Designing Implicit Gaze-Aware Interactions for Scatterplot Analysis

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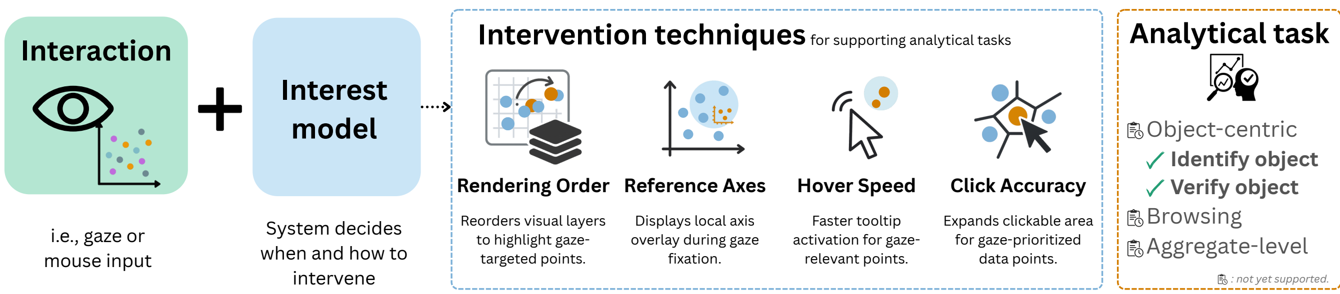

Figure 1: Overview of the gaze-aware interaction workflow. Gaze input informs an interest model, which drives the system's decision to adapt visualization behaviour through one of four intervention techniques. These techniques support task performance for identify and verify objects (object-centric) scatterplot analysis.

Abstract

We present a task-driven approach to designing implicit gaze-aware interactions for scatterplot analysis. Building on Sarikaya and Gleicher's taxonomy of scatterplot tasks, we focus on two foundational object-centric tasks—*Identify Object* and *Verify Object*—to guide the development of real-time, gaze-responsive interventions. Our design uses a gaze-based interest model to adapt the visualization interface without requiring explicit input from the user. We contribute four interaction techniques: rendering order, reference axes, hover speed, and click accuracy. These techniques respond passively to user attention, aiming to reduce occlusion, improve feedback responsiveness, and support more precise interactions. A user study with 24 participants demonstrates that gaze-aware adaptations can improve task efficiency and reduce cognitive load. Hover Speed emerged as the most effective and preferred technique, while other interventions showed promise for refinement. Our findings underscore the potential of real-time attention modelling in visualization systems and motivate future research on adaptive, user-aware interaction design.

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CCS Concepts

• **Human-centered computing** → **Visualization techniques**; **Interaction design**.

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1 Introduction

Scatterplots are foundational for revealing patterns, relationships, and outliers in multivariate data. Yet they often face interaction challenges from overplotting and visual clutter [Veras and Collins 2019; Ward et al. 2010], which hinder tasks such as locating points or comparing objects [Jeon et al. 2023]. Perception of cluster structure and mean position can also vary among users [Hong et al. 2021; Jeon et al. 2023], motivating adaptive, user-centered interaction strategies. Traditional mouse-, keyboard-, or touch-based operations (selection, filtering, zooming, panning) interrupt analytic flow and add cognitive load, particularly in dense scenes.

Advances in eye tracking enable two broad paradigms of gaze-based interaction (GBI): *explicit* interaction, where gaze acts as a direct control input, and *implicit* interaction, where the system infers attention and intent from gaze without requiring deliberate commands [Duchowski 2018; Hornbæk and Oulasvirta 2017; Serim and Jacucci 2019]. Most visualization research, however, has used gaze for explicit control (susceptible to the "Midas touch" problem) or passive post-hoc analysis [Blascheck et al. 2014]. Recent work, such as Active Gaze Labeling [Koch et al. 2025], explores real-time, uncertainty-aware gaze input, yet lightweight, task-specific gaze adaptations for analysis remain underexplored [Duchowski 2018; Vojtechovska et al. 2025].

We investigate *implicit gaze-aware techniques* for scatterplots that adapt to inferred user interest in real time. Grounded in Sarikaya and Gleicher's scatterplot task taxonomy [Sarikaya and Gleicher 2017], we focus on two fundamental object-centric tasks—*Identify Object* and *Verify Object*. Building on models of gaze-derived data-of-interest [Jianu and Alam 2017; Wang 2021] and design insights on perceptual ambiguity [Quadri et al. 2023; Tseng et al. 2023], we introduce four interventions: (1) reordering rendering to reduce occlusion, (2) displaying a local reference axis for detailed inspection, (3) accelerating tooltip timing for points of inferred interest, and (4) expanding clickable areas to reduce misclicks. These interventions respond passively to gaze, preserving analytic continuity while supporting precise, object-focused reasoning.

We describe the design rationale for each technique and report results from a controlled user study ($n = 24$) evaluating performance, preference, and workload. Findings show that even minimal gaze-aware adaptations can enhance efficiency and user experience, demonstrating the potential of implicit gaze signals as a foundation for adaptive visualization systems that support attention without explicit input.

2 Related Work

Scatterplots are among the most commonly used visualization techniques for representing relationships between variables in multivariate datasets [Hong et al. 2021; Ward et al. 2010]. However, as data complexity increases, scatterplots become visually dense, introducing challenges such as overplotting, ambiguity, and occlusion [Jeon et al. 2023; Veras and Collins 2019]. These issues make it harder for users to locate specific data points or perceive cluster boundaries, motivating the need for interaction techniques that mitigate visual overload and support exploratory tasks.

Recent studies have further shown that user perception of scatterplot structures is subject to significant variability and cognitive biases [Hong et al. 2021; Jeon et al. 2023]. These findings underscore the importance of adaptive, user-centered approaches to interaction design, particularly in dense visualizations.

2.1 Visual Attention and Gaze Behaviour

Human visual attention is inherently selective and limited [Healey and Enns 2012], influenced by both bottom-up saliency and top-down goals. Before conscious focus occurs, pre-attentive features such as colour, size, or motion steer gaze deployment [Healey and Enns 2012; Ward et al. 2010]. The guided search theory [Wolfe 1994, 2021; Wolfe et al. 1989] formalizes this interplay via a priority map that integrates bottom-up and top-down activation to model where attention is likely to land.

Eye-tracking captures the dynamics of visual attention, offering a window into user intent during data exploration. Three main eye movement types are relevant in gaze-based systems [Ward et al. 2010; Ware 2019]: *fixations* (stable gaze on a location), *saccades* (rapid shifts between fixations), and *smooth pursuits* (tracking moving objects). These signals allow modelling not only where users look but also how they interact with visual content.

2.2 Modelling Interest from Gaze Data

To interpret eye-tracking data in the context of visualization, researchers have introduced models of user interest beyond simple gaze position. Jianu and Alam [Jianu and Alam 2017] proposed the *Data-of-Interest* (DOI) model, which links gaze to data semantics rather than screen regions (i.e., AOIs). Building on this, Wang [Wang 2021] introduced the *Group-of-Interest* (GOI) model, which estimates user attention by clustering gaze fixations based on visual similarity (e.g., colour) and scoring groups based on dwell time and fixation frequency.

Recent approaches, such as Active Gaze Labeling [Koch et al. 2025], have explored real-time, uncertainty-aware gaze interpretations to support more transparent interactions. However, task-specific, lightweight gaze-driven adaptations for visualization workflows remain an underexplored area.

Building on these models, we design real-time, interest-driven interventions for scatterplot analysis tasks.

2.3 Interaction in Visualization Systems

Interaction in data visualization is broadly defined as the interplay between user actions and system responses aimed at facilitating data-driven goals [Dimara and Perin 2019]. These actions can be explicit — such as clicking, filtering, or zooming — or implicit, triggered by observed user behaviour without direct intent [Hornbæk and Oulasvirta 2017].

While traditional visualization systems rely on explicit interaction, gaze input enables novel opportunities for *implicit interaction* [Chandra et al. 2015; Chowdhury et al. 2024]. As defined by Serim and Jacucci [Serim and Jacucci 2019], implicit interaction occurs when system responses are appropriate but not deliberately invoked. In this paradigm, systems continuously monitor user behaviour and adapt in response to inferred needs, reducing cognitive effort and interaction cost.

In the context of our work, we leverage gaze-based implicit interaction for scatterplot analysis, adapting visualization behaviours in real time based on inferred user interest. Our design targets lightweight, real-time interventions informed by task-specific goals, cognitive models of attention, and recent findings on perceptual variability and scatterplot optimization [Quadri et al. 2023; Tseng et al. 2023].

3 Gaze-Based Interest Model

We adapt the Group-of-Interest (GOI) framework proposed by Wang [Wang 2021] as a real-time interest model that drives our gaze-aware interaction techniques. The GOI model extends earlier gaze frameworks such as Areas- and Data-of-Interest by grouping fixated objects based on spatial proximity and visual similarity, providing a continuous estimate of where attention is concentrated in the scatterplot. In our system, GOIs act as an intermediate layer linking gaze behaviour to real-time visualization feedback.

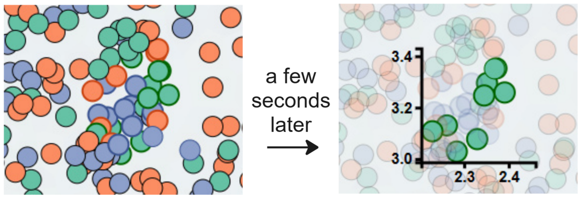

Figure 2: Example of REFERENCE AXIS activation—showing the smaller axis closer to the user's interested region and highlighting the dots of *interest colour* in that gaze region.

Gaze coordinates *(x, y)* are tracked and converted to angular velocity. Fixations (velocity < 30°/s) are identified using the standard I-VT algorithm [Holmqvist et al. 2011; Salvucci and Goldberg 2000]; only fixations contribute to interest scoring. During these periods, a Bubble Cursor-inspired selection [Grossman and Balakrishnan 2005] includes points within an angular region of about **5**°, corresponding to the foveal-parafoveal field [Holmqvist et al. 2011; Rayner 1998]. This range was pilot-tuned for stability against gaze jitter.

Interest scores are integrated over a sliding window of approximately ten gaze samples. The model re-evaluates GOI only after three new samples enter the window, balancing responsiveness with stability [Wang 2021]. A new GOI is inferred only when its cumulative score exceeds others by 50%, a heuristic that prevents flicker from transient fixations [Duchowski 2007; Jacob and Karn 2003]. These parameters follow Wang's implementation and align with common fixation and gaze-contingent display thresholds [Duchowski 2007; Holmqvist et al. 2011]. The inferred *GOI* provides a shared signal for the four gaze-aware techniques described in Section 4, functioning purely as a real-time adaptation mechanism rather than a post-hoc analysis model [Alam and Jianu 2017].

4 Tasks and Intervention Techniques for Scatterplots

We designed four implicit gaze-aware interaction techniques to support object-centered analytical tasks in scatterplot exploration. Our design rationale follows two principles commonly discussed in gaze-based interaction research: (1) using gaze as an implicit signal of user interest, and (2) augmenting visual representations without requiring explicit gaze control. Rather than replacing traditional input modalities, the proposed techniques adapt visual feedback based on inferred gaze attention to reduce perceptual and interaction costs during analysis. Specifically, the techniques target different aspects of the interaction pipeline, each addressing a distinct bottleneck in object-centric scatterplot tasks: visual prioritization to mitigate occlusion during point identification (Rendering Order), spatial reference to support value estimation in dense regions (Reference Axes), feedback timing to reduce tooltip latency for points of interest (Hover Speed), and interaction precision to reduce misclicks in crowded areas (Click Accuracy). Together, these interventions explore how implicit gaze awareness can assist users during identification and verification tasks in scatterplot analysis.

We situate the design of our techniques within prior work on gaze-based interest modelling and visualization task taxonomies. We apply this interest model to investigate how gaze-based implicit interactions can support analytical tasks in scatterplot visualizations. While Wang demonstrated the technical feasibility of modelling user interest from gaze data, his work did not connect these adaptations to specific visualization tasks or empirically assess their impact on user performance and perceived workload.

To ground the design of our techniques, we draw on Sarikaya and Gleicher's task taxonomy [Sarikaya and Gleicher 2017], which identifies twelve abstract analysis tasks commonly performed with scatterplots. We focus on two object-centric tasks — *Identify Object* and *Verify Object* — which are foundational, frequent, and well-aligned with gaze-based interest estimation, as both tasks require locating and confirming individual points under conditions of visual crowding and occlusion.

Based on these tasks and the design principles outlined above, we designed four implicit interaction techniques that adapt scatterplot elements in real time in response to inferred user interest. These techniques are not intended as mutually exclusive alternatives, but rather as complementary gaze-aware adaptations that can be applied independently or in combination. A baseline *hover information* tooltip was also included to support comparison.

While gaze-driven adaptation may alter peripheral context, our design constrains updates to fixation periods and introduces hysteresis to preserve visual stability.

Rendering Order. Points are dynamically reordered based on the user's inferred interest model. It is designed to prioritize visually attended elements and mitigate occlusion during object identification tasks. During saccadic movements — when updates are less perceptible [Simons and Rensink 2005] — points associated with higher inferred interest are re-rendered on top of others, making them more visually prominent without altering their underlying attributes.

Reference Axis. A contextual axis overlay is introduced in regions of visual attention. It is designed to assist spatial comparison and value estimation during verification tasks. When a user maintains a stable gaze within a region of the scatterplot, a local axis overlay appears, showing nearby axis labels (Figure 2). The overlay persists during fixations and smooth pursuits—slow, continuous gaze movements that occur when a user tracks along a region of interest—but disappears on saccades to avoid interference with broader navigation. Here, fixation is defined as a stable gaze maintained within a small region for a minimum duration, based on standard eye-tracking thresholds.

Hover Speed. Tooltip activation delays are adjusted for points that receive sustained visual attention. It is designed to provide faster access to contextual information for points receiving sustained visual attention. As shown in Table 1, tooltip delays vary depending on whether a point is associated with the inferred interest colour. Once activated, reduced delay times persist until a saccadic reset occurs. Although tooltips are triggered via cursor hover, gaze-informed delay modulation allows the system to anticipate points of interest prior to explicit interaction.

Table 1: Tooltip activation delays by interest and activation state.

Delay Time	Interest Colour	Non-interest Colour
1.3 sec (Slow)	–	Before activation
0.6 sec (Medium)	Before activation	After activation
0.0 sec (Fast)	After activation	–

Click Accuracy. Interactive regions are adjusted using a weighted Voronoi diagram informed by gaze-derived interest. It is designed to make interaction with visually attended targets more tolerant to input imprecision. Points associated with higher inferred interest are assigned larger interaction regions, modifying the effective clickable area without changing the visual representation. Figure 3 shows the underlying Voronoi structure; users do not see these boundaries, but interact with the adapted regions. As this adaptation operates implicitly, users may not be explicitly aware of changes in interaction regions.

Hover Information. A standard tooltip appears on mouse hover, displaying each point's ID and coordinates. This static condition serves as a non-gaze-adaptive baseline for comparison with the Hover Speed technique.

5 Preliminary Evaluation

To evaluate the task-level effectiveness of our gaze-aware interaction techniques, we conducted a controlled user study comparing four individual techniques, a baseline (None), and a combined condition (All). Our goal was to assess whether these implicit interactions could improve task performance and user experience in dense scatterplot analysis.

5.1 Study Design

Participants completed two visual analysis tasks — *Identify Object* and *Verify Object* — under six conditions: each individual technique (Rendering Order, Reference Axis, Hover Speed, Click Accuracy), no technique (None), and all techniques together (All). Each condition included 10 trials (5 per task), resulting in a total of 60 trials per participant.

Performance was measured by completion time and accuracy (number of incorrect attempts). Participants also completed a NASA-TLX workload assessment after each task and a post-study questionnaire regarding technique preferences.

5.2 Tasks

Identify Object. Participants were given the *(X, Y)* coordinates and colour of a target point and asked to locate it on a dense scatterplot. They clicked to submit a response and were required to retry until correct.

Verify Object. Participants were given a colour, ID, and coordinate range, then asked to find the target and report its exact *(X, Y)* coordinates via text input. Incorrect entries required reattempts.

5.3 Conditions and Hypotheses

We hypothesized that each intervention would improve performance relative to the baseline (None), see Table 2. Conditions were presented in a semi-counterbalanced order. The All condition was always last, and its results may therefore partly reflect learning or familiarity effects rather than purely combined-technique benefits. This condition's primary purpose was to explore which techniques participants preferred when given a choice. The baseline condition was evenly distributed across positions to reduce bias, and the remaining conditions varied in order due to their distinctiveness and the impracticality of full counterbalancing.

Table 2: Improvement hypotheses per condition.

Condition	Hypothesis
Rendering Order	Reduced occlusion improves accuracy and completion time.
Reference Axis	Local axis aids numeric reasoning, improving both metrics.
Hover Speed	Faster tooltip display reduces search time.
Click Accuracy	Enlarged hit areas improve selection accuracy.
All	Allows participants to choose to use their preferred techniques after experiencing them.

5.4 Dataset and Materials

We generated 15 scatterplot datasets with `Scikit-Learn`, each containing 600 points across three colour classes. Visual variation and complexity were controlled by adjusting cluster standard deviation and class overlap parameters. Datasets were assigned randomly per condition and task to minimize repetition. The study system was built using HTML/CSS/JavaScript (D3.js) and integrated with a Tobii Eye Tracker 5. Data collection included gaze logs, interaction events, and all trial-level performance metrics.

5.5 Participants and Procedure

We recruited 24 participants at our institution, who completed the 90-minute in-person session. All had normal or corrected vision and no colorblindness. Prior experience was assessed via a pre-study questionnaire. Most participants were familiar with scatterplots: 45.8% viewed and created charts monthly, while 41.7% viewed and 25% created charts more frequently. Regarding eye tracking, 87.5% had never used an eye tracker or were unfamiliar with it, and 12.5% had prior experience with eye tracking in gaming or research contexts. No participant had previously used eye tracking as a chart interaction tool. After consent and eye tracker calibration, participants completed the pre-study questionnaire, the six condition blocks (with a NASA-TLX raw workload assessment using a 21-point scale per dimension [Hart and Staveland 1988] administered after each block), and a post-study questionnaire. Participants were compensated $30.

The post-study questionnaire consisted of six sections: two sections covering general study experience and technique preferences, and one section per intervention technique. Questions included Likert-scale ratings, quantitative items, and open-ended responses about perceived helpfulness and distraction.[1]

Data were analyzed for performance (completion time and incorrect attempts), workload (NASA-TLX), and technique preference. To assess normality, we applied the Shapiro-Wilk and D'Agostino-Pearson tests. As the data were not normally distributed, we used the Kruskal-Wallis test to assess overall condition effects, followed

[1]Full questionnaire items are provided in the supplemental materials.

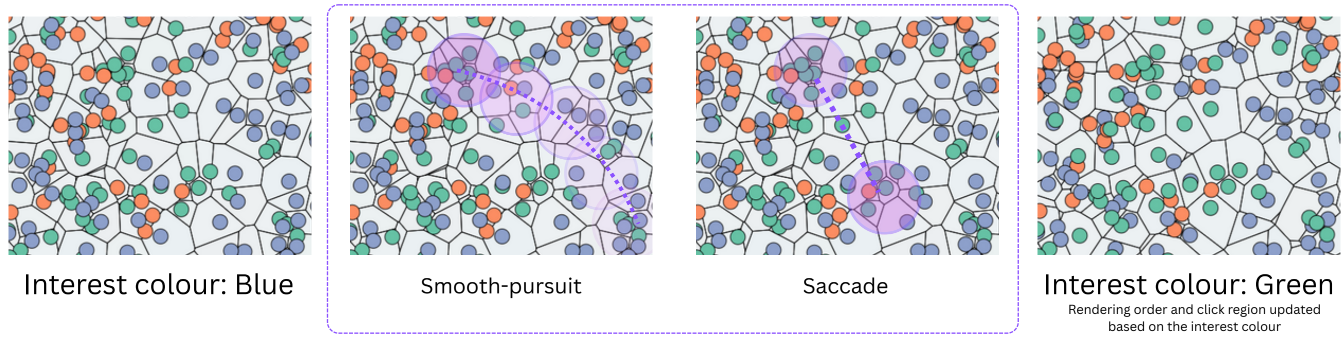

Figure 3: Voronoi diagram used to expand or contract clickable regions during Click Accuracy. The first panel presents the plot and clickable regions with blue as the interest colour. The second panel represents a smooth pursuit, where the user's gaze gradually shifts across the plot, updating the inferred interest colour to green. However, the rendering order and weighted Voronoi update only after a saccadic movement is detected (third panel). The last panel shows the updated plot with green dots rendered to the top and recalculated clickable regions.

by pairwise Mann-Whitney U tests with Bonferroni correction for multiple comparisons.

5.6 Results and Insights

The study results suggest that gaze-aware implicit interactions can improve task performance and user experience in scatterplot analysis—particularly for more complex analytic tasks.

Hover Speed Was the Most Effective Technique. Hover Speed was both the top-performing and most preferred technique. In the All condition, it reduced tooltip wait time by 61%—saving over one minute of cumulative delay compared to the fixed-delay baseline. It was also the second-fastest condition for the *Verify Object* task, averaging 6.4 minutes—just behind All (4.9 minutes—Fig. 4). Participants consistently rated Hover Speed as the most useful technique: 100% reported that it helped them complete tasks, 83.3% found it non-distracting, and 66.7% selected it as their favourite for *Identify Object*. Observation logs showed that participants often hovered repeatedly over dense regions before clicking, highlighting the need for improved click precision and tooltip timing. Participants also noted that the Reference Axis helped them confirm nearby values without looking away from the region of interest, reinforcing the utility of implicit contextual cues (e.g., *"closer axis view… helped [to] double-check their position"* [P06]). Participants described Hover Speed as helpful and largely non-distracting; one noted it *"helped to identify the point… and the time differences made it faster"* [P18].

Gaze-Driven Adaptations Support Complex Tasks. While both tasks—*Identify Object* and *Verify Object*—benefited from intervention techniques, improvements were more pronounced for the more complex *Verify Object* task. In the All condition, participants completed this task significantly faster ($p < 0.05$, Bonferroni-corrected) and reported lower perceived workload than in other conditions. The NASA-TLX score for All during this task was 9.1, compared to 12.8 for Rendering Order, 12.2 for Reference Axis, and 11.3 for Click Accuracy—highlighting the effectiveness of combining techniques in reducing cognitive load. These findings suggest that implicit gaze interaction is particularly valuable for cognitively demanding analysis. Pairwise comparisons between individual techniques revealed no statistically significant differences across conditions ($p > .05$, Bonferroni-corrected), suggesting that while each technique provides task-specific benefits, none consistently outperformed the others in isolation. Detailed NASA-TLX results for all dimensions and conditions are provided in App. A.

Technique Impact Varies by Interaction Type. Rendering Order and Reference Axis showed mixed results. Some participants remarked that visual updates could feel sudden during rapid scanning—*"a different colour pops up while focusing on a specific area"* [P11]—and that the reference axis could *"pop up"* unexpectedly [P09], suggesting the need for smoother transition effects or a brief hold option. Although both were frequently activated during the All condition, feedback highlighted challenges with user awareness and control. Participants noted that rendering changes were most noticeable during rapid scanning, occasionally drawing unintended attention to newly foregrounded points, while the reference axis was particularly helpful for verifying outliers or points near axis boundaries where precise comparison was otherwise difficult. Participants sometimes overlooked these passive adaptations or found them distracting when triggered unintentionally. A hybrid activation model (e.g., gaze + manual trigger) may improve usability. While colour served as a convenient encoding for gaze-derived interest, we acknowledge it can amplify perceptual grouping bias [Hong et al. 2021] and plan to explore alternative encodings.

Click Accuracy Was Underutilized. Click Accuracy had limited impact in this study (e.g., *"I feel like I clicked the points mostly accurately each time, but this would be good for those who do not always click exactly where they want"* [P15]). Participants rarely activated it during tasks and often expressed uncertainty about its purpose. A few mentioned that they clicked more confidently once they realized the system subtly expanded target regions in response to gaze, suggesting a potential learning effect with repeated exposure. It may prove more effective in high-pressure scenarios with tighter time constraints or smaller target regions. Future work could further explore its utility in those contexts.

Interest Model Accuracy Was Promising. Across all conditions, the gaze-based interest model predicted the correct target colour in 50% of trials—substantially above chance (33%). While not perfect, this level of accuracy was sufficient to enable meaningful adaptations in most cases, supporting its feasibility for real-time interaction.

Participants Would Use These Techniques. Across conditions, participants gradually adapted their gaze–cursor coordination, slowing cursor movement near regions where gaze feedback was active. In post-study feedback, over 90% indicated they would use gaze-aware techniques in future analysis workflows, with Hover Speed emerging as the top choice for both tasks.

Study Limitations. As a preliminary evaluation, this study has several limitations that should be considered when interpreting the results. The completion time data show high standard deviations across conditions (e.g., 6.23 min for Hover Speed and 9.28 min for Rendering Order in the *Verify Object* task), reflecting substantial individual variability in task strategy, gaze behaviour, and familiarity with scatterplot analysis. This variability is consistent with individual differences in gaze behaviour commonly observed in gaze-based interaction studies [Duchowski 2018; Vojtechovska et al. 2025]. As a result, the observed effects should be interpreted as indicative trends rather than uniform improvements across all participants. The semi-counterbalanced condition order may also have introduced learning effects, particularly for the All condition, which was always presented last. Additionally, the study was conducted with a general university population on a single visualization type, limiting generalizability to expert users or other chart types. The interest model's 50% accuracy, while above chance, means adaptations were not always aligned with the user's actual target, which may have contributed to inconsistent technique performance across participants. Future work should explore designs that are more robust to gaze noise and individual differences.

Implications for Visualization Systems. Our findings suggest that even lightweight implicit gaze-driven adaptations can improve analytic workflows, particularly in dense or cognitively demanding scenarios. As visualizations become more interactive and complex, incorporating real-time attention modelling opens new opportunities for designing systems that respond to user intent without requiring explicit input—reducing friction and enhancing engagement. These results support the potential of implicit gaze signals as a low-friction mechanism for adaptive interaction [Duchowski 2018; Vojtechovska et al. 2025]. This aligns with prior gaze-based interaction research showing that implicit gaze input can reduce interaction costs, mitigate issues such as the "Midas touch" problem, and better preserve users' analytic flow compared to explicit gaze control paradigms. More broadly, our findings suggest that effective implicit gaze-aware interaction design can be understood as aligning lightweight, task-specific adaptations with inferred user attention, rather than treating gaze as a direct control modality. This perspective provides a foundation for designing future gaze-aware systems that support analysis through subtle, context-aware intervention. This suggests a shift in gaze-based interaction design from treating gaze as an input modality toward leveraging it as a continuous signal for adaptive system behaviour.

Task	Condition	Mean Completion Time (min)	Mean Incorrect Attempts
Identify Object	None (baseline)	2.66 ± 2.36	0.26 ± 1.79
	Rendering Order	2.72 ± 2.27	0.28 ± 1.55
	Reference Axis	3.49 ± 2.71	0.15 ± 0.52
	Hover Speed	2.73 ± 2.33	0.08 ± 0.38
	Click Accuracy	3.19 ± 3.21	0.71 ± 1.43
	All Techniques	3.10 ± 4.47	0.17 ± 1.05
Verify Object	None (baseline)	6.56 ± 5.69	0.07 ± 0.33
	Rendering Order	7.46 ± 9.28	0.10 ± 0.35
	Reference Axis	7.33 ± 6.26	0.03 ± 0.18
	Hover Speed	6.32 ± 6.23	0.06 ± 0.23
	Click Accuracy	6.78 ± 7.46	0.58 ± 0.27
	All Techniques	4.87 ± 3.98	0.07 ± 0.34

Figure 4: Mean (±SD) completion time and incorrect attempts per condition and task. Brackets indicate significant pairwise differences (* p < .05, ** p < .001, Bonferroni-corrected). No significant differences were found between individual techniques.

6 Conclusion and Future Work

This paper introduces a task-driven approach to designing implicit gaze-aware interaction techniques for scatterplot analysis. Grounded in Sarikaya and Gleicher's taxonomy [Sarikaya and Gleicher 2017], we focused on two foundational object-centric tasks—*Identify Object* and *Verify Object*—and developed four gaze-responsive interaction techniques based on real-time interest modelling.

A user study with 24 participants demonstrated that gaze-aware adaptations can improve analytic efficiency and reduce perceived workload. Among the techniques, Hover Speed—which dynamically adjusts tooltip timing—was consistently preferred by participants and yielded measurable improvements in task time and satisfaction. Rendering Order and Reference Axis showed potential for supporting more complex analyses but raised design questions around implicit activation and user control. Click Accuracy, while less impactful in this context, may benefit from further refinement or evaluation under different task demands.

These findings suggest that implicit gaze interaction offers a promising path toward more adaptive, context-aware visual analysis systems, consistent with the growing body of work on gaze-contingent and attention-aware interfaces [Duchowski 2018; Vojtechovska et al. 2025]. In particular, our results reinforce established GBI principles that leveraging gaze implicitly—rather than as a direct control signal—can support more seamless and less disruptive interaction. Our contributions include: (1) a theoretically grounded framework for designing gaze-driven interactions tied to analytic task types, (2) the implementation of four novel interaction techniques tailored for scatterplots, and (3) a preliminary empirical validation of their impact on user performance and experience.

Although our evaluation focused on behavioural outcomes, the underlying gaze events—fixation stability, saccade frequency, and pursuit behaviour—likely mediate these effects by reflecting shifts in visual attention. Future work will relate these gaze features directly to performance metrics. Our study was limited to scatterplots and a general user population; the efficacy of gaze-driven techniques across other visualization types and tasks remains to be explored. Additionally, interaction quality is constrained by the accuracy and responsiveness of the eye-tracking hardware.

We see several directions for future research. Expanding these techniques to additional visual encodings and analytic task types—especially within group- and relation-centric categories—would generalize our approach. Hybrid interaction models that blend gaze signals with explicit controls may improve usability and mitigate distraction. Finally, more adaptive systems could learn user preferences over time, dynamically adjusting interaction strategies to better support individual analytic workflows.

Together, this work lays a foundation for integrating real-time attention modelling into visualization systems, enabling subtle, user-aware interactions that support efficient and personalized data analysis.

Privacy and Ethics Statement

Approved under institutional ethics review, this study used informed consent and local, anonymized gaze data processing to protect participant privacy. The work promotes responsible, non-intrusive gaze-aware interaction design.

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References

Sayeed Safayet Alam and Radu Jianu. 2017. Analyzing Eye-Tracking Information in Visualization and Data Space: From Where on the Screen to What on the Screen. *IEEE Transactions on Visualization and Computer Graphics* 23, 5 (2017), 1492–1505. doi:10.1109/TVCG.2016.2535340

T. Blascheck, K. Kurzhals, M. Raschke, M. Burch, D. Weiskopf, and T. Ertl. 2014. State-of-the-Art of Visualization for Eye Tracking Data. In *EuroVis - STARs*, R. Borgo, R. Maciejewski, and I. Viola (Eds.). The Eurographics Association, Goslar, Germany. doi:10.2312/eurovisstar.20141173

Sushil Chandra, Greeshma Sharma, Saloni Malhotra, Devendra Jha, and Alok Prakash Mittal. 2015. Eye tracking based human computer interaction: Applications and their uses. In *Int. Conf. on Man and Machine Interfacing (MAMI)*. IEEE, New York, NY, USA, 1–5. doi:10.1109/MAMI.2015.7456615

Mashrur Chowdhury, Kakan Dey, and Amy Apon. 2024. *Data analytics for intelligent transportation systems*. Elsevier, Amsterdam, Netherlands.

Evanthia Dimara and Charles Perin. 2019. What is interaction for data visualization? *IEEE Trans. on Visualization and Computer Graphics* 26, 1 (2019), 119–129. doi:10.1109/TVCG.2019.2934283

Andrew T. Duchowski. 2007. *Eye Tracking Methodology: Theory and Practice* (2 ed.). Springer, New York, NY, USA.

Andrew T Duchowski. 2018. Gaze-based interaction: A 30 year retrospective. *Computers & Graphics* 73 (2018), 59–69. doi:10.1016/j.cag.2018.04.002

Tovi Grossman and Ravin Balakrishnan. 2005. The bubble cursor: Enhancing target acquisition by dynamic resizing of the cursor's activation area. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '05)*. Association for Computing Machinery, New York, NY, USA, 281—-290. doi:10.1145/1054972.1055012

Sandra G Hart and Lowell E Staveland. 1988. Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. In *Advances in psychology*. Vol. 52. Elsevier, Amsterdam, Netherlands, 139–183. doi:10.1016/S0166-4115(08)62386-9

Christopher Healey and James Enns. 2012. Attention and Visual Memory in Visualization and Computer Graphics. *IEEE Transactions on Visualization and Computer Graphics* 18, 7 (2012), 1170–1188. doi:10.1109/TVCG.2011.127

Kenneth Holmqvist, Marcus Nyström, Richard Andersson, Richard Dewhurst, Halszka Jarodzka, and Joost Van de Weijer. 2011. *Eye Tracking: A Comprehensive Guide to Methods and Measures*. Oxford University Press, Oxford, UK.

Matt-Heun Hong, Jessica K Witt, and Danielle Albers Szafir. 2021. The weighted average illusion: Biases in perceived mean position in scatterplots. *IEEE Trans. on Visualization and Computer Graphics* 28, 1 (2021), 987–997. doi:10.1109/TVCG.2021.3114783

Kasper Hornbæk and Antti Oulasvirta. 2017. What is interaction?. In *Proc. of the SIGCHI Conf. on Human Factors in Computing Systems* (Denver, Colorado, USA) *(CHI '17)*. Association for Computing Machinery, New York, NY, USA, 5040–5052. doi:10.1145/3025453.3025765

Robert J. K. Jacob and Keith S. Karn. 2003. Eye Tracking in Human–Computer Interaction and Usability Research: Ready to Deliver the Promises. In *The Mind's Eye: Cognitive and Applied Aspects of Eye Movement Research*, Jukka Hyönä, Ralph Radach, and Heiner Deubel (Eds.). Elsevier Science, Amsterdam, Netherlands, 573–605.

Hyeon Jeon, Ghulam Jilani Quadri, Hyunwook Lee, Paul Rosen, Danielle Albers Szafir, and Jinwook Seo. 2023. Clams: A cluster ambiguity measure for estimating perceptual variability in visual clustering. *IEEE Trans. on Visualization and Computer Graphics* 30, 1 (2023), 770–780. doi:10.1109/TVCG.2023.3327201

Radu Jianu and Sayeed Safayet Alam. 2017. A data model and task space for data of interest (DOI) eye-tracking analyses. *IEEE Trans. on Visualization and Computer Graphics* 24, 3 (2017), 1232–1245. doi:10.1109/TVCG.2017.2665498

Maurice Koch, Nan Cao, Daniel Weiskopf, and Kuno Kurzhals. 2025. Active gaze labeling: Visualization for trust building. *IEEE Trans. on Visualization and Computer Graphics* 31, 7 (2025), 3942–3956. doi:10.1109/TVCG.2024.3392476

Ghulam Jilani Quadri, Jennifer Adorno Nieves, Brenton M. Wiernik, and Paul Rosen. 2023. Automatic scatterplot design optimization for clustering identification. *IEEE Trans. on Visualization and Computer Graphics* 29, 10 (2023), 4312–4327. doi:10.1109/TVCG.2022.3189883

Keith Rayner. 1998. Eye Movements in Reading and Information Processing: 20 Years of Research. *Psychological Bulletin* 124, 3 (1998), 372–422. doi:10.1037/0033-2909.124.3.372

Dario D. Salvucci and Joseph H. Goldberg. 2000. Identifying Fixations and Saccades in Eye-Tracking Protocols. In *Proceedings of the Eye Tracking Research & Applications Symposium (ETRA)*. ACM, New York, NY, USA, 71–78. doi:10.1145/355017.355028

Alper Sarikaya and Michael Gleicher. 2017. Scatterplots: Tasks, data, and designs. *IEEE Trans. on Visualization and Computer Graphics* 24, 1 (2017), 402–412. doi:10.1109/TVCG.2017.2744184

Barış Serim and Giulio Jacucci. 2019. Explicating "Implicit Interaction": An Examination of the Concept and Challenges for Research. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–16. doi:10.1145/3290605.3300647

Daniel J Simons and Ronald A Rensink. 2005. Change blindness: Past, present, and future. *Trends in Cognitive Sciences* 9, 1 (2005), 16–20. doi:10.1016/j.tics.2004.11.006

Chin Tseng, Ghulam Jilani Quadri, Zeyu Wang, and Danielle Albers Szafir. 2023. Measuring categorical perception in color-coded scatterplots. In *Proc. of the SIGCHI Conf. on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, 1–14. doi:10.1145/3544548.3581416

Rafael Veras and Christopher Collins. 2019. Saliency deficit and motion outlier detection in animated scatterplots. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–12. doi:10.1145/3290605.3300771

Michaela Vojtechovska, Stanislav Popelka, and Petr Kubíček. 2025. Gaze controlled maps: scoping review of gaze-based interactions in geovisualisations. *International Journal of Digital Earth* 18, 1 (2025), 2510563. doi:10.1080/17538947.2025.2510563

Feiyang Wang. 2021. *Implicit Gaze Interaction for Information Visualization*. Master's thesis. Ontario Tech University. https://hdl.handle.net/10155/1372

Matthew O Ward, Georges Grinstein, and Daniel Keim. 2010. *Interactive data visualization: Foundations, techniques, and applications*. AK Peters/CRC Press, Natick, MA.

Colin Ware. 2019. *Information visualization: Perception for design* (4 ed.). Morgan Kaufmann, San Francisco, CA.

Jeremy M Wolfe. 1994. Guided search 2.0 a revised model of visual search. *Psychonomic Bulletin & Review* 1 (1994), 202–238. doi:10.3758/bf03200774

Jeremy M Wolfe. 2021. Guided Search 6.0: An updated model of visual search. *Psychonomic Bulletin & Review* 28, 4 (2021), 1060–1092. doi:10.3758/s13423-020-01859-9

Jeremy M Wolfe, Kyle R Cave, and Susan L Franzel. 1989. Guided search: An alternative to the feature integration model for visual search. *J. of Experimental Psychology: Human Perception and Performance* 15, 3 (1989), 419. doi:10.1037/0096-1523.15.3.419

A NASA TLX Results

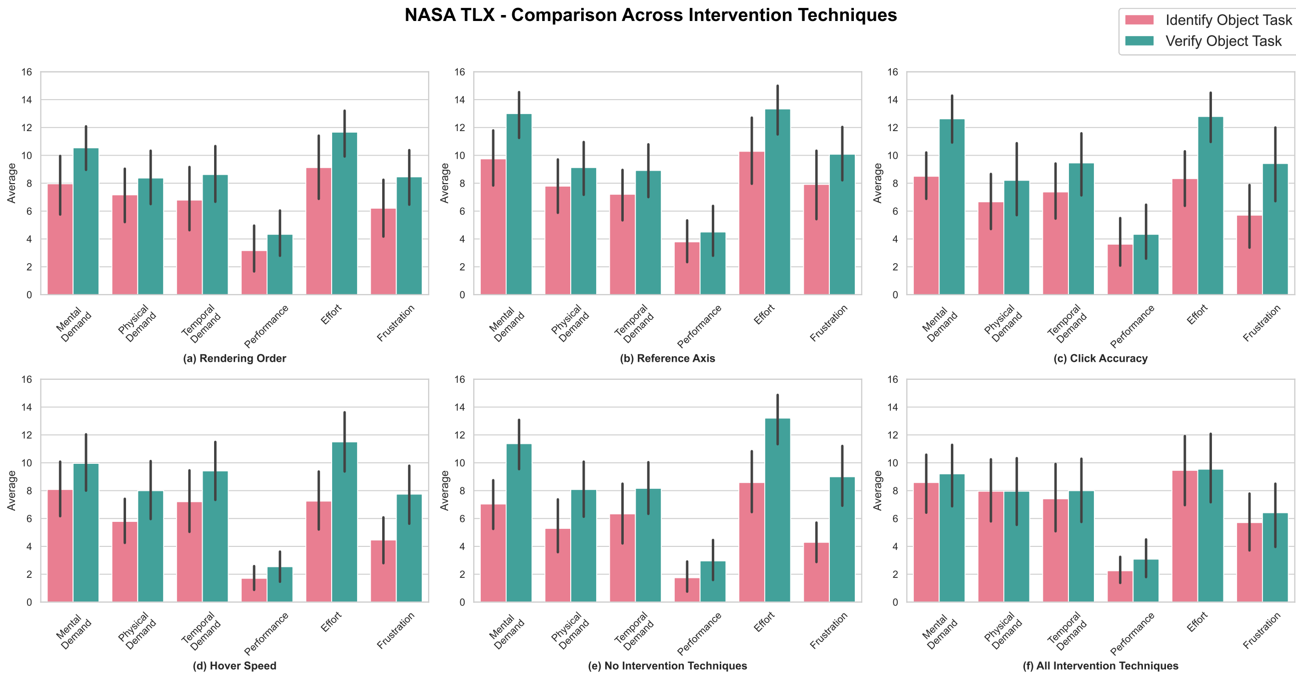

Figure 5: NASA-TLX workload ratings across six intervention conditions for both tasks. Bars show mean scores (1–21 scale) for Mental, Physical, and Temporal Demand, Performance, Effort, and Frustration. Error bars represent standard deviation across 24 participants. The Hover Speed technique consistently yielded lower perceived workload relative to other conditions.