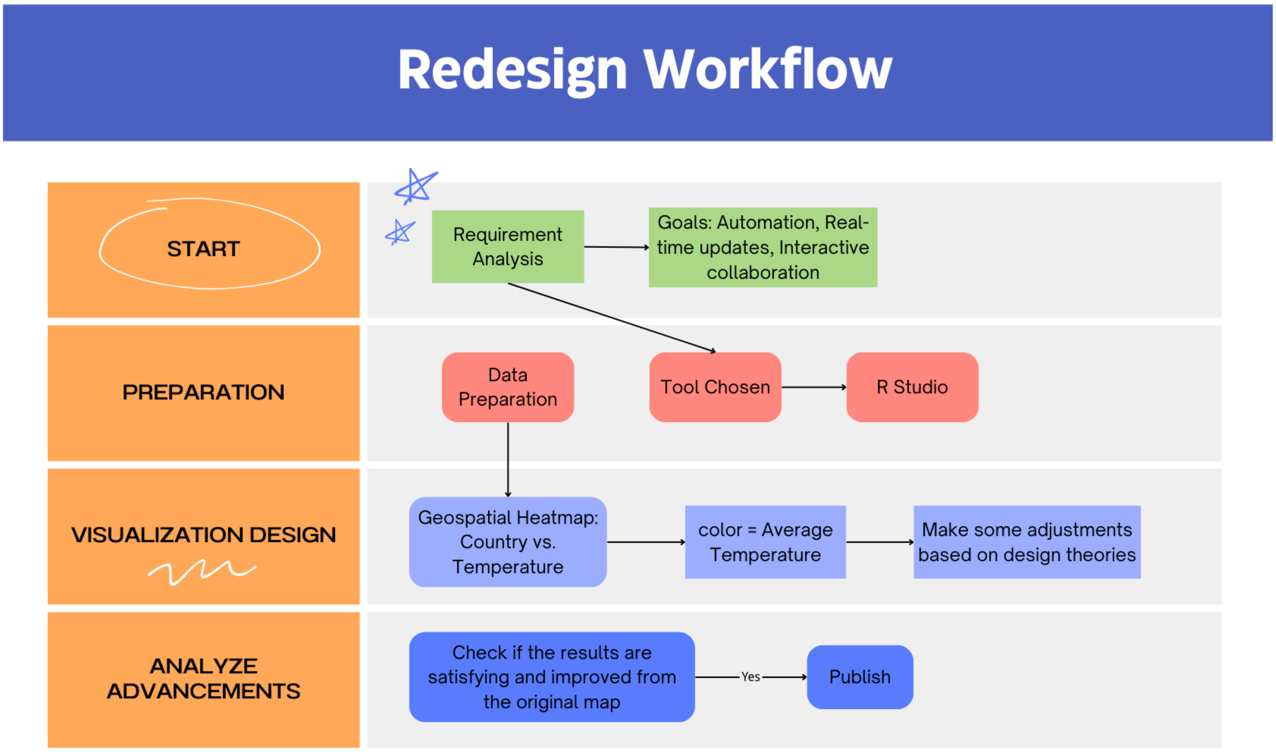

Figure 9. The Overall Redesign Process

Acknowledgments:
I would like to express my sincere gratitude to Professor Luyao Zhang for instructions and feedback, open source communities like Plotly and RStudio, whose powerful visualization tools made this project possible. Special thanks to David Schaaf, Deputy Head of Chemistry Education and Head of the NanoBioLab at Saarland University, whose presentation during Week 2 provided invaluable insights into the integration of immersive technology and education. I also wish to thank Dongping Liu from Amazon, whose talk during the conference program offered practical perspectives on data application and industry insights.