Seeing an Insight: An Eye-Tracking Analysis of How Data Visualization Shapes Decision-Making

Rafael Camacho-Aguilar [1]; Javier Rojas-Segura[2]; Jose Martinez-Villavicencio[3]; Marco Martinez-Mora[4]
[1, 2, 3, 4] Tecnologico de Costa Rica, Costa Rica, *fitacam@gmail.com, jarojas@tec.ac.cr, jomartinez@tec.ac.cr, marco.martinez@tec.ac.cr*

Abstract*– The exponential increase in data volume and complexity has made techniques such as Visual Analytics an essential approach for transforming information into actionable insights. However, while visual dashboards are often assumed to accelerate decision-making, there is limited empirical evidence about how different layouts influence users' cognitive effort and visual attention that will, in the end, trigger knowledge. This study investigates the impact that graphical versus tabular data designs have on decision-making processes, using objective measures from eye-tracking technology. In a controlled environment with 52 participants, we measured two key physiological indicators: pupil dilation, as a proxy for cognitive load, and fixation count, as a measure of visual exploration. Mixed-effects models revealed that, overall, graphical displays did not significantly increase cognitive load, in direct contradiction of the common assumption that visuals inherently reduce mental effort. However, graphical formats prompted a more exploratory mode of attention, evidenced by higher fixation counts and wider dispersed patterns. These findings highlight the importance of aligning data visualization designs with specific analytical tasks, rather than adopting a one-size-fits-all approach. The study contributes to a deeper understanding of how visual environments shape cognitive processes and offers practical recommendations for designing dashboards and decision support tools that are cognitively efficient and fit for purpose.

Keywords-- Visual analytics, neuroscience, experimental design, decision-making, cognitive load.

I. Introduction

Today's business data reality is marked by enormous amounts of data available, a direct result of datafication, the process by which nearly every aspect of our lives—our interactions, preferences, and even everyday decisions—is transformed into quantifiable digital info [1]. While this explosion of data holds immense potential for improving decision-making for business, it also presents a fundamental dilemma: How can individuals and organizations meaningfully process and interpret such vast amounts of information without becoming overwhelmed?

Humans rely on automation and analytical tools to keep up, as our cognitive abilities cannot match the pace at which data is generated. This disparity between the overwhelming volume of data and our limited capacity to process it has been recognized as a phenomenon called Perceived Data Overload (PDO) [2]. In practical terms, any professional who has faced a dashboard crowded with visualizations and tables has likely experienced this sense of uncertainty and even mental fatigue that PDO entails. Simply put, more data does not automatically translate into better decisions; in many cases, it can lead to confusion, stress, or even poor judgments.

To tackle these challenges, multiple technological solutions have emerged. Among them, Visual Analytics (VA) has become a cornerstone in the effort to transform raw data into actionable insights. At its core, VA can be described as the science of analytical reasoning facilitated by interactive visual interfaces [3]. At its full potential, VA tools empower users to dynamically investigate data, reveal concealed patterns, and derive insights that might otherwise go unnoticed, particularly as new data continuously floods existing datasets. The promise of VA lies not only in its ability to display harmonized information but in its capability to fundamentally reshape how people engage with data during the decision-making process.

However, VA adoption faces persistent challenges, including scalability constraints, training requirements, and integration difficulties with legacy systems [4]. More critically, despite widespread adoption in business intelligence, empirical studies examining how these tools influence users' cognitive processes remain surprisingly limited [5]. Fundamental questions persist: Does graphical representation genuinely reduce cognitive load, or merely redistribute it? Are visual dashboards objectively superior to tabular data, or might they inadvertently introduce new forms of visual noise?

We contend that the latter scenario frequently occurs, yet practitioners constantly overlook these empirical dimensions. Emerging research raises these concerns - controlled studies confirm visualizations successfully attract attention, but their exact impact on cognitive load and decision accuracy requires far more rigorous examination [6]. While VA's potential is undeniable, a more fundamental question emerges: Do these tools merely enhance analytical efficiency, or do they qualitatively transform cognitive processing itself? This research gap surpasses academic interest [7], it also has significant practical implications for how organizations develop decision-support systems and train personnel to use them effectively

The present study seeks to address this gap by empirical examination of how alternative data presentation formats influence both cognitive workload and visual attention outcomes. By using eye-tracking technology, we capture neuroscientific measures of these typically elusive variables. Our findings aim to clarify the advantages and constraints of visual analytics, informing best practices for designing data interfaces that enhance rather than hinder human judgment.

II. Theoretical Framework

The Evolution of Visual Analytics and Human Interaction

The term VA emerged in the early 2000s in response to the growing need to make sense of increasingly complex, fragmented data environments, more specifically in the domain of national security and intelligence analysis after September 11^{th} attacks [8]. This influential definition was centered on "analytical reasoning assisted by interactive visual interfaces," emphasizing the role of technology in enhancing human judgment [8]. Since then, the concept has evolved into a more holistic one that integrates visualization, algorithmic processing, and active user engagement [9].

This evolution of VA emphasizes an essential principle: human cognition remains at the center of effective data interpretation. Unlike purely automated analytics pipelines, VA is inherently an interactive process in which users over and over again explore, question, and refine their understanding of the data [10], describe this as a paradigm, highlighting the continuous feedback loop between the user and the system. Through this dynamic interplay, VA supports deeper comprehension, sensemaking, and the discovery of insights that static reports often fail to reveal. In a nutshell, data becomes an insight only after a human can "see it" and not because it is gathered and presented on a screen.

Graphic Comprehension and Visual Narrative

Once we establish the importance of human interaction, the effectiveness of any visualization will then depend not only on its technical design but also on the viewer's ability to comprehend and mentally process what is shown. Ref. [11] seminal work described graphic comprehension as a multistage cognitive process: identifying what real-world concepts the graphic represents, mapping visual properties like size and color to variables, and finally using this information to draw a conclusion. Notice how this is a process inherently subjective, as two individuals looking at the same chart may arrive at different interpretations, influenced by their prior knowledge, expectations, and cognitive biases.

Building on this, Pinker's Principle of Graph Difficulty suggests that the more inferential steps a visualization demands—such as mentally aggregating values, recalling hidden context, or translating unfamiliar symbols—the greater the cognitive load imposed on the user [12]. For example, a map may seem intuitive at first glance, but it could require considerable mental effort to decode if the user needs to perform calculations on it.

In recent years, the notion of incorporating more narrative in visualizations has gained traction. Ref. [13] argue that structuring visualizations as stories—with clear beginnings, transitions, and conclusions—can guide users more effectively through complex datasets. This perspective emphasizes that effective visualization is not merely about presenting data but about communicating meaning in a way that resonates with human cognitive and emotional processes, a task that storytelling achieves since ancient times.

Cognitive Load and Neuroscience in Decision-Making

To understand how VA tools affect users in real time, it is essential to consider Cognitive Load Theory (CLT) [14]. According to CLT, mental workload can be divided into three types:

1. Intrinsic load (the inherent complexity of the task),
2. Extraneous load (imposed by how information is presented), and
3. Germane load (devoted to building new understanding).

An effective visualization should reduce extraneous load, freeing up cognitive capacity for deeper analysis. Yet here we return to a fundamentally subjective process—one shaped by individual differences in perception and skill.

Neuroscience has further enriched our understanding of how visual and cognitive processes interact during decision-making. The *Two-Streams Hypothesis* suggests that the brain processes visual information along two parallel pathways: the ventral stream, responsible for recognizing "what" an object is, and the dorsal stream, responsible for determining "where" it is and guiding actions in space [15].

At the same time, Damasio's Somatic Marker Hypothesis highlights the role of emotion in shaping judgment, proposing that past emotional experiences leave "markers" that subtly guide decisions, even when we are not consciously aware of them [16].

These insights combine to reveal how we process new information, forming a framework that treats data interpretation not as a purely rational task, but as an embodied experience—one that weaves together perception, memory, and emotional responses. This perspective highlights a crucial reality: every individual brings their own subjectivity to data analysis.

In business environments, this personal dimension becomes especially significant, as pressures of time constraints, uncertainty, and high-stakes outcomes mean that each decision carries not just analytical weight, but the imprint of the interpreter's unique cognitive and emotional landscape.

Neuroscience also offers objective methods to measure these processes, eye-tracking is a powerful tool as it captures real-time physiological responses. In this study, we focus on:

1. Pupil Dilation: The pupil's size is controlled by the sympathetic (dilation) and parasympathetic (contraction) nervous systems. Beyond reacting to light, pupil diameter is a reliable physiological indicator of cognitive load; as a task demands more mental effort, the pupils dilate [17].
2. Fixation Count: Eye movements consist of fixations (pauses to acquire information) and saccades (rapid movements between points). The number of times the eyes pause in a specific area reflects visual attention. A higher fixation count can indicate that an area is of high interest, importance, or difficulty [18].

By integrating theories from cognitive psychology and neuroscience, we framework a comprehensive basis for understanding how different data presentation formats may shape users' cognitive effort and decision-making behavior.

Hypotheses

Based on this theoretical framework, our study tests the following hypotheses:

H1: The cognitive load, measured by pupil dilation, will be significantly higher for participants using graphical displays compared to tabular displays.

H2: Visual attention, measured by fixation count, will be significantly lower for participants using graphical displays compared to tabular displays.

III. Methodology

This study employed a quantitative, controlled experimental design to investigate how different data presentation formats—graphical versus tabular—influence cognitive load and visual attention during analytical tasks. The experiment was conducted in a specialized laboratory setting, the Neuroscience Business Lab at Tecnológico de Costa Rica, which was chosen to ensure that environmental conditions remained consistent and that extraneous distractions were minimized.

Participants

A total of 52 participants were recruited for the experiment. All were university students enrolled in business or data analytics programs and had prior experience working with data visualization tools such as Microsoft Excel, Tableau, or Power BI. To ensure a degree of homogeneity, participants were screened based on three criteria:

1. Completion of at least one formal course in data analysis.
2. Familiarity with interpreting both tabular and graphical data displays.
3. Normal or corrected-to-normal vision.

Participants were randomly assigned to one of two groups:

- The experimental group (*n = 26*), which interacted exclusively with graphical stimuli (thematic maps).
- The control group (*n = 26*), which interacted with tabular representations of identical data.

Random assignments helped control potential confounding variables related to prior visualization preferences or experience.

Stimuli and Tasks

The tasks were designed to emulate realistic business decision scenarios, in which participants needed to analyze demographic information about counties in Costa Rica. The visual stimuli were carefully developed using the *Data* Visualization Literacy Framework *(DVL-FW)* [19], which emphasizes aligning visualization types to specific analytical goals.

Three distinct tasks were created to represent graduated levels of intrinsic cognitive load:

1. Density Task (Low Difficulty): Participants were asked to identify the county with the highest population density. This task required basic pattern recognition and straightforward comparison.
2. Launch Task (Medium Difficulty): Participants analyzed demographic trends to recommend the most suitable location for launching a new community service. This task involved integrating multiple variables.
3. Second Option Task (High Difficulty): Participants needed to determine a secondary option if the first-choice location proved infeasible, requiring more complex comparison and reasoning.

Although the data content, color-coding, and labels were identical across groups, the presentation format (graphical maps vs. tables) was the sole manipulated variable.

Equipment and Data Collection

Eye-tracking data were collected using Tobii Pro Lab, a high-resolution system that captures both gaze position and pupil diameter in real time. Before each session, the device was calibrated for each participant using a 9-point calibration procedure to ensure precision and reduce measurement error.

During each task, the system recorded:

- Pupil Diameter (in millimeters): As an indicator of cognitive load.
- Fixation Count: As a measure of visual attention.
- Recording Duration: To control time-on-task effects.

Participants were instructed to work at their own pace but were encouraged to complete all tasks within 15 minutes.

Statistical Analysis

Given the nested nature of the data—multiple measurements nested within individuals—Mixed Linear Models were employed. This analytical approach was chosen because it allows researchers to account for:

- Fixed effects: The impact of presentation format and task type on dependent variables.
- Random effects: Variability between individual participants' baseline performance and responses.

Two separate models were constructed:

1. A model predicting Pupil Dilation, representing cognitive load.
2. A model predicting Fixation Count, representing visual attention.

All analyses were conducted in Python using Pandas, Statsmodels and Seaborn libraries, which provides robust estimation of mixed-effects models for behavioral and physiological data [20].

IV. Results

The analysis of the eye-tracking data yielded nuanced insights into how data presentation format influenced cognitive processing and visual behavior. In total, 52 recordings were collected across the three experimental tasks and two participant groups. The following subsections describe the main findings derived from the mixed-effects models, complemented by visual evidence from aggregated heatmaps.

Cognitive Load (Pupil Dilation)

The first model examined pupil dilation as a proxy for cognitive load. Contrary to our initial expectations, the results indicated that there was no statistically significant difference in the overall average pupil diameter between the graphical group (maps) and the tabular group. Specifically, the estimated coefficient for the group variable was 0.038 (p = 0.727), suggesting that, on average, neither presentation format imposed a consistently higher level of sustained mental effort.

However, a closer look at interaction effects between presentation format and task type revealed a more differentiated pattern. For the simplest "Density" task, participants using the tabular format exhibited a significant reduction in pupil dilation compared to those working with maps (coefficient = –0.051, $p < 0.001$). This finding implies that when the task requires straightforward retrieval of a specific value, tables can reduce cognitive effort by providing a more direct path to the answer.

Conversely, for the more complex tasks ("Launch" and "Second Option"), the difference between formats was attenuated or even reversed, highlighting that the cognitive demands of a visualization are closely intertwined with the nature of the analytical activity.

These patterns are visualized in Fig. 2 and Fig. 3, which display aggregated fixation heatmaps demonstrating where participants focused their attention. The graphical group's heatmaps showed concentrated clusters on key map regions, while the tabular group's heatmaps appeared more evenly distributed across the entire table. Nevertheless, in Fig. 1 although the analysis detected no statistically significant differences in central tendency measures (median/mean) between groups, a clear multimodal distribution emerged - most notably within the Tables group. These multiple modes likely reflect fluctuating cognitive demands across different task types.

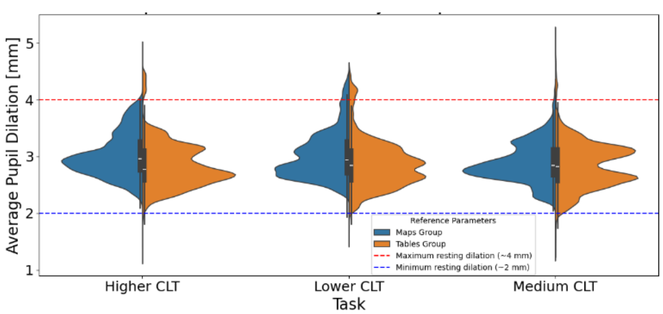

Fig. 1. Pupil Dilation Distribution by Group and Stimulus.

To validate the model and assess measurement quality, results were compared against prior research findings. Notably, no single standard for pupil size exists, as it varies across stimuli and anatomical conditions. However, medical, and neuroscientific literature documents that under moderate lighting at rest, the average adult pupil diameter ranges from 2–4 mm, potentially expanding to 8 mm in low-light conditions [21][22][23]. Fig. 1 demonstrates that most measurements fall within expected ranges, particularly in high-data-density regions. This alignment reinforces the instrument's consistency and reliability.

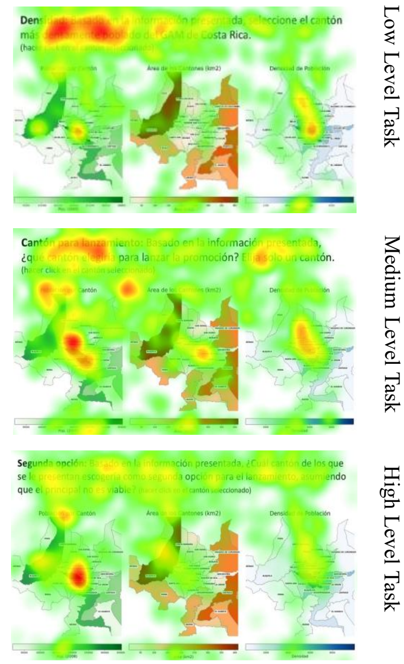

Fig. 2. Aggregated fixation heatmap Experimental (Graphical) Group.

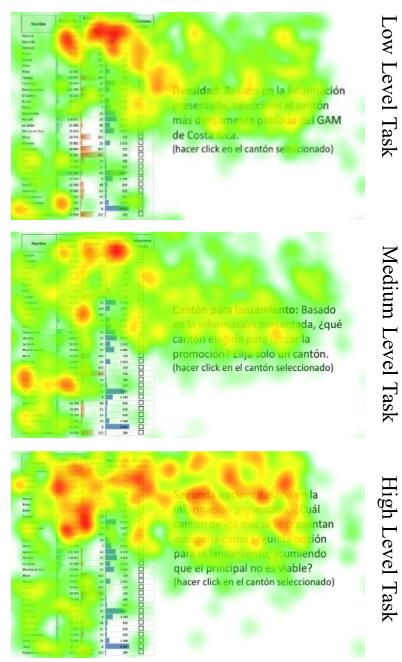

Fig. 3. Aggregated fixation heatmap Control (Tabular) Group.

Visual Attention (Fixation Count)

The second model assessed fixation count, a measure of how often participants paused to acquire information from specific areas of the display. Here, the results were more decisive. The tabular group had, on average, significantly fewer fixations compared to the graphical group (coefficient = –1116.079, $p < 0.001$). This finding contradicts our second hypothesis (H2), which predicted that tables would elicit higher fixation counts due to the need to scan rows and columns systematically.

Instead, data suggests that graphical maps promote a more exploratory and intensive visual search process, leading participants to engage with multiple regions of interest before deciding. This interpretation is reinforced by the substantial interaction effects observed between presentation format and task complexity. For example, during the "Density" task, the combination of tabular format and low complexity was associated with the fewest fixations, indicating a more targeted, efficient search strategy.

TABLE I
Mixed-Effects Models

Coefficient	Estimate	Std. Error	z-value	p-value
Model 1: Pupil Dilation				
Intercept	3.091	0.206	15.016	< .001***
Group (Tables)	0.038	0.108	0.349	0.727
Task (Density)	0.051	0.001	36.923	< .001***
Task (Launch)	0.009	0.001	7.015	< .001***
Group (Tables) × Task (Density)	-0.051	0.002	-27.115	< .001***
Group (Tables) × Task (Launch)	-0.009	0.002	-4.979	< .001***
Recording Duration			-1.171	0.242
Participant Variance (Random Effect)	0.15	0.202		
Model 2: Fixation Count				
Intercept	-393.673	417.376	-0.943	0.346
Group (Tables)	-1116.079	218.439	-5.109	< .001***
Task (Density)	-1732.301	8.594	-201.58	< .001***
Task (Launch)	-306.487	8.289	-36.975	< .001***
Group (Tables) × Task (Density)	1538.044	11.807	130.263	< .001***
Group (Tables) × Task (Launch)	1238.168	10.839	114.236	< .001***
Recording Duration	0.011	0.002	7.208	< .001***
Participant Variance (Random Effect)	615338.884	133.387		

Note: *** p < .001. The baseline for 'Group' is the Graphical (Maps) group, and the baseline for 'Task' is the '2nd Option' task.

Table I summarizes the coefficients, standard errors, and significance levels for both models. Notably, the variance attributed to individual participant differences was substantial, confirming that personal factors—such as prior experience or cognitive style—played an important role in shaping visual behavior.

Qualitative Observations

Beyond quantitative metrics, the heatmap visualizations revealed distinct qualitative patterns. Participants in the tabular condition exhibited sequential fixation patterns, indicative of methodical information retrieval. Conversely, those in the graphical condition showed more scattered, clustered fixations, consistent with exploratory visual scanning of map narratives. Both groups, however, demonstrated concentrated fixations on task-relevant areas containing critical insights. These observed differences highlight how visualization formats not only influence cognitive load but fundamentally shape users' attentional strategies and meaning-making processes.

V. Discussion

The study provides an important perspective on the actual cognitive impact of data visualization techniques, which may be contrary to assumptions prevalent in both academic literature and industry practice. Perhaps the most counterintuitive result is the absence of a significant overall difference in cognitive load, as measured by pupil dilation, between graphical and tabular formats. This finding challenges the prevailing assumption that graphical displays inherently reduce cognitive effort and enhance decision-making efficiency. Our results demonstrate that properly structured tabular data can achieve comparable cognitive efficiency to visual maps when aligned with specific task requirements. The experimental tasks were deliberately designed to reflect common business intelligence scenarios, suggesting direct relevance to real-world analytical workflows.

This understanding reinforces the principle articulated by Pinker in the Principle of Graph Comprehension [12], which argues that the difficulty of a visualization depends less on its format and more on the inferential steps required to interpret it. For simpler tasks like the "Density" scenario, where the objective was to retrieve a specific value quickly, the tabular format provided a clear advantage by offering a direct path to the answer without demanding mental translation from spatial regions to numerical estimates. In contrast, maps imposed an additional layer of cognitive effort due to their reliance on spatial reasoning. The implications for visual analytics dashboards are profound: effective design requires a priori task analysis, demanding greater business acumen from designers and product owners. This complexity further raises the stakes for frameworks like the DVL-FW, suggesting that current taxonomies must evolve to systematically address cognitive load management.

However, the findings regarding visual attention were both surprising and illuminating. The significantly higher fixation counts observed in the graphical group suggest that maps inherently encourage a more exploratory mode of analysis without raising cognitive load. This pattern aligns with the perspective of [13], who argue that visual narratives can foster richer engagement and deeper understanding. In our study, this exploratory behavior was clearly visible in the heatmaps, where participants' gaze clustered around multiple regions and the accompanying task instructions, confirmed with the number of fixations recorded as well.

This reveals a fundamental duality in exploratory attention: while enabling unforeseen discovery, it risks inefficiency and fatigue when temporal or cognitive resources are limited. The resulting task-visualization alignment problem negates one-size-fits-all solutions. We posit that adaptive BI systems should implement either:

1. Prescriptive interfaces matched to goal types, or
2. Reactive systems that detect and respond to user strategies

Our results also invite a reconsideration of widely cited frameworks, such as Shneiderman's Visual Information-Seeking Mantra: "Overview first, zoom and filter, then details on demand" [24]. While this approach emphasizes starting with broad exploration, our evidence suggests that, in many business intelligence scenarios, a "details-first" approach—prioritizing direct access to specific values—may be more efficient and cognitively economical.

This study highlights the critical role of neuroscientific methods—particularly eye-tracking—as complementary tools to conventional usability research, bridging a key gap in dashboard design. While surveys and interviews capture subjective perceptions, physiological measures provide objective, real-time evidence of cognitive load and visual attention patterns, enabling organizations to create interfaces that balance aesthetic appeal with genuine cognitive efficiency. Importantly, the significant individual differences observed—driven by factors like domain expertise, prior experience, and cognitive preferences—underscore the limitations of one-size-fits-all solutions. These findings not only caution against overgeneralizing visualization effectiveness across diverse user populations but also advocate for adaptive design strategies, such as user-customizable views or context-aware interfaces, to accommodate this variability. By combining neuroscientific rigor with traditional methods, designers can move beyond assumptions about universal "best" formats and instead develop dashboards tailored to both task requirements and human cognitive diversity.

VI. Conclusion

This study contributes new empirical evidence to the ongoing debate about the cognitive impact of data visualization formats. Using neuroscientific measures—including pupil dilation and fixation count—we have demonstrated that graphical displays and traditional tabular formats each carry distinct cognitive implications, and that their effectiveness depends largely on the nature of the analytical task at hand.

One of the central takeaways is that graphical interfaces do not inherently reduce cognitive load. Instead, they appear to encourage a more exploratory, distributed form of attention, prompting users to scan widely and integrate information across multiple regions of a display. In contrast, tables support a more focused, efficient search for specific values, which can be advantageous in decision-making contexts that demand precision and speed.

These insights challenge the common perception that visual dashboards are automatically superior to simpler tabular representations. Rather than endorsing a one-size-fits-all approach, our findings underscore the importance of selecting visualization formats deliberately, based on the specific goals, context, and constraints of the analysis.

For practitioners, the implications are clear: effective data storytelling is not merely about making information look appealing. It is about designing visual environments that align with users' cognitive processes, minimize unnecessary mental effort, and provide the right level of detail when and where it is needed. This perspective has the potential to inform the development of next-generation business intelligence tools and training programs that better equip professionals to navigate complex information landscapes.

Limitations and Future Research

While this study provides valuable insights, it was conducted in a controlled laboratory setting with a student population. Future research should aim to build on these findings in three key areas:

Improvements in Measurement: To capture a more holistic view of the user's cognitive and emotional state, future experiments should integrate more advanced neuro-measurement tools. For example, combining eye-tracking with electroencephalography *(EEG)* would allow for the real-time capture of brain activity, while facial expression analysis could measure emotional responses to the data. This would allow for a deeper exploration of how factors like frustration or confidence influence decision-making.

Improvements in Experimental Design: To better simulate real-world analytical scenarios, future studies should move beyond static images. Experiments could involve more complex and interactive tasks, such as navigating interactive reports, comparing multiple variables simultaneously, or integrating data from different sources. This would provide a more realistic test of cognitive load under the demanding conditions faced by today's data analysts.

Improvements in Statistical Analysis: The rich, high-dimensional data generated by eye-tracking is ideally suited for more advanced analytical methods. Future work should consider applying machine learning and neural network models to identify complex, non-linear patterns in user behavior. Such models could be trained to predict when a user is having trouble, identify visual patterns that lead to bias, or even forecast the quality of a decision based on the user's visual exploration strategy.

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