

GC-Analyzer – Analyzing Spatiotemporal Correlations for Demand-Driven Services: Using an Interactive GeoVisual Analytics Approach in Decision-Making

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Abstract: Understanding spatiotemporal relationships is essential for effective urban decision-making. In this context, interactive geovisualizations offer the promising potential to support precise, rational-analytical decision processes. This paper examines a refined version of our GeoVisual Analytics tool called GC-Analyzer for analyzing spatiotemporal relationships in urban environments. We report the results of a case study where the tool was utilized in planning parking garages in a city and discuss the benefits of an interactive, geovisual analysis approach. We compare the GC-Analyzer approach with a conventional tabular representation of spatiotemporal correlations in a controlled usability study with expert users, evaluating two real-world analysis scenarios. Findings reveal that the GC-Analyzer provides substantial added value in spatiotemporal analysis, particularly enhancing users' comprehension of complex correlations. Notably, decision-making with the GC-Analyzer was more analytical and objective, fostering a deeper understanding of spatiotemporal relationships than the tabular representations typically used for correlation results.

Keywords: Spatiotemporal correlations, 3D-geovisualization, geovisual analytics, decision-making, user evaluation.

1. Introduction

The analysis and comprehension of spatiotemporal correlations are crucial for informed urban planning, especially in addressing the challenges posed by rapid urbanization and the dynamic evolution of cities. Geodata provides a foundation for computer-aided, data-driven approaches to urban analysis (Tominski and Schumann (2020)). In this context, the mobility sector is central in realizing sustainable assessments of these changes (Benevolo et al. (2016), Biryk et al. (2021)). Demand-driven services, such as parking management, benefit significantly from a comprehensive understanding of spatiotemporal relationships (Jiang and Yao (2010), Li et al. (2016)). More precisely, geospatial factors – such as nearby restaurants, shops, or healthcare facilities – characterize the area around parking garages. The critical challenge is to identify the impact of these geospatial factors on parking utilization at various times to enable informed decision-making.

Spatiotemporal correlation analysis often relies on conventional forms of presentation, such as figures and tables. However, these prove insufficient because they neglect spatial aspects and just present the data in complex statistical summaries (Chen et al. (2011), Andrienko and Andrienko (2020)). Spatial information can only be incorporated via additional material, such as city maps. Visual representations can provide crucial support by facilitating exploratory analysis, uncovering spatiotemporal correla-

tions, and enabling targeted analysis of hypotheses (Ali et al. (2016), Andrienko and Andrienko (2020), Bikakis (2019)). This paper addresses these aspects by conducting an in-depth user study to explore the value of geovisualization for urban analysis.

Our research question is as follows: *How does an interactive GeoVisual Analytics approach enhance comprehensibility and decision-making in spatiotemporal correlation analysis compared to conventional statistical correlation tables?*

To investigate this question, we build on the geospatial correlation analysis method by Rolwes and Böhm (2021) and an existing interactive GeoVisual Analytics approach called *GC-Analyzer* (GeoCorrelation-Analyzer) by Rolwes et al. (2023), and adapt it to a new use case scenario. Our study focuses on parking garages in Mainz, Germany, and uses empirical real-world data to validate the approach.

We present fundamentals and related work in Section 2. In Section 3, we provide an insight into the GC-Analyzer, show the component-based structure, and point out three highlights. Section 4 outlines the evaluation design of the study with the specific objectives, the methodological approach, and the group of participants. In Section 5, we present the evaluation results, organized into sections on comprehensibility and decision-making, followed by a discussion of these findings in Section 6. Finally, in Section 7,

we summarize our findings and discuss potential directions for future research based on our study.

2. Fundamentals and Related Work

The increasing availability of large geospatial datasets promotes the development of advanced visual analysis systems. Cartographically interactive geovisual tools enable users to explore multifactorial spatiotemporal correlations, offering targeted support for planning decisions (Arbesser et al. (2017)). However, the long-term success of any visual analysis system or new geovisual tool depends on user involvement and thorough evaluation (Kulyk et al. (2007), Wilkening et al. (2019)). One of the main challenges in information visualization research remains improving usability and integrating user-centric design (Forsell and Cooper (2012)). High usability minimizes cognitive load and ensures users' clarity and ease of understanding (Vanicek and Popelka (2023)). According to ISO 9241-11 (International Organization for Standardization (2018)), usability encompasses three key dimensions – effectiveness, efficiency, and user satisfaction – that enable users to achieve their goals within a specific environment. In this study, we emphasize effectiveness, focusing on the success of analytical tasks to gain insights into decision-making processes.

Usability assessments generally rely on two primary evaluation types: analytical and empirical (Kerren (2007)). Analytical evaluations include heuristic methods and cognitive walkthroughs. In contrast, empirical evaluations involve gathering qualitative (e.g., think-aloud protocol (Lewis (1982))) and quantitative data (e.g., surveys, benchmark tasks, eye tracking Tanenhaus and Spivey-Knowlton (1996)) from implemented prototypes. Lam et al. (2012), Domik et al. (2014) provide comprehensive overviews of evaluation methods in information visualization.

These evaluation methods are also applicable to spatiotemporal analyses. For instance, Kveladze et al. (2019) assessed spatiotemporal applications to enhance cartographic design and data exploration. Bogucka and Jahnke (2018) combined benchmark tasks with eye tracking to evaluate differences across visualization scenarios of spatiotemporal datasets. Despite the effectiveness of the think-aloud protocol as a qualitative approach for usability evaluation, it has been used only sporadically in cartography (Vanicek and Popelka (2023)).

The think-aloud protocol requires participants to verbalize their thoughts during the analysis process (Lewis (1982)). This method enables external observation, providing insights into participants' actions, thoughts, and comments. Widely recognized as a valuable technique for assessing product usability, it serves as a cost-effective alternative to eye tracking (Chen et al. (2018)). It offers deep insights into cognitive processes and supporting conclusions about decision-making in analytical tasks (Nielsen (1994)). As a practical example, Quayle-Ballard (2007) applied the think-aloud protocol to evaluate a 3D visualization prototype designed for real estate agents.

Based on these findings, we aim to engage expert users in evaluating our GeoVisual Analytics approach within a new use case. We aim to use the think-aloud protocol as a method to investigate comprehension and decision-making in analyzing spatiotemporal correlations for demand-driven services. Additionally, we seek to identify the differences in geospatial visualization compared to conventional statistical correlation tables.

3. GC-Analyzer

In our study, we adapted the interactive GeoVisual Analytics approach developed by Rolwes et al. (2023) to address a new use case. Initially, this approach was prototyped for a limited set of bike-sharing stations in Hamburg, Germany. The visualization design is characterized by seamlessly integrating 2D and 3D graphics and providing user-centered guidance and visual explanations that enhance comprehension. It supports exploratory analysis through multiple interactive, domain-focused analysis tools and aims for deeper user engagement and discovery of spatiotemporal correlations.

Our adaptation applies this approach to analyze 12 parking garages in Mainz, Germany, incorporating spatiotemporal correlation results between parking occupancy and geospatial factors determined by Rolwes and Böhm (2021). Further background information on these methods and details of the technical implementation are available in both papers (Rolwes and Böhm (2021), Rolwes et al. (2023)).

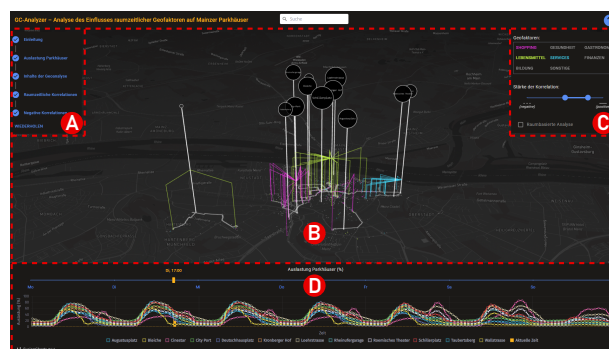


Figure 1. Analysis board of the GC-Analyzer.

The GC-Analyzer organizes the layout into four core components (see Figure 1): (A) a left-hand guidance bar with explanatory content for the data, analysis, and resulting correlations, (B) a central map view displaying spatiotemporal correlations, (C) a right sidebar for setting customization parameters and applying filters, and (D) a time series diagram at the bottom showing the occupancy rate of the individual parking garages over time. Each component includes interactive features, allowing users to engage dynamically with the data and customize their analysis experience. Below, we briefly present three specific features of the GC-Analyzer.

Based on flow maps (Andrienko and Andrienko (2020)), 3D arcs in Figure 2 represent a visual connection between POI and parking garages, which is used in component (B). The height of the arc represents the strength of the respective spatiotemporal correlation.

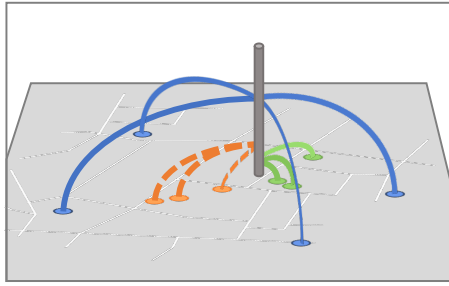


Figure 2. Conceptual visualization of 3D arcs for spatiotemporal correlations.

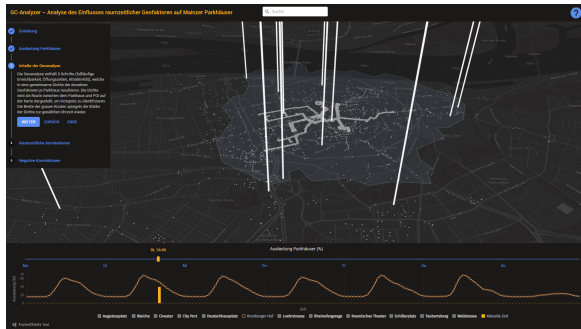


Figure 3. Exemplary guidance step for visually explaining a reachability analysis.

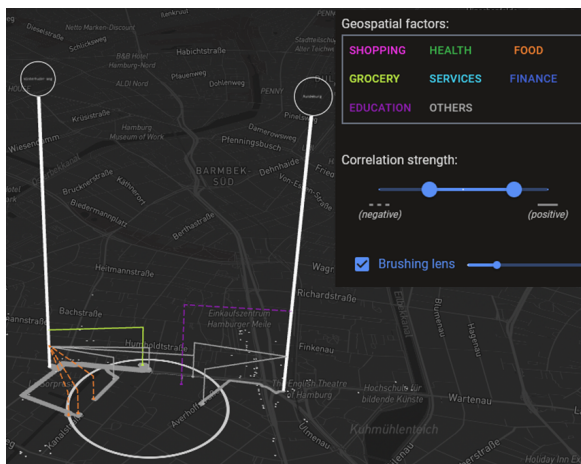


Figure 4. Brushing lens for customized area-based analysis (Rolwes et al. (2023)).

Figure 3 shows an example of the guidance to convey the analysis and the area of influence of a parking garage to users, which is used in component ①. Here, the guidance bar provides textual explanations while the map provides visual explanations.

Figure 4 depicts a tool for customized area-based analysis using a brush lens used in component ③. This tool focuses exclusively on POIs located within the spatial boundaries of the lens for analysis cases.

4. Evaluation Design

This section outlines the evaluation design of our study, detailing the methods and approaches used to assess the com-

prehensibility and decision-making of the GC-Analyzer in spatiotemporal correlation analysis.

4.1 Evaluation Objectives

Our evaluation aims to assess the GC-Analyzer compared to a conventional geostatistical tabular representation of spatiotemporal correlations (below referred to as GeoTab-STC) by Rolwes and Böhm (2021), supplemented by a city map. Our evaluation approach is use case driven, i.e., we evaluate how experts utilize the visualization tools provided in order to solve real-world problems. To ensure relevance to current challenges and research questions within the application domain, we defined two real analysis tasks in collaboration with three domain experts associated with our research project.

Analysis task 1: *The department store chain “Galeria Karstadt Kaufhof” has filed for bankruptcy, impacting its location in downtown Mainz. Investigate which parking garages will likely experience changes in demand on Saturday morning (11 a.m.) due to the store’s closure.*

Analysis task 2: *The city of Mainz is planning a re-design of the pedestrian zone in the city center and has requested support. Please identify streets near the parking garage “Deutschhausplatz” that would be suitable for traffic calming measures on Saturdays.*

4.2 Methodology

We conduct the evaluation using a summative empirical methodology, primarily relying on qualitative content analysis and observations (Mayring (2010)), supplemented by questionnaires. This approach is based on the ISO 9241-11 standard, emphasizing user-centered quality criteria for assessing usability.

We use the think-aloud protocol to evaluate the effectiveness of an analysis task. Additionally, we derive a success rate from observations based on an objective comparison to the predefined sample solution for the analysis task, using a three-level scale: *analysis task not solved (0 points)*, *analysis task partially correctly solved (0.5 points)*, *analysis task correctly solved (1 point)*. To strengthen our findings, we implemented a statement-based questionnaire (see Appendix, Table 1), to provide quantitative support for qualitative observations. We applied quantitative analysis to corroborate the qualitatively collected results. Since the Shapiro-Wilk test indicated no normal distribution within the sample, we used the non-parametric Wilcoxon test at a significance level of 0.05 to determine statistical significance.

The evaluation follows a within-subjects design (Greenwald (1976)), whereby each participant interacts with both, the GC-Analyzer (see Figure 1) and the GeoTab-STC (see Figure 5). The execution sequence was randomly varied in order to reduce distortions and learning effects.

We provided participants with two types of visualizations: (1) The GeoTab-STC for all parking garages in Mainz and occupancy data presented in figures and diagrams in an Excel file. Additionally, we supply a city map in PDF format that displays all parking garages and categorized POIs

	time of day	services and specialty retail	grocery	health	food services	shopping	adjusted R-squared
Weekday	00:00 - 07:00	0.114***	0.000	0.000	0.000	-0.071	0.005
	07:00 - 12:00	0.255***	0.034	0.126	0.244***	0.171*	0.639
	12:00 - 18:00	-0.008	0.063	0.240***	0.168***	-0.133***	0.058
	18:00 - 00:00	-0.009	0.020	0.049	0.405***	0.132	0.335
Saturday	00:00 - 07:00	0.000	0.000	0.000	-0.109	0.114	0.003
	07:00 - 12:00	0.000	-0.195***	0.004	0.747***	0.227*	0.658
	12:00 - 18:00	0.000	-1.478	0.343	0.033	1.616*	0.141
	18:00 - 00:00	0.008	0.237	0.000	0.155	-0.021	0.005
Sunday	00:00 - 07:00	0.000	0.000	0.028	-0.044*	0.000	0.002
	07:00 - 12:00	-0.059	0.177	-0.038	0.217***	-0.051	0.036
	12:00 - 18:00	0.057	0.059	0.028	-0.145***	-0.241	0.015
	18:00 - 00:00	0.158	-0.040	0.049	0.207***	0.004	0.090

Significance level at 0.001 (***), 0.01 (**), 0.05 (*), n = 43,815 observations

Figure 5. Geostatistical table of spatiotemporal correlation results (GeoTab-STC) for “Kronberger Hof” parking garage in Mainz, Germany (Rolwes and Böhm (2021)).

within the study area. This visualization establishes the baseline for the evaluation. (2) The GC-Analyzer, which contains all data mentioned above in a different way with specific features for analysis. Within the scope of these visualizations, participants can independently perform interactions such as marking, selecting, or sorting.

4.3 Group of Participants

The participant group comprises 14 unpaid, voluntary expert users (male = 10, female = 4) aged between 23 and 56 (mean = 35.6, SD = 10.1), with professional experience in geospatial analysis ranging from 1 to 30 years (mean = 7.3, SD = 7.8). These participants work in mobility, urban planning, and geoinformatics, making them suitable expert users of the GC-Analyzer for planning decisions. The study aimed to encompass a broad range of expertise to yield diverse evaluation results. Specifically, the group includes five participants from *GIS and geoinformatics*, four from *urban and spatial planning*, three from *mobility behavior and transport*, and two from *geo-data analytics*. We conducted the evaluation in April and May 2024, each lasting between 60 and 80 minutes and including a general introduction.

Overall, each participant completed four analysis sessions for the two analysis tasks mentioned above: two using the GeoTab-STC and two with the GC-Analyzer. This totaled 28 analysis sessions per task.

5. Evaluation Results

To address the research question in Section 1, we distinguish two aspects in the evaluation results: *comprehensibility* and *decision-making*.

5.1 Comprehensibility

Expert users encountered considerable challenges in understanding and tracing the spatiotemporal correlations presented in the **GeoTab-STC**. Specifically, they struggled with interpreting correlation coefficients and distinguishing between positive and negative correlations. For instance, one participant asked, “Or am I interpreting the correlation coefficients here completely wrong?” [Interview E13], while another noted, “Now I just have to think again about what the correlation coefficients mean.” [Interview E4].

Beyond interpretative difficulties, users also expressed uncertainty in applying the GeoTab-STC. This was reflected in questions like, “Can it be interpreted that way?” [Interview E13]. Participants questioned whether users generally possess sufficient statistical knowledge to comprehend a table of spatiotemporal correlations without accompanying spatial information: “You have statistical figures that, let’s say, you normally wouldn’t know how to interpret at first.” [Interview E7]. One participant highlighted the absence of a spatial component, noting that it would visually link statistical values to the map, enhancing interpretability: “The spatial component is missing, which brings statistical values into relation to the map and presents them visually.” [Interview E14]. Another participant echoed this need for spatial visualization, commenting, “You can’t quite imagine it visually and spatially by yourself.” [Interview E3].

Additionally, one participant observed that the GeoTab-STC allows for subjective interpretation, potentially leading to misinterpretation and arbitrary analysis decisions: “[...] leaves scope for interpretation.” [Interview E11]. This finding is also supported by observations in the thinking-aloud protocol: 22 of the 28 analysis sessions revealed at least one instance of misinterpretation of the statistical results within the GeoTab-STC.

Compared to a tabular presentation, the **GC-Analyzer** significantly improves users’ understanding of spatiotemporal relationships ($p_{C3} = 0.0089$). Participant 5 highlighted this advantage: “I could understand the data better with the visual analysis tool than with the table and city map.” [Interview E5]. To enhance spatiotemporal comprehension, we emphasize the 3D arcs, which users found intuitively understandable. Participant 12 noted that relationships are “easier to understand with the visualization, i.e., with the 3D arcs.” [Interview E12], allowing for a visual grasp of varying strengths of influence and relationships. For instance, another participant remarked, “I can see the relationship because these are the only ones that have a connection to shopping, especially to my selected POI.” [Interview E7]. Users “no longer need to guess where people park to access specific POI; instead, they can directly identify the category and relevant connections.” [Interview E2].

When asked about the relative influence on different parking garages, participants confirmed the intuitive insights provided by the visualization: “That’s probably where the line is higher.” [Interview E12], and “Exactly, that would be the parking garage Löhrrstraße, because this arc is simply higher.” [Interview E14]. Additionally, users evaluated the guiding features positively, noting them as effective tools to build confidence and ease in handling the analysis. Compared to the GeoTab-STC, participant 3 remarked, “What the GC-Analyzer is particularly good at is helping you to familiarize yourself with it. [...] In contrast to the table, if you can’t determine what a statistic means, there’s not much you can do with it.” [Interview E3]. Less experienced users, in particular, benefit from this analyzing tool. One participant said, “I need it, especially if I’ve never worked with it before.” [Interview E8], and another

added, “Especially when you consider that someone with little experience is using the tool. I think it’s good to be introduced to it like this.” [Interview E12].

In addition, the brushing lens improves the participants’ understanding and helps them to focus their analysis on specific spatial areas. Participant 11 noted, “This aligns with a planning-oriented approach, which is rarely found in tools like this. I find it very innovative and valuable.” [Interview E11]. However, another participant noted a limitation of the interaction tool, mentioning that “it was not easy to attach the brushing lens on the map.” [Interview E9].

Participants confirmed these findings in the questionnaire, rating the tool as significantly more helpful ($p_{C4} \leq 0.0001$). Additionally, participants reported that combining textual hints and specific analysis snapshots on the map during the guidance phase significantly enhanced their comprehension ($p_{C5} \leq 0.0001$).

However, participants expressed uncertainty about the traceability of correlation results, particularly when the *GC-Analyzer* displayed no visual content on the map because of uncorrelated locations. Many assumed that correlations should always be present. When visual feedback was absent, they suspected implementation errors. Participant 12 illustrated this concern: “I was somehow a bit confused. I switched on all the geospatial factors, and only gastronomy was displayed. I wondered if this was an error if all the other factors were really selected, or if I clicked on the wrong place.” [Interview E12].

Figure 6 provides an overview of value distributions for comprehension-focused statements from the statement-related questionnaire, presented as box-and-whisker plots.

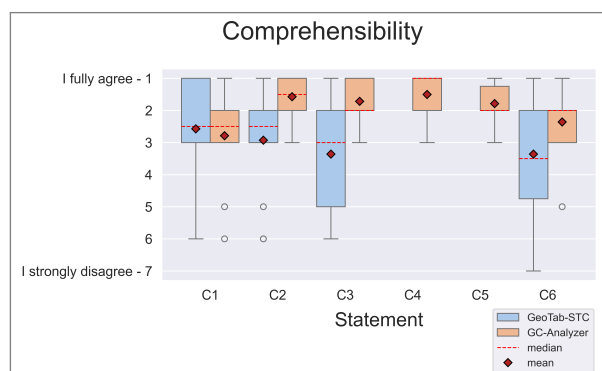


Figure 6. Box-and-whisker plots for comprehension-focused statements in the questionnaire (see Table 1).

5.2 Decision-Making

We focus on the decision-making supported by the visualizations and the success rate relative to the sample solution in the analysis task.

Observations reveal that participants struggled to perform high-quality, precise analyses using the **GeoTab-STC**. Participant 2 noted, “I found it harder to make a decision” [Interview E2], while Participant 3 added, “You can’t quite visualize it well spatially” [Interview E3]. Participant 10

summarized the decision-making experience, saying, “It feels more like guessing than analyzing” [Interview E10].

Further comments highlight that participants increasingly relied on intuitive and subjective judgments when making spatial decisions using the *GeoTab-STC*. Participant 2 stated, “Here, I would just make an assumption” [Interview E2], and Participant 5 admitted, “It was a bit of a guess, to be honest” [Interview E5]. Participants’ decisions are also based on personal or professional experience rather than conducting detailed analyses. In analysis task 2, for example, Participant 5 chose streets for traffic calming along the Rhine River, explaining, “I know from experience that people gather along the Rhine, especially in summer and spring” [Interview E5]. Similar intuitive choices emerged in the first analysis task, with participants saying, “I often park there when heading to the city center” [Interview E13] and “As a traffic planner, I generally assume that shopping and dining are important on Saturdays” [Interview E4].

In contrast, tasks analyzed with the **GC-Analyzer** show that participants approached decisions rationally and analytically. For spatial analyses, participants found the *GC-Analyzer* more effective than the *GeoTab-STC*. Three participants shared their positive experiences: “It was much easier to answer specific spatial questions” [Interview E10], “It felt more productive to work with the map than with the table” [Interview E8], and “It required fewer steps” [Interview E7]. These impressions align with questionnaire results, where participants rated the first analysis task (see Figure 7, G2) as significantly easier ($p_{G2} = 0.0278$) with the *GC-Analyzer* compared to the *GeoTab-STC*. For the second analysis task (see Figure 7, G3), participants also favored the *GC-Analyzer*, though without reaching statistical significance ($p_{G3} = 0.1742$).

Participants valued the *GC-Analyzer* as a supportive tool, especially in combination with human decisions. One participant voiced a consideration, saying, “If the *GeoVisual Analytics System* made decisions independently, replacing the traffic planning office, I would have serious concerns. However, as a supportive tool, it offers substantial added value” [Interview E9]. Overall, participants expressed interest in using the *GC-Analyzer* again, in contrast to the *GeoTab-STC* (see Figure 7, G5), particularly for inner-city decisions. Statistical tests confirmed these findings ($p_{G4} = 0.0035$ and $p_{G5} = 0.0070$).

When choosing one supporting material, 12 of the 14 participants preferred the *GC-Analyzer* for spatiotemporal analyses, with the *GeoTab-STC* selected by only 2 participants. This preference proved statistically significant ($p = 0.0052$). Those who favored the *GeoTab-STC* emphasized its simplicity and quick accessibility, appreciating the familiarity of Microsoft Office tools and static maps. One participant explained, “I’m used to reading tables and looking at city maps” [Interview E9]. They preferred tables for quick information retrieval without in-depth spatial analysis: “If I need to look something up quickly, I will check a table” [Interview E3].

In contrast, 12 participants favored the GC-Analyzer for its interactive and visual capabilities. They described the interface as “manageable and much easier” [Interview E12] and “much more pleasant to use” [Interview E12]. The GC-Analyzer’s enhanced exploration capabilities mainly supported the discovery of new spatial relationships. Participants valued the integration of geographic and statistical data into a single view: “The biggest benefit is that I can see spatial information and statistics together” [Interview E13], and “I would gladly do without the GeoTab-STC with the city map in favor of the GC-Analyzer” [Interview E6].

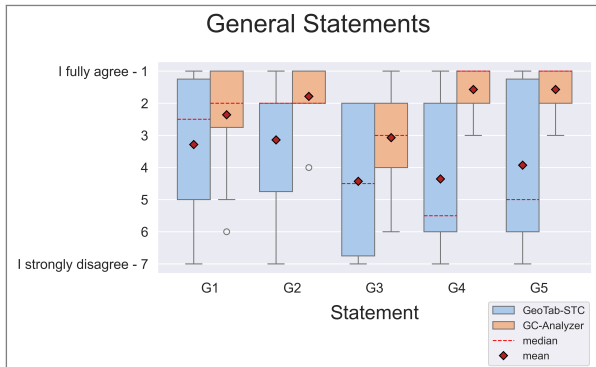


Figure 7. Box-and-whisker plots for general statements in the questionnaire (see Table 1).

Beyond qualitative insights into decision-making, we also evaluated the success rate in the two analysis task as a measure of effectiveness. Figure 8 displays the success rate, measured on a three-level scale (see Section 4.2), showing results by visualizations and participants. On average, participants completed more analysis tasks correctly using the GC-Analyzer than the GeoTab-STC, achieving higher success rates in both the first task ($\bar{O} = 0.68$ vs. $\bar{O} = 0.46$) and the second task ($\bar{O} = 0.79$ vs. $\bar{O} = 0.39$). Statistical analysis confirmed a significant difference favoring the GC-Analyzer in the second task ($p = 0.0126$). In the first task, we could not make any statistically significant observations ($p = 0.1408$).

A notable finding is the frequency of entirely incorrect solutions (0 points), which occurred in 10 out of 28 analysis sessions with the GeoTab-STC across both tasks, compared to only 3 out of 28 sessions with the GC-Analyzer. Additionally, 9 out of 14 participants achieved entirely correct solutions in at least two of four sessions, though none managed to solve all sessions correctly. Both tools

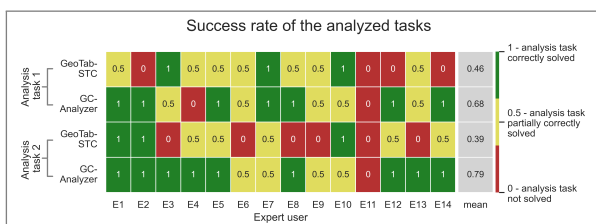


Figure 8. Quantitative success rate analysis of the analyzed tasks.

posed challenges that participants found difficult to overcome fully. Moreover, 10 out of 14 participants performed at least one incorrect analysis session, with one participant standing out as an outlier, who had solved all sessions incorrectly.

6. Discussion

The evaluation results demonstrate that the GC-Analyzer significantly enhances users’ comprehensibility and traceability of spatiotemporal correlations. Spatial elements and the visual linking of spatiotemporal correlation results are substantially easier to grasp, such as directly associating parking garages with geospatial factors on the map. In contrast, the GeoTab-STC, lacking direct geovisual connections, complicates interpretation, often leading to misinterpretations and requiring higher statistical competence. To address these issues, specialized training, such as statistics workshops, may reduce misunderstandings and incorrect conclusions.

Feedback from expert users further underscores that visualizing the strengths of geospatial factors through “3D arcs” improves their ability to identify key factors and their intensity. Integrated guidance in the GC-Analyzer also boosts user confidence, particularly for novices or those with limited analytical experience, by simplifying the understanding of data and results. However, limitations arose in interpreting correlation results when users did not receive indicators for non-existent correlations or abrupt visual changes on the map. In these cases, participants often suspected system or operational errors, leading to increased, unfocused interactions with the interface. Addressing this gap with visual cues for “empty states” – for instance, through a dialog window – could enhance clarity.

The findings confirm that the GC-Analyzer enables participants to understand and trace spatiotemporal correlations more effectively than the GeoTab-STC. Observations and statistical analyses also show that the GC-Analyzer significantly aids successful decision-making in spatiotemporal analyses. In contrast, the GeoTab-STC presented challenges for users in making informed, accurate decisions, often resulting in intuitive, subjective spatial decisions. By comparison, expert users predominantly made rational-analytical decisions with the GC-Analyzer, forming hypotheses that were then analytically verified. The study demonstrated in one instance that the GC-Analyzer facilitated spatial decision-making.

Participants noted that the GC-Analyzer demonstrates particular strength when combined with other applications, a finding supported by survey results, where participants expressed interest in future use. This preference showed statistically significant support. A clear preference also emerged in selecting materials for spatiotemporal analyses: 12 of the 14 users favored the GC-Analyzer for future use. Two participants recommended integrating tabular results within the GC-Analyzer, which could be achieved through a detailed view and dynamic linking with other components, aligning with the Brushing and Linking paradigm by Keim (2002) to improve human-machine interaction.

As a measure of effectiveness, quantitative success rate analysis reveals that more participants correctly solved both tasks using the GC-Analyzer than with the GeoTab-STC. Statistical significance was, however, only observed in the second analysis task, focusing on redesigning the pedestrian zone in the Mainz city center. Notably, no expert user solved both tasks entirely correctly across both visualizations, highlighting specific challenges in each task that merit further investigation in future studies with larger samples. This also suggests that both visualizations pose unique hurdles, proposing further investigations of identified challenges.

Overall, the GC-Analyzer enhances spatiotemporal analysis by facilitating the identification of geospatial key factors and reducing interpretation errors. Its geovisual components strengthen spatiotemporal understanding compared to the GeoTab-STC and conventional city maps. Enhanced human-machine interaction reduces intuitive, subjective decision-making, fostering more analytically grounded analyses.

7. Conclusion and Future Works

Analyzing and understanding spatiotemporal correlations can significantly enhance decision-making in urban contexts. Conventional statistical tables, however, are insufficient for effectively capturing these complex relationships. This paper investigates the utility of an interactive GeoVisual Analytics approach for urban decision-making through a user evaluation conducted with expert users.

Our findings indicate that the GC-Analyzer enhances comprehension of spatiotemporal correlations, mainly through its spatial representation and visual linkage of different components. For instance, the GC-Analyzer visually links geospatial factors and parking garages on an integrated digital map. User feedback underlines that the visual links in the form of 3D arcs improve the identification of geospatial key factors. In contrast, geostatistical results tables without geovisual linkages hinder understanding, often leading to interpretive challenges and potential misinterpretations. These insights extend to the decision-making process: our observations and statistical findings reveal that the GC-Analyzer is crucial in enabling precise and effective decision-making in spatiotemporal correlation analyses. In contrast, the geostatistical tables alone posed significant obstacles for expert users, making it challenging to reach precise and data-informed conclusions. Notably, participant behavior suggested that spatial decisions without the GC-Analyzer were often based on intuition and subjective knowledge. By contrast, the enhanced interaction between humans and the system provided by the GC-Analyzer supported users in rational, analytical decisions.

For future research, users could benefit from additional explanations in interpreting specific or absent correlations. Moreover, advancing the GC-Analyzer toward a simulation system could further strengthen users' analytical capabilities, enabling proactive exploration of potential future scenarios. Urban prediction models and collaborative

decision-making methods represent promising avenues for further enhancement of this tool's capabilities.

8. Acknowledgements

This study is part of ongoing Ph.D. research at RheinMain University of Applied Sciences and Mainz University of Applied Sciences.

9. Appendix

Table 1. Statement-related questionnaire on the visualization material based on Wehrend and Lewis (1990), Seebacher et al. (2021); rating on a 7-point Likert scale (1 – I fully agree, 7 – I strongly disagree); We evaluate ID* statements exclusively in the GC-Analyzer.

Comprehensibility	
C1	I require expert knowledge and additional explanations to understand the information and results.
C2	I can use the material effectively after a brief familiarization period.
C3	I can comprehend spatiotemporal relationships.
C4*	The step-by-step user instructions in the GC-Analyzer were beneficial.
C5*	Combining textual references in the user guidance and specific examples on the map is helpful.
C6	I can infer the causes of spatiotemporal relationships.
General Statements	
G1	Overall, I am satisfied with the time required to complete the task.
G2	I found analysis task 1 (Department store) easy to solve using the provided material.
G3	I found analysis task 2 (Pedestrian zone) easy to solve using the provided material.
G4	I can envision using this material again.
G5	I believe this material would provide valuable support in making inner-city decisions, such as location planning.

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