IEEE Open Journal of the
Computer Society

Received 2 October 2025; revised 26 December 2025; accepted 1 February 2026. Date of publication 3 February 2026; date of current version 24 February 2026. The review of this article was arranged by Associate Editor Francesco Rundo.

Digital Object Identifier 10.1109/OJCS.2026.3660917

ECommVis: Supporting E-Commerce Marketplace Advertising Outcomes Through a Visual Analytics System

HENRIQUE L. S. GINO [1], JEAN R. PONCIANO [1], CLAUDIO D. G. LINHARES [2], AND AGMA J. M. TRAINA [1] (Member, IEEE)

[1]Institute of Mathematics and Computer Sciences, University of São Paulo, São Carlos 13566-590, Brazil
[2]Department of Computer Science and Media Technology, Linnaeus University, 351 95 Växjö, Sweden

CORRESPONDING AUTHOR: AGMA J. M. TRAINA (email: agma@icmc.usp.br).

This work was supported in part by the Brazilian agencies: Coordenação de Aperfeiçoamento de Pessoal de Nivel Superior (CAPES, Finance Code 001), São Paulo Research Foundation (FAPESP) and CNPq. ieee1, and FAPESP under Grant 2023/18026-8 and Grant 2024/13328-9, in part by Conselho Nacional de Desenvolvimento Cientifico e Tecnologico (CNPq), and in part by University of São Paulo ieee11032, ieee1Process 22.1.09345.01.2.

ABSTRACT E-commerce marketplace platforms rely increasingly on digital advertising to drive merchant sales, yet existing analytics tools often fail to provide contextual insights that connect advertising performance with actionable business strategies. This paper introduces ECommVis, a visual analytics platform designed to address the gap between complex advertising metrics and merchant decision-making in e-commerce marketplaces. ECommVis integrates five complementary visualization components that provide temporal, spatial, and comparative perspectives on advertising performance: Orders Over Time (OS) tracks historical organic versus ad-driven sales through adjustable time frames; Geospatial Interactions (GS) visualizes spatial performance patterns using hexagonal grid mapping; Merchant Metrics (MC) displays advertising KPIs via interactive stacked charts correlating budget with engagement; Interactions by Weekday and Shift (HM) identifies optimal advertising windows across daily shifts and weekday patterns; and Time Period Comparison (TP) benchmarks campaigns across time frames using correlation, trend, and search term analyses. We demonstrate the usefulness and effectiveness of ECommVis through two usage scenarios and a user study with 11 participants.

INDEX TERMS Advertising performance, visual analytics, online marketplace.

I. INTRODUCTION

In today's hyper-competitive digital marketplace, e-commerce platforms have evolved from online stores to complex ecosystems that connect providers, consumers, and system operators through sophisticated technological infrastructures [1]. Global e-commerce sales have reached multi-trillion dollar levels in recent years, accounting for a significant and growing share of worldwide retail sales [2], [3]. This exponential growth, accelerated by global shifts in consumer behavior, has intensified the need for analytics capabilities that support decision-making across stakeholders within these digital ecosystems [4].

E-commerce platforms exemplify environments where data analytics directly drive critical business choices. Platform developers employ analytics to improve discovery algorithms and guide design decisions, while providers (sellers) rely on analytics to enhance visibility and product positioning towards customers [5]. This three-part *framework of system, provider*, and *user perspectives* highlights the interdependencies shaping value creation in digital marketplaces [6]. At the same time, platform dynamics often generate superstar effects, where a few top products dominate sales. These effects may result either from amplified quality signals and social consumption [7] or from algorithmic prioritization of customer engagement at the expense of seller fairness [8].

Advertising in e-commerce platforms represents a critical lever for balancing these forces, merging technological capabilities, business strategy, and user experience. System operators must weigh revenue optimization against platform integrity, while providers—ranging from small merchants to large brands—use advertising as a mechanism to gain visibility and drive sales in competitive environments [9]. By offering placement opportunities, advertising allows small sellers to reach customers more effectively, expanding product diversity and strengthening the long-tail phenomenon in online retail [10].

The literature demonstrates that descriptive analytics and visualization enhance both marketing and e-commerce performance, enabling more effective decisions and improved customer satisfaction [11]. Analytics-driven advertising further boosts performance, yielding higher revenues, increased customer acquisition, and stronger repeat business [12]. Yet widely used tools such as Google Analytics often provide generic dashboards rather than contextual insights tailored to specific business environments [13].

To address this gap, our research introduces *ECommVis*, an analytics system designed to support providers in optimizing advertising campaigns on e-commerce platforms. We present two usage scenarios based on real data from a food delivery marketplace and a comprehensive expert evaluation, which highlight ECommVis's advantages in contextual analysis, responsiveness, and independence from paid external services. These results underscore the potential of domain-specific visualization to enhance transparency, effectiveness, and engagement in digital marketplaces.

II. RELATED WORK

A. DIGITAL PLATFORMS

Digital platforms have become critical infrastructure for economic and social activity, generating new research questions as platform innovation and architectural complexity expand. These platforms rely on modern IT stacks, cloud services, in-memory databases, and analytics to scale and support diverse industry applications [14], [15]. In e-commerce, platforms intermediate transactions between providers and customers, shaping ecosystem interactions (platform- vs product-based) and enforcing governance rules determined by ownership—e.g., Airbnb and Uber [16], [17].

E-commerce marketplaces produce massive volumes of behavioral and sales data that platforms can algorithmically analyze to generate market intelligence for merchants. While platforms can provide data invisible to individual sellers, distributing analytics back to sellers, especially when merchants also share data, can materially improve seller outcomes and overall platform value [18], [19].

B. ADVERTISING IN DIGITAL PLATFORMS

In competitive digital marketplaces, sellers rely heavily on advertising to acquire and retain customers. Advertising connects promotional initiatives directly to purchasing decisions and is now a critical revenue stream for both sellers and platform operators [20], [21]. Marketplaces typically combine multiple fee structures—listing fees, sales commissions, and optional advertising fees—linked to metrics such as impressions (CPM), clicks (CPC), or actions (CPA). By purchasing visibility in search rankings or results pages, sellers enhance product discovery, while platforms monetize access to these top placements.

Two major forms of marketplace advertising dominate: search and display. Search advertising integrates promotions into consumer queries, making ads more relevant and effective than traditional formats [21]. Display advertising—ranging from banners to video—enables behavioral targeting and personalization, aligning offers with consumer preferences through audience segmentation [22]. Both forms not only boost sales and visibility but also reinforce customer loyalty and repeat engagement, underscoring advertising's dual role as a discovery mechanism and a driver of sustained platform growth.

C. AD PERFORMANCE ANALYTICS

Measuring advertising effectiveness has become a strategic necessity in digital marketplaces, where performance indicators drive campaign evaluation and investment returns [23]. Modern analytics platforms enable advertisers to uncover consumer behavioral patterns, identify market opportunities, and optimize revenue generation. Increasingly, artificial intelligence (AI) enhances targeting precision and message personalization by integrating consumer and advertiser data, though the opacity of these algorithmic processes often reduces transparency and user trust [24], [25]. As a result, advertisers may focus more on optimizing interaction metrics than understanding placement mechanics, even though research shows that market orientation and analytics adoption are strongly correlated with campaign success [26], [27].

Digital marketplace advertising further benefits from data-driven insights into consumer histories and geographic patterns, enabling predictive modeling of future purchases [26]. Advanced analytics can significantly boost retailer performance, but access is not easy: platforms often retain control of key performance data and metrics, creating asymmetries that limit smaller sellers' capabilities [19], [28], [29]. Information control is tightly linked to pricing structures, where access and exchange form the basis for value creation across participants, while barriers such as tool awareness, resource constraints, and implementation costs hinder widespread analytics adoption [18].

Visualization plays a critical role in translating complex advertising data into actionable insights. Dashboards provide interactive interfaces that allow advertisers to monitor campaigns, adjust parameters, and reallocate budgets in response to performance feedback [5], [30], [31]. Beyond generic solutions such as Google Analytics, researchers emphasize the need for domain-specific dashboards that reflect contextual requirements of different business environments [13]. Without such adaptation, standardized tools risk delivering overwhelming or insufficiently relevant information [32].

Overall, effective ad performance analytics depends on both technological capability and contextual fit. While

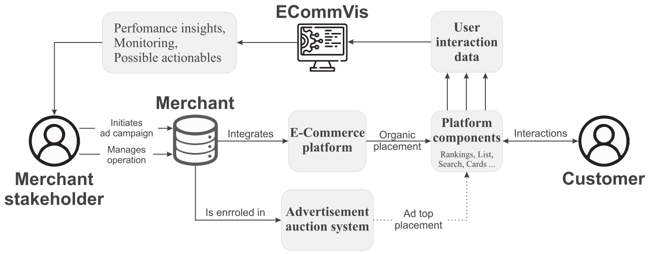

FIGURE 1. **An overview of the e-commerce workflow, highlighting the process of a merchant participating in an ad campaign, the interactions users have with the merchant, and the analysis conducted by merchant stakeholders to evaluate campaign performance.**

TABLE 1. **List of Metrics Used and Their Definitions**

Metric	Definition
Ad impression	Instance when an advertisement is displayed to a user
Ad click	User clicking on an advertisement
CTR	Percentage of users who click on an ad after seeing it
Conversion rate	Percentage of users who place an order after clicking on an advertisement
Ad budget	Ad campaign financial allocation, expressed as potential ad click volume
Unused ad clicks	Number of ad clicks that were not used within the ad budget
GMV	Total monetary value of all orders processed through the platform

AI-driven systems and advanced visualization tools promise substantial benefits, their potential is often constrained by opacity, data asymmetries, and organizational barriers. Addressing these challenges remains central to enabling advertisers, particularly smaller enterprises, to fully capitalize on digital marketplace advertising opportunities.

III. REQUIREMENTS AND TASKS

A. E-COMMERCE WORKFLOW

This study focuses on e-commerce interactions, particularly merchants operating within a food delivery platform. The platform features various components, including rankings, search systems, lists, and interactive cards, which customers use to discover and connect with merchants and their products. An advertising system within the platform allows enrolled merchants to secure top placements in these components, enhancing their visibility and making it easier for customers to discover them. The system's performance page shows a summarized version of merchants' key ad metrics over time.

Advertisement campaigns operate on a budget-based system, where the budget is deducted whenever a merchant secures a top placement (ad impression) and a customer clicks on the ad (ad click). These top placements, referred to as ad-positioning, are labeled for customers and appear as the leading results in interactive platform components, such as the top rankings on the home page or the first positions in search results. Fig. 1 illustrates the workflow outlining the steps a merchant stakeholder takes during an advertisement campaign contract between the merchant and the e-commerce platform, and subsequent customer interactions on the platform.

After the campaign has been active for some time, the stakeholder analyzes the merchant's performance data to assess whether the advertisement has enhanced business performance. Typically, this step involves examining historical changes in engagement metrics like clicks and sales or evaluating shifts in sales patterns during the ad campaign. Relevant ad metrics are described in Table 1. With ECommVis, the stakeholder gains comprehensive insights into how advertisements (ads) impact customer interactions with the merchant, utilizing new geospatial and temporal granularities to organize interaction data. Additionally, it allows stakeholders to compare the merchant's performance with the average competitor. Once the ECommVis analysis is complete, the stakeholder can determine the campaign's success and consolidate insights to enhance the merchant's performance further.

B. THE PROPOSED PLATFORM REQUIREMENTS

The food delivery platform surveyed merchant stakeholders to gather insights on their perception of the effectiveness of the advertising campaign. Merchant stakeholders provided predominantly neutral or negative feedback when asked about the current performance page. They expressed concerns that "advertising doesn't appear to impact sales numbers" and complained that "the page fails to distinguish between ad-generated sales and organic transactions clearly."

After examining the challenges faced by merchant stakeholders, such as drawbacks in their current systems, and consulting with platform specialists, we identified issues related to effective advertisement performance analysis. Based on these insights, we developed the following requirements that our proposed platform's components must explicitly meet.

R1: Identify variations in the merchant's performance resulting from advertising.

R2: Compare various aspects across different periods of historical performance, including conversion and click metrics, efficiency of advertising channels, and budget allocation.

R3: Obtain relevant metrics associated with the advertisement e-commerce and marketplace sector, such as return on investment, cost per click, ad engagement metrics, and revenue over time.

R4: Enable performance benchmarking against average competitors.

C. DESIGN TASKS

Following the assessment of each requirement, four visualization tasks were developed to guide the design and development of the new platform ECommVis.

T1: The platform should provide an overview of the historical evolution of orders segmented by origin (organic or ads) (R1) and include competitors' metrics (R4). This involves clearly displaying aggregated order metrics with distinct granularity for organic and advertisement orders, highlighting the ad campaign's impact on overall sales (R3). Additionally, showcasing competitors' aggregated sales metrics allows for meaningful comparison.

T2: The ECommVis platform should offer clear evolution graphs of engagement metrics relevant to the advertisement domain (R3), illustrating both the merchant's and competitors' aggregated performance (R4).

T3: The platform must feature an overview of geospatial merchant performance in comparison to competitors (R4).

T4: The platform must facilitate comparison across different timestamps of historical performance data (R1, R2, R3). This allows stakeholders to infer valuable information from the ad campaign duration, identify past trends, and gain insights applicable to current scenarios.

IV. ECOMMVIS

The primary ECommVis user, referred to as the *merchant stakeholder*, typically falls into one of two roles. The first role includes individuals involved in merchant management, such as account managers or commercial analysts/consultants, aiming to boost sales through ad campaigns and assess their impact on merchant performance. The second role involves scientists or analysts from the e-commerce platform, seeking to understand the effect of advertisements on merchant sales and enhance the advertising campaign as a product for merchants. Both roles are familiar with advertising and e-commerce metrics.

In ECommVis, the distinction between the two roles is based on the merchant data displayed. By default, ECommVis only displays data from a single merchant. However, if needed, analysts can input data from various sources into the system, allowing them access to the performance of multiple merchants.

A. DATA SET

ECommVis input data includes ad performance metrics from a merchant on an online e-commerce platform. As stated, this study focuses on data from a food delivery platform, analyzing interaction data from merchants who participated in advertising campaigns offered by the platform.

The data set includes customer interactions like impressions, clicks, and orders with timestamps, noting whether each was "organic" or "ad-based." Advertising info includes the campaign's active period and the merchant's advertising budget. It identifies users who interacted with the merchant and details sales data. It also covers platform metrics such as the merchant's ranking and search results position, the interface component displaying the merchant (e.g., home page, contextual product list), and search terms employed by users to find the merchant. The final analysis excludes interactions involving missing values. Fig. 2 summarizes all relevant data sources.

ECommVis also utilizes similar data from the merchant's competitors. Competitor identification was determined through three key attributes: dish category, geographic location, and business scale. For instance, two merchants can be considered competitors if they both operate Italian cuisine restaurants with comparable monthly order volumes within the same city. Importantly, the algorithms used to identify competitors are not central to the study, and all competitor data is aggregated and anonymized, making it impossible for system users to identify them. The system prioritizes self-performance analysis over competitor profiling, ensuring that aggregated benchmarks remain informative without exposing sensitive business metrics from other individual merchants.

Lastly, although most of the dataset was sourced from the e-commerce company's consolidated databases, data manipulation was necessary to format it for ECommVis layouts. The system uses a simple ETL process that ingests multiple data sources and produces all required outputs. This workflow can be automated using the same mechanisms already in place for other data generation pipelines. That way, separate datasets for advertising information, merchant profiling, and user interactions across various platform components are easily transformed to align with ECommVis's unified and individual views.

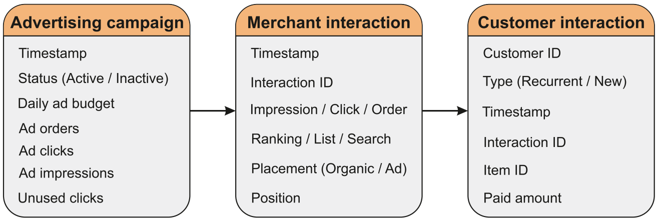

FIGURE 2. Schema for relevant merchant and user data sources, with the advertising campaign, merchant, and customer interactions.

TABLE 2. ECommVis Components and Respective Tasks. Abbreviations: OS = Orders Over Time, GS = Geospatial Interactions, MC = Merchant Metrics, HM = Interactions by Weekday and Shift, TP = Time Period Comparison.

Components	Task 1	Task 2	Task 3	Task 4
OS	✓	✓		✓
GS			✓	
MC		✓		✓
HM	✓			
TP				✓

B. VISUAL DESIGN

This section outlines the visual features designed to aid our tasks and how the integration of the system components is carried out, as shown in Table 2. The open vertical interface of one page, characterized as an analytic dashboard, consists of an overview feature, main components ("Orders over time" (OS), "Geospatial interactions" (GS), "Merchant metrics" (MC), and "Interactions by weekday and shift" (HM)) — these are illustrated in Fig. 3, and a final "Time period comparison" component (TP), illustrated in Fig. 4. The design aligns with industry-standard patterns, featuring an interactive

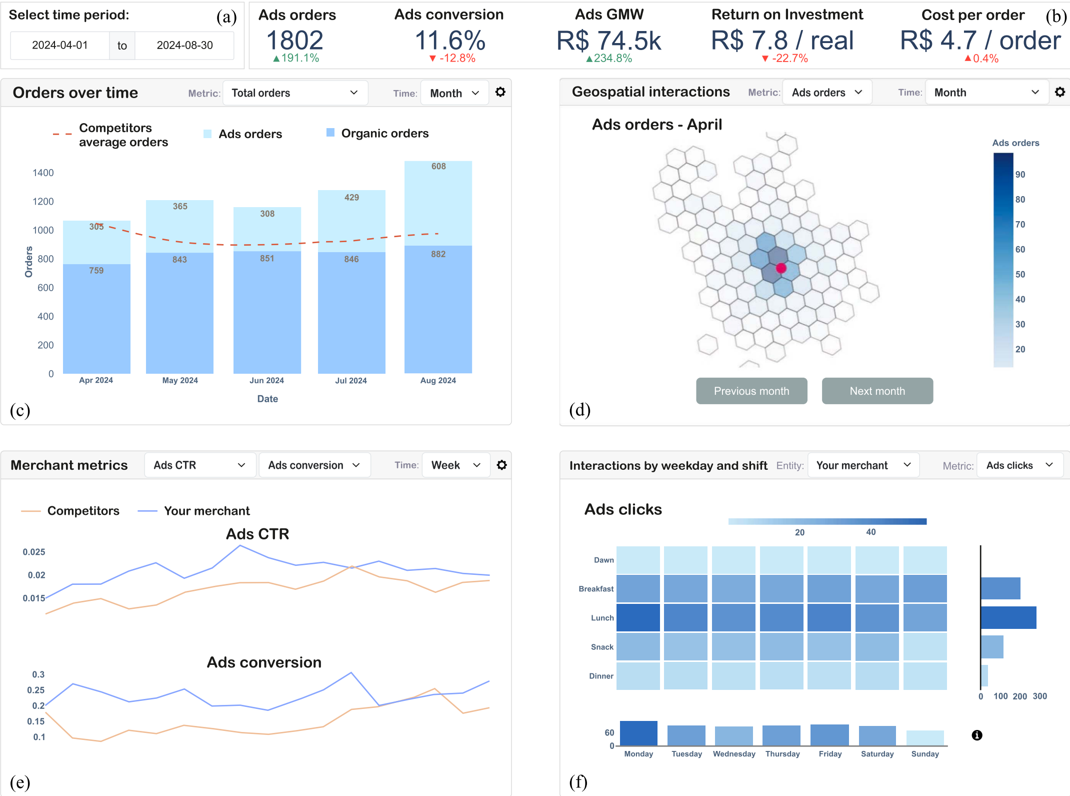

FIGURE 3. **ECommVis overview (a), (b) and main components (c), (d), (e), and (f). (a) is the time selection widget and (b) are the ad campaign overview numbers; (c), (d), (e), and (f) refer to the "Orders over time" (OS), "Geospatial interactions" (GS), "Merchant metrics" (MC), and "Interactions by weekday and shift" (HM) layouts, respectively.**

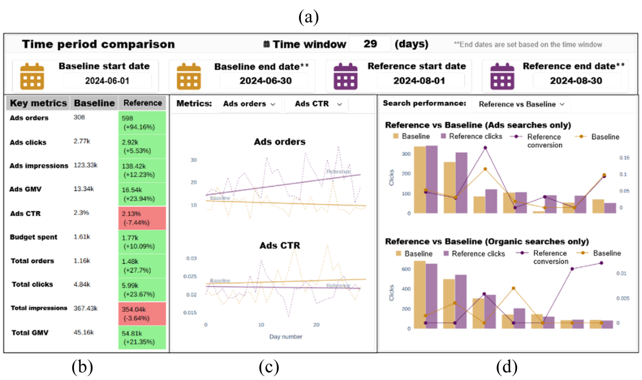

FIGURE 4. **Time period comparison component. (a) is the time window selection widget; (b) is the summary of key metrics; (c) is the metrics line chart; and (d) is the search performance layout.**

overview for period selection, followed by general data and visualizations detailing advertising performance, similar to a single-merchant performance report.

The "Overview" feature includes an interactive time period selection (Fig. 3(a)) that influences all system layouts as an interactive filter. The visual encoding shows key performance metrics like order volumes and advertising results as single values for the period, benchmarked against competitor averages (Fig. 3(b)). The "Orders over time" layout (OS) (Fig. 3(c)) highlights historical sales performance across various timestamps (T4), focusing on the impact of the advertisement campaign (T2). The bars are segmented to show orders from organic sources versus ad discovery, enabling analysis of the advertisement's effect on total orders (T1).

Additionally, data on competitor averages is provided for each metric. The "Metric" widget at the top of the layout visualizes two performance-related variables: the change in advertisement orders from new customers (users with no prior orders from that merchant) and from returning customers (customers with at least one previous order from that merchant). This allows for an understanding of how many new customers were attracted by the ad placements and how many existing customers were retained. The "Time" widget in the top right corner allows adjustments to the x-axis time aggregation, defaulting to 'week', but also offering 'month' and 'day' options to help analyze performance changes over different time periods. The gear icon provides visual configuration options for the layout, including sliders to adjust the opacity of bars or lines and an option to hide date labels on the x-axis.

The "Geospatial interactions" layout (GS) visually organizes performance data by density across grid cells within a specified territory (T3). In the context of a food delivery operation, merchant orders are typically concentrated within city boundaries, allowing for hexagonal resolution equivalent to a neighborhood. Fig. 3(d) displays the default layout configuration, where the red circle represents the merchant location and the color scale represents the number of advertisement orders in each grid cell, based on order data from the entire period selected in the Overview feature. A white background is used, instead of a Mapbox, to preserve merchant information. Similarly to the previous layout, the "Metric" widget at the top allows visualization of two additional performance variables. The first one is the total number of orders (both organic and advertisement), akin to the default configuration. The second compares the performance with the average of competitors, classified as inferior, balanced, or superior. In areas where the merchant exceeds competitors in orders, a superior label is assigned with a blue color. This provides a spatial understanding of performance, highlighting areas where the merchant outperforms competitors. The "Time" widget allows for changing the analyzed period, with an option to view data by "Month" for successive months. The gear icon offers a minor visual adjustment for the opacity of hexagons.

The "Merchant metrics" layout (MC) (Fig. 3(e)) features two stacked line charts displaying advertisement and performance metrics (T2) across various timestamps (T4). Two widgets at the top allow selection of metrics represented in the charts, such as the number of clicks, CTR (click-through rate), conversion rate, etc. Positioning the charts one above the other facilitates the correlation between metrics, such as unused advertisement clicks and the ad budget spent. It also enables comparison of growth or stagnation performance trends against competitor averages. This design is simple, user-friendly, and aligns with dashboard standards for illustrating performance over time. The "Time" widget in the top right corner allows adjustments to the x-axis time aggregation, defaulting to 'week', with an option for 'day' configuration, to identify short-term performance fluctuations and detect time-specific anomalies.

The "Interactions by weekday and shift" layout (HM) (Fig. 3(f)) features a heatmap of click performance across each day of the week (x-axis) and daily shifts (y-axis). Alongside, bar charts on each axis display aggregated click performance without heatmap segmentation, offering finer granularity. This heatmap is particularly beneficial in the food delivery sector, where customer behavior is heavily influenced by time and day. It helps identifying optimal advertisement times (breakfast, lunch, dinner) or days of the week, considering factors like merchants being unavailable on specific days (e.g., Mondays) and the increased consumption typically seen on weekends. The "Entity" widget at the top of the layout allows for viewing the merchant or the competitors' average, while the "Metric" widget on the top right provides a detailed view of click performance by segmenting the metric into total clicks, organic clicks, or advertisement clicks (T1).

The "Time period comparison" component is uniquely structured, independent of the global period configuration in the "Overview" component. It facilitates direct performance comparisons between two advertising periods (T4), referred to as "reference" and "baseline", with baseline defaulting to the previous period. Users choose a time window (in days) and a starting day for each period. The period selection is managed through a window to ensure consistent day counts across periods (Fig. 4(a)). Once selected, three layouts present comparison details on advertisement metrics.

The first layout (Fig. 4(b)) is a table summary showcasing key metrics, including the number of impressions, clicks, and orders related to the advertisement campaign, along with all organic metrics. It directly contrasts the metrics from both periods (T4), using a green-red color scale to indicate increases or decreases. The second layout (Fig. 4(c)) is the metrics line chart, similar to the "Merchant metrics" layout (MC). It features two vertical subplot charts that facilitate correlational analysis between sequential timestamps. This layout emphasizes performance differences between the baseline and reference periods (T4), displaying moving averages for weekly values. Additionally, the slope chart highlights variations in each period, while dashed lines provide detailed, discriminated values.

The third layout (Fig. 4(d)) is the search performance layout, represented with a vertical subplot and linked to the binary analysis of Reference vs. Baseline periods (T4) and Advertisement vs. Organic interactions. It uses bar charts to display search terms used by users to interact with the merchant, whether through top placement or organic ranking. We note that the figure displays masked search terms to protect the merchant's identity. In addition, it shows the conversion rate for each term, allowing us to identify if certain terms result in better conversion rates, even if they are less frequently used by customers. In the default configuration (Reference vs. Baseline), each subplot directly compares the performance of these two periods. The top plot represents only advertisement interactions, while the bottom plot shows organic interactions. The widget at the top allows for changes to this hierarchical setup. The "Ads vs. Organic" option instead compares advertisement with organic interactions, with the top plot focusing on the reference period and the bottom one on the baseline period. This configuration enhances the flexibility of the period analysis.

C. DESIGN CHOICES

ECommVis features a single-page interface that functions as an interactive performance dashboard, eliminating complex navigation by centralizing essential information in one view. The design principles follow established dashboard patterns, prioritizing clarity and minimalism. The interface presents one component at a time in a stratified layout, with charts arranged symmetrically and grouped by attributes to reduce visual clutter.

Recognizing that users aren't visualization experts, performance data appears in consolidated yet simple formats, such as bar and line charts or as clear visual indicators. Geospatial information utilizes hexagonal grid cells on maps, while heatmaps display performance metrics with daily granularity, incorporating appropriate time shifts for each weekday. All layouts control screen space through parameterization, with select components offering meta information that briefly describes layout elements. Tabular formats were limited to the TP summary, as the design prioritized trend visibility over raw data exploration. Complex visualizations like parallel coordinates and networks were omitted to avoid analytical complexity, particularly since the data lacked multidimensional characteristics.

The color palette maintains consistent patterns across the system, enhancing readability and highlighting key metrics. Merchant data appears in blue tones, dark blue for organic sales and light blue for ad sales, while competitor data is consistently highlighted in orange. Positive variations appear in green and negative in red, with additional visual indicators ensuring increases and decreases remain distinguishable for colorblind users (e.g., arrows in Fig. 3(b)).

D. IMPLEMENTATION DETAILS

ECommVis was developed in Python, using Plotly to model most charts, and Uber's H3 to represent geospatial data on choropleth maps. The web application layout is built with Shiny, and the online system is hosted via Shinyapps. The data used in ECommVis consists of tabular e-commerce data, with advertising campaign information stored with daily timestamps. For user interactions, hourly data and geospatial information (latitude and longitude) are required. ECommVis is available at https://github.com/henrique-gino/ecommvis.

V. USAGE SCENARIOS

The two usage scenarios described in this section demonstrate how ECommVis can be employed to analyze performance data and thus aid strategic decision-making for improved e-commerce outcomes. Both cases involve analyzing performance data from April 2024 to the end of August 2024.

A. MERCHANT 1

In this usage scenario, the merchant is a medium-to-large-sized restaurant that regularly implements advertisement campaigns on the food delivery platform. By early 2024, it had already integrated advertisements into its strategy. Setting the overview period from April 1 to Aug. 30, 2024, provides a clear picture of the merchant's performance, particularly regarding advertisement metrics. During this period, the merchant achieved 1,802 orders through advertisement, averaging about 12 ad orders daily. Compared to the average of direct competitors (943 ad orders per individual competitor), the merchant had a significantly higher number of ad-driven orders (nearly +200% increase), despite a minimal difference in the cost per order metric (+0.4%).

Examining the monthly performance in the "Orders over time" (OS) layout (Fig. 5(a)), it becomes evident that in April, competitors averaged the same number of total orders (top chart). However, this gap widened in the following months. This change can be attributed mainly to the growing number of orders from the advertisement campaign, as evidenced by the rise in advertisement orders. In April, 28.6% of the merchants' orders were from ads (305 out of 1064 orders), and by

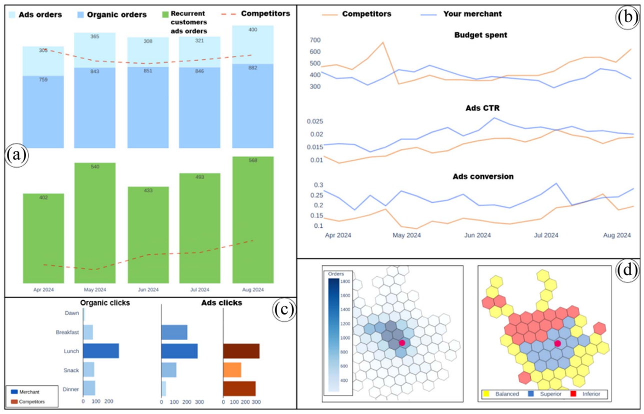

FIGURE 5. ECommVis components for Merchant 1. (a) is *Orders over time* (OS) in the default and 'Recurrent customers' configurations; (b) is *Merchant metrics* (MC) for three different metrics; (c) is the aggregated bars from *Interactions by Weekday and Shift* (HM), focusing on shift; and (d) is *Geospatial interactions* (GS) with 'Total orders' and 'Vs. competitors' configurations.

August, this percentage had increased to 31.2% (400 out of 1282 orders). While the 'New Customers Ads Orders' metric remained stable over the months, the 'Recurrent Customers Ads Orders' metric showed an upward trend. This indicates a growing loyal customer base for the merchant, even when discovery is facilitated through top advertisement placements.

"Merchant metrics" (Fig. 5(b)) reveal that, despite maintaining a similar advertisement budget, the merchant outperforms competitors in both click and conversion rate. This suggests a successful advertising strategy, with customers being attracted to the merchant even in top placement positions. The "Interactions by Weekday and Shift" (Fig. 5(c)) provides intriguing insights into the merchant's seasonality. Firstly, unlike its competitors, the merchant has a significant operation during breakfast. Secondly, breakfast clicks are more likely to be ad clicks rather than organic ones, whereas during the dinner shift, nearly all clicks are organic, with almost no ad clicks at night. The "Geospatial interactions" layout (Fig. 5(d)) highlights strong performance trends near the merchant's location (left chart), whereas the territories to the north and northwest consistently showed poor performance compared to competitors throughout the year (right chart). When examining the 'Total Orders' metric, it's clear these regions are crucial to overall performance, as they account for a significant number of sales and are geographically close.

B. MERCHANT 2

Now the merchant is a medium-sized restaurant that began adopting an advertising strategy at the beginning of 2024. However, the launch was challenging, and by the end of the period in August, there were no significant changes in the total number of orders. This time, the overview section presents a different scenario, with competitors outperforming in advertisement metrics. Examining the "Orders over time" component (Fig. 6(a)) reveals that in early April, the

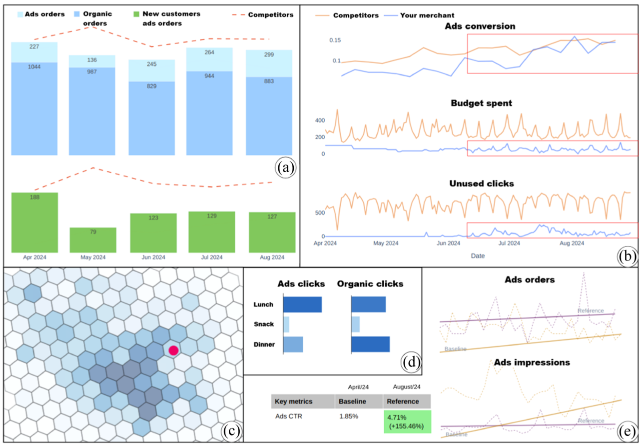

FIGURE 6. **ECommVis components for Merchant 2. (a) is OS in the default and 'New customers' configurations; (b) is MC for three different metrics; (c) is GS showing 'Total orders'; (d) is the aggregated bars from HM, focusing on shift; and (e) is the TP component showcasing different ad metrics variations.**

merchant and its competitors had nearly the same number of total orders. However, during the period from April 1 to June 30, 2024, competitors increased sales while the merchant remained stagnant. Switching the metric to New Customers Ads Orders highlights how fewer new customers engaged with the merchant compared to competitors.

The "Merchant metrics" layout (Fig. 6(b)) reveals that the ad performance is tied to the merchant's budget in advertising, which is significantly less than that of competitors. Up until mid-June, there were nearly zero unused advertisement clicks, suggesting that the budget should be increased. Additionally, the advertising conversion rate was noticeably lower than the competitors' average, indicating that customers were less likely to make a purchase after clicking on the merchant from the top placement position compared to competitors' catalogs. During the analyzed period, the geospatial layout (Fig. 6(c)) indicates that most orders are concentrated southwest of the merchant's location, an area where competitors also demonstrate superior performance. Since this territory is not strictly close to the merchant, strategies should be employed to enhance operational efficiency for customers in that region, such as offering discount coupons for delivery fees. The "Interactions by weekday and shift" layout (Fig. 6(d)) offers another key insight into the advertisement metrics. Examining ad clicks across daily shifts reveals that the majority occur at lunch. In contrast, most organic clicks happen during dinner, indicating that advertisement top placements are concentrated only during lunch and not during other shifts. This trend is particularly pronounced in May, the merchant's period of poorest performance. This discrepancy may be due to the advertising budget being fully allocated to top placements for lunch, leaving nothing for the remaining shifts.

From previous insights from the "Orders over time" component, we know the total order count did not change significantly between those months. However, using the "Time period comparison" component, we can perform a deeper analysis from the beginning of the period (April) to the end (August), particularly focusing on advertising metrics (Fig. 6(e)). There's a notable 30% increase in ad orders, despite fewer ad clicks and impressions. This suggests enhanced customer engagement metrics (CTR and conversion) in August, indicating the merchant is chosen more frequently for top ad placements, and customers are more likely to purchase after viewing the merchant's catalog. Remarkably, these improved metrics were achieved with a lower budget in August, reflecting a more effective advertising strategy. Additionally, the Orders component for August shows a significant increase in recurrent ad customers.

VI. USER STUDY

We performed a user evaluation to gather feedback on the system's usefulness and usability and to collect ideas for improvement. The user study adopted methodologies established in visual analytics literature and widely used in other studies [33], [34], [35].

A. PROCEDURE

Participants used ECommVis to examine data from one anonymous medium- to large-sized merchant on an e-commerce platform. The data set covers performance data for five months, spanning from April 1 to August 31, 2024. The merchant contracted advertisement campaigns during this period to increase sales. Competitors' aggregated data is also included.

Our study was conducted online, with participants completing the questions remotely at their own pace, using their personal computers. This meant that we had no control over their testing environment. To familiarize participants with the system, we provided a six-minute instructional video covering basic concepts and functionalities. The video remained accessible to the participants throughout the experiment.

The questionnaire was written in Brazilian Portuguese, in which all participants were fluent. We divided the questions into (i) background and experience; (ii) 11 multiple choice questions to test the user's comprehension among all ECommVis visual components; (iii) Likert scale-based questions to evaluate the user's preference for the system, along with open questions to justify their choices; and (iv) a mix of multiple choice and open questions to collect the user's feedback on the system. This questionnaire structure was based on similar user studies evaluating layouts or systems.

The questions were designed to evaluate the system's functionality and layout, as well as participants' perceptions while performing various tasks. First, we assessed the comprehension of the overview functionalities of ECommVis using two basic multiple-choice questions about the "Overview" and the "Orders over time" layout. Then, there were three sets of two multiple-choice questions, for each layout: "Geospatial interactions", "Merchant metrics", and "Interactions by weekday and shift". Throughout the questions, the participants were asked to interact with different configurations of each layout. Finally, the last three questions are related to the "Time period comparison" component, one for each individual layout: "Summary table", "Metrics comparison", and "Search performance". After exploring all the ECommVis layouts, participants were asked a general question about the perceived impact of advertising on merchant performance.

A pilot study was conducted with one participant (excluded from the final analysis) to evaluate response time, system functionality, questionnaire clarity, instructional video effectiveness, and difficulty of questions. Based on the feedback, we streamlined the assessment by reducing multiple-choice options from four to two, rewording questions, eliminating redundant items, and shortening the instructional video. These modifications ensured that the entire user evaluation could be completed in thirty minutes to one hour.

B. RESULTS

Participants' background: The experiment recruited 11 participants, who participated voluntarily in the experiment. They are analysts and scientists working in the e-commerce platform, all having a background in Computer Science and experience in the Visualization science field. Three of them work directly with advertisement campaign analysis and optimization. Most of the participants have extensive experience working with data science in their daily routines. We also asked if they were aware of any visual difficulties, such as color blindness, but no one indicated limitations. They had no access to our usage scenarios.

We divided the participants into non-overlapping groups based on their experience using a scale with None, Basic, Intermediate, and Advanced knowledge for each field (Visualization and Online Advertising). We consider the participant a Specialist if he/she has advanced knowledge in both fields (we have two specialists). If he/she has advanced knowledge in only one field, we included him/her in the Advanced group (4 individuals). Participants with intermediate knowledge in at least one of the two fields were included in the Intermediate group (5 individuals). These three groups were sufficient to categorize all 11 participants.

The participants spent 37 m 36 s on average to answer the questionnaire and perform exploratory analyses. Among the groups we analyzed, questionnaire completion time decreased with experience. Specialists finished in under thirty minutes. We believe this is because participants with greater expertise in these areas were already familiar with key advertising metrics and terminology, as well as the technical aspects of the layouts, allowing them to analyze and respond more quickly. Table 3 presents the participant group data, taking into consideration the three distinct groups (Intermediate, Advanced, and Specialists), their respective sizes, and the average time taken to execute the user study.

Questionnaire answers: The multiple-choice questions were aimed at validating the layouts and components individually. All participants correctly answered the first question, which evaluated the advertising campaign's success metric compared to competitor averages.

TABLE 3. Participants Groups Information, Including Size Distribution and Time Taken to Answer the User Study

Group	Size	Avg. time taken (min)
Intermediate	5	46
Advanced	4	31
Specialist	2	22

In question 2, about the "Orders over time" (OS) component, 82% of the participants answered correctly that the advertisement campaign was the reason for the merchant's success over competitors. The chart showed increasing ad orders while organic orders remained stagnant. Questions 3 and 4 were formulated to enable the understanding of the merchant's performance over geospatial data, also showcasing the city areas where competitors had better results. Both questions emphasized that orders (organic or ad-based) concentrate near merchant locations, maintaining this performance advantage over competitors. 91% got the right answer.

Questions 5 and 6 were designed to allow participants to compare two performance metrics displayed in the line plots, showing that better engagement metrics (CTR and conversion) enable improved ad performance despite lower campaign spending. All participants chose the correct answers. Questions 7 and 8 guided participants in understanding performance by weekday and shift, and in comparing the merchant's weekly performance against competitors. The analysis highlighted how ad performance varies across daily shifts, with merchants showing different strengths throughout the day. Question 8 had one wrong answer.

The final questions (9, 10, and 11) focused on the "Time period comparison" component, requiring participants to manually select and compare different time slices of merchant performance by interacting with the layout. Question 9 was centered around the aggregated metrics over the two periods, which all participants got right. Question 10 examined the correlation between spending and ad performance over time, revealing that larger budgets don't necessarily improve results. 91% answered correctly. Question 11 compared customer perceptions of merchants found through ads versus organic search results, with data indicating that keywords in ad campaigns influence the discovery process. 82% of the participants answered correctly.

ECommVis performance: We used two 5-point Likert-scale questionnaires to measure the participants' preferences about ECommVis (Fig. 7(a)) and about each layout used (Fig. 7(b)). We evaluated five main aspects of the system: whether the system is intuitive and easy to use (QT1), is useful (QT2), is fast (QT3), is effective in its context (QT4), and how it compares to similar systems (QT5).

Regarding QT1, one participant (with intermediate experience) was neutral about the system's capability on this matter (Fig. 7(a), QT1), however, indicating that following along with the questionnaire helped establish the system usage. In contrast, the specialists and other participants positively

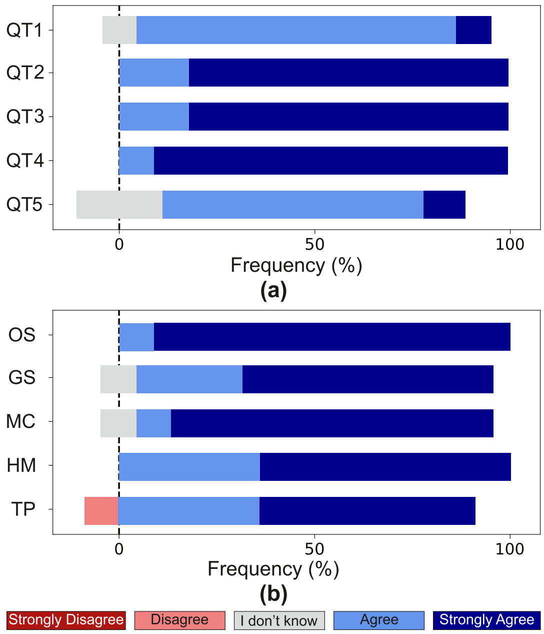

FIGURE 7. Participants' answers related to (a) ECommVis and (b) individual layouts. The bar length is the percentage of respondents who chose a specific Likert level.

evaluated the system, noting that *"the system has labels that help with data interpretation"*, and that *"the interactive plots are easy to manipulate and perform analyses with"*. The other two aspects (Fig. 7(a), QT2 – QT3) were positively evaluated by all participants. Some interesting aspects highlighted by the participants about the system's usefulness in QT2 were that *"with the way data is presented I can gather lots of useful information about the advertisement campaign"* and that *"the system synthesized well macro indicators; the aggregation levels, along with the performance competition data, are helpful for analyses"*. As for QT3, participants strongly agreed with the system being fast, noting that *"the system is responsive, not suffering any kind of delay during usage"* and *"the system is well optimized, with everything loading almost instantly"*.

With QT4, participants were asked to rate the overall effectiveness of the system in helping them understand the impact of the advertising campaign on the restaurant's performance. All participants provided positive feedback. They praised ECommVis for its ability to *"present clearly and objectively the advertisement impact"* and appreciated how it *"simplifies understanding the effectiveness of an ad campaign, including its profitability, operation, and potential areas for improvement"*.

The final question (QT5) explored participants' awareness of alternative systems to ECommVis. 82% responded positively, with most identifying general-purpose visualization and analytics platforms, including Thoughtspot, Databricks, Tableau, Power BI, Metabase, and Looker Studio. Only two participants mentioned domain-specific alternatives for marketing performance analysis: Google Ads and Semrush. According to them, ECommVis is preferable for e-commerce analysis, with its most positive points being performance (*"much faster than Thoughtspot"*, *"simplicity, quicker and more responsive interface"*) and being tuned for the task-specific job of analyzing advertisement data (*"better than generic looking dashboard made in Power BI or Looker"*, *"offers lots of great visualizations that are important to the e-commerce context"*). Conversely, user feedback inspires potential new personalization features. Given that the system tailors the layout to convey the best applicable metaphor for the data domain, it was noted that *"because it was developed for a specific purpose, it's difficult to make modifications or the inclusion of other metrics"*, and *"It would be interesting to create my own analyses inside the system"*.

The user study results show a strong correspondence between the ECommVis layout components (Fig. 7(b)) and the intended design tasks (Table 2). Positive agreement was computed by aggregating participants' *Agree* and *Strongly Agree* responses on the Likert scale. Task **T1** achieved 100% positive agreement, indicating that users clearly perceived the platform as effective in presenting the historical evolution of orders, distinguishing between organic and advertisement-driven sales, and enabling competitor comparison. Task **T2** reached 95% positive agreement, suggesting that the evolution of engagement metrics for merchants and competitors was generally well supported, despite the higher interpretative complexity of these metrics. Task **T3** obtained 90% positive agreement, confirming that the geospatial component adequately supports spatial comparison of merchant performance. Finally, Task **T4** achieved approximately 93% positive agreement, highlighting users' ability to compare different time periods and identify historical trends.

Feedback on individual layouts: Participants' assessments of each layout's quality evaluated usefulness and effectiveness in analyzing advertisement campaign performance. The results are summarized in Fig. 7(b). Having important information about the merchant's and the advertisement campaign performance, the first evaluated layout was "Orders over time" (OS). Participants gave the layout strong positive ratings, with one noting that the component *"made clear how helpful the advertisement campaign was for the merchant, especially concerning its competitors"*.

"Geospatial interactions" (GS) also received positive assessments, with participants noting that *"it is an extremely useful and relevant visualization in the context of the e-commerce platform, whose business is so heavily dependent on geographical information"*, *"it easily summarizes a complex KPI"*, and *"it's not a usual form of analysis and definitely can help bring new ideas and more understanding about ads metrics, which is not possible to get from aggregated metrics"*. GS is the most cited component in the open questions, with two-thirds of participants classifying it as the most useful visual resource from the system.

Moreover, 82% of participants gave strong positive feedback to "Merchant metrics" (MC), with one participating citing that *"comparing ad budget and merchant performance gets much easier"* and another that *"it is useful for qualitative comparisons with different ad indicators"*. "Interactions by weekday and shift" (HM) received unanimous positive responses. It is the second most cited layout as the most useful visual resource from the system, with one-third of participants stating that. One complemented this idea by saying that *"it helps understand consumption patterns from customers and also facilitates managing supply chain, and employing marketing strategies based on weekly frequency"*.

Participants considered that "Time period comparison" (TP) is useful because it enables the comparison between two different periods from the advertisement campaign. According to one participant, *"the layout assists in identifying opportunities to improve merchant performance"*. Two users reported difficulty interpreting the search performance visualization, which was subsequently redesigned to reduce visual complexity. Based on the written feedback, participants recognized GS and HM over the others as the most unique and useful visual resources, while also generally giving the consensus positive ratings to OS and MC, as they display important data from the advertisement campaign.

Suggestions for improvement: Participants from all levels of expertise made suggestions, with most of them relating to the addition of new components that can benefit the overall system. One participant suggested implementing an automatic feature that would, based on the analysis presented by ECommVis, highlight insights about how to improve the merchant's performance. Another one said that a different layout that facilitates a more in-depth analysis of the merchant's item ad performance may be beneficial. Some suggested minor layout changes to improve intuitive navigation, which were later added to the system.

VII. DISCUSSION

Visualization and analytics have the potential to improve seller performance in online platforms. This study introduces ECommVis, an innovative system that brings new visualization metaphors tailored to e-commerce marketplaces and enhances advertising performance management through interactive visual techniques. By addressing analytical gaps in current platform tools, ECommVis provides merchants with intuitive, multi-dimensional interfaces to understand performance patterns and optimize campaign strategies. It bridges the gap between raw advertising data and performance knowledge by visualizing ad metrics alongside organic interactions across temporal and spatial dimensions, uncovering patterns often hidden in traditional tabular formats. Anonymous competitor benchmarking further transforms isolated metrics into contextual insights, creating a data ecosystem that benefits both merchants and the platform.

Developed from platform sellers' requirements and pain points, ECommVis incorporates established principles of visualization and dashboard design [36]. It integrates complementary approaches such as temporal trends, geospatial heatmaps, engagement metrics, and time-shift analyses into a unified system, enabling users to build a comprehensive understanding through an intuitive, report-like interface. Our evaluation, conducted through a structured user study with analytics experts, employed consolidated visualization methodologies and confirmed that the comparative visualization approach significantly improved participants' ability to contextualize metrics and identify optimization opportunities across multiple dimensions. In particular, users highlighted ECommVis's responsiveness and processing speed compared to analytics tools like Tableau and ThoughtSpot. This contextual design approach also fits marketplace dynamics [37], reducing reliance on generic tools or disconnected dashboards.

The evaluation of ECommVis emphasizes the validity and usefulness of the system's features through expert feedback rather than through controlled comparisons with established baseline systems, which we acknowledge as a limitation of the current study. While this approach does not aim to benchmark performance against existing analytics tools, it enables a deeper qualitative assessment of how the proposed visual components support sense-making and decision-making in realistic usage contexts. Additionally, the user study involved 11 participants and primarily relied on descriptive analysis, which may limit the generalization of the findings. These design choices reflect a common trade-off in applied visual analytics research: prioritizing in-depth, domain-informed insights over large-scale quantitative validation.

Evaluation results corroborate existing visual analytics literature, showing that domain-specific visualization systems substantially enhance marketing analytics capabilities [19], [26], [27]. Positive feedback from industry experts validates our design choices and confirms ECommVis's practical utility in e-commerce. Its ability to rapidly identify temporal and spatial performance gaps represents a valuable advancement for data-driven merchant decision making in competitive environments. Beyond immediate application, this research offers insights for practitioners building advertising analytics platforms and for researchers investigating visual systems for performance management. Online marketplaces can leverage these findings to enhance business intelligence and foster equitable discovery mechanisms. Since popularity bias often hinders visibility, improved ad performance analytics can counterbalance such effects, supporting transparency and fairness across platform ecosystems.

ECommVis was validated using food delivery merchant data. Adapting this framework to other domains requires visual refinements; for instance, a nationwide sales distribution across a country or region would necessitate dynamic geospatial granularity to maintain analytical rigor. Similarly, the shift segmentation critical to food delivery must be reconfigured to align with the temporally relevant patterns inherent to each specific domain. At the same time, minor layout updates could further enrich these visualizations by incorporating domain-specific entities and characteristics, such as custom filters and specialized result segmentation. By prioritizing these contextual refinements, this research demonstrates how visual analytics can enhance performance management in food delivery while remaining adaptable to broader e-commerce contexts. The primary contribution lies in this seamless integration and domain tailoring, rather than the introduction of new visual encodings.

VIII. CONCLUSION AND FUTURE WORK

This work presented ECommVis, a visual analytics platform for advertising performance analysis in e-commerce marketplaces. By integrating temporal, spatial, and comparative visualization components, it enables merchants to contextualize their strategies against competitors and historical trends, addressing key challenges in data-driven optimization. User studies showed that ECommVis outperforms alternative systems by combining spatial and temporal insights while offering an offline architecture that ensures responsiveness and avoids subscription costs.

Beyond immediate applications in e-commerce, the platform illustrates how domain-specific visual analytics can transform complex business data into actionable insights, supporting informed decision-making in competitive environments. Feedback from users suggests future improvements should focus on enhanced customization, allowing merchants more flexibility in tailoring analyses. Another key direction is automation: integrating machine learning for anomaly detection, recommendations, and predictive outcomes to complement human judgment and better support strategic decision-making.

REFERENCES

[1] J. M. Sanchez-Cartas and G. Leon, "Multisided plataforms and markets: A survey of the theoretical literature," *J. Economic Surv.*, vol. 35, pp. 452–487, 2021, doi: 10.1111/joes.12409.
[2] V. Radhakrishnan, "E-commerce industry and its effect on the world today," *Int. Res. J. Adv. Sci. Hub*, vol. 3, no. 2, pp. 23–29, 2021.
[3] A. Andonov, G. P. Dimitrov, and V. Totev, "Impact of E-commerce on business performance," *Tem J.*, vol. 10, no. 4, pp. 1558–1564, 2021.
[4] A. A. Alsmadi, A. Shuhaiber, M. Al-Okaily, A. Al-Gasaymeh, and N. Alrawashdeh, "Big data analytics and innovation in E-commerce: Current insights and future directions," *J. Financial Serv. Marketing*, vol. 29, no. 4, pp. 1635–1652, 2023.
[5] R. Lal, N. Deb, and D. M. Gogoi, "Assessing the role of digital data visualization tools in the advertising industry for informed business decision-making," in *Proc. Data Visualization Tools Bus. Appl.*, 2025, pp. 189–208.
[6] M. Hänninen, L. Mitronen, and S. K. Kwan, "Multi-sided marketplaces and the transformation of retail: A service systems perspective," *J. Retailing Consum. Serv.*, vol. 49, pp. 380–388, 2019.
[7] M. P. Coelho and J. Z. Mendes, "Digital music and the death of the long tail," *J. Bus. Res.*, vol. 101, pp. 454–460, 2019.
[8] A. Klimashevskaia, D. Jannach, M. Elahi, and C. Trattner, "A survey on popularity bias in recommender systems," *User Model. User-Adapted Interaction*, vol. 34, no. 5, pp. 1777–1834, 2024.
[9] Y. J. Purnomo, "Digital marketing strategy to increase sales conversion on E-commerce platforms," *J. Contemporary Admin. Manage.*, vol. 1, no. 2, pp. 54–62, 2023.
[10] T. T. Ke, S. Lin, and M. Y. Lu, "Information design of online platforms," *SSRN*, 2022, pp. 1–40. http://dx.doi.org/10.2139/ssrn.4149349
[11] P. Varsha and A. Karan, "Descriptive analytics and data visualization in E-commerce," in *Handbook of Big Data Research Methods*. Cheltenham, UK: Edward Elgar Publishing, 2023, pp. 86–104.
[12] R. Berman and A. Israeli, "The value of descriptive analytics: Evidence from online retailers," *Marketing Sci.*, vol. 41, no. 6, pp. 1074–1096, 2022.
[13] L.-S. Lê, "P-R-Dash: A dashboard-constructing tool for twinning business processes," *SN Comput. Sci.*, vol. 5, no. 5, 2024, Art. no. 550.
[14] A. Asadullah, I. Faik, and A. Kankanhalli, "Digital platforms: A review and future directions," in *Proc. Pacific Asia Conf. Inf. Syst.,* 2018, pp. 6–30.
[15] M. De Reuver, C. Sørensen, and R. C. Basole, "The digital platform: A research agenda," *J. Inf. Technol.*, vol. 33, no. 2, pp. 124–135, 2018.
[16] T. Derave, T. Princes Sales, F. Gailly, and G. Poels, "Understanding digital marketplace business models: An ontology approach," in *Proc. PoEM-WS*, 2021, vol. 3031. pp. 15–26.
[17] Y. E. Rachmad, "Perception of social media marketing by users of e-commerce marketplace and online food delivery," in *Proc. Int. Conf. Econ. Bus.*, 2022, vol. 1, pp. 121–134.
[18] Y. Liu and F. Long, "Data and algorithms: Designing marketplace analytics for platform sellers," pp. 1–94, 2024. [Online]. Available: https://ssrn.com/abstract=4890943
[19] Y. Chen, X. Cui, A. Li, B. Wu, and L. Yang, "The role of digital platforms in data markets: How platform-shared market data through advanced analytics empower firm innovation," pp. 1–42, 2024. [Online]. Available: http://dx.doi.org/10.2139/ssrn.4878048
[20] J. Barajas, R. Akella, M. Holtan, and A. Flores, "Experimental designs and estimation for online display advertising attribution in marketplaces," *Marketing Sci.*, vol. 35, no. 3, pp. 465–483, 2016.
[21] H. Choi and C. F. Mela, "Monetizing online marketplaces," *Marketing Sci.*, vol. 38, no. 6, pp. 948–972, 2019.
[22] E. Bayer, S. Srinivasan, E. J. Riedl, and B. Skiera, "The impact of online display advertising and paid search advertising relative to offline advertising on firm performance and firm value," *Int. J. Res. Marketing*, vol. 37, no. 4, pp. 789–804, 2020.
[23] J. T. Yun, C. M. Segijn, S. Pearson, E. C. Malthouse, J. A. Konstan, and V. Shankar, "Challenges and future directions of computational advertising measurement systems," *J. Advertising*, vol. 49, no. 4, pp. 446–458, 2020.
[24] M. Sharma and S. Joshi, "Online advertisement using web analytics software: A comparison using ahp method," *Int. J. Bus. Analytics,* vol. 7, no. 2, pp. 13–33, 2020.
[25] J. Ford, V. Jain, K. Wadhwani, and D. G. Gupta, "AI advertising: An overview and guidelines," *J. Bus. Res.*, vol. 166, 2023, Art. no. 114124.
[26] E. Khamoushi, "AI in food marketing from personalized recommendations to predictive analytics: Comparing traditional advertising techniques with ai-driven strategies," 2024, *arXiv:2410.01815*.
[27] M. Moinuddin, M. Usman, and R. Khan, "Decoding consumer behavior: The role of marketing analytics in driving campaign success," *Int. J. Adv. Eng. Technol. Innovations*, vol. 1, no. 4, pp. 118–141, 2024.
[28] F. Long, K. Jerath, and M. Sarvary, "Designing an online retail marketplace: Leveraging information from sponsored advertising," *Marketing Sci.*, vol. 41, no. 1, pp. 115–138, 2022.
[29] L. Klimek and R. Funta, "Data and E-commerce: An economic relationship," *Danube: Law, Econ. Social Issues Rev.*, vol. 12, no. 1, pp. 33–44, 2021.
[30] W. B. Putra and K. G. Ayu, "Analysis and visualization of digital advertising data using EDA on payment point online bank applications," *Matrix: Jurnal Manajemen Teknologi Dan Informatika*, vol. 14, no. 2, pp. 74–83, 2024.
[31] Y. Xiao et al., "Click without compromise: Online advertising measurement via per user differential privacy," in *Proc. IEEE Symp. Secur. Privacy*, 2025, pp. 2919–2937, doi: 10.1109/SP61157.2025.00187.
[32] O. Mintz, Y. Bart, P. Lenk, and D. Reibstein, "Drowning in metrics: How managers select and trade-off metrics for making marketing budgetary decisions," *SSRN Electron. J.*, pp. 1–57, 2019. [Online]. Available: https://opus.lib.uts.edu.au/handle/10453/138409
[33] M. Tian, G. Li, and X. Yuan, "LitVis: A visual analytics approach for managing and exploring literature," *J. Visualization*, vol. 26, no. 6, pp. 1445–1458, 2023.
[34] C. D. Linhares et al., "ClinicalPath: A visualization tool to improve the evaluation of electronic health records in clinical decision-making," *IEEE Trans. Vis. Comp. Graph.*, vol. 29, no. 10, pp. 4031–4046, Oct. 2022.
[35] C. D. Linhares, J. R. Ponciano, D. S. Pedro, L. E. Rocha, A. J. Traina, and J. Poco, "LargeNetVis: Visual exploration of large temporal networks based on community taxonomies," *IEEE Trans. Vis. Comp. Graph.*, vol. 29, no. 1, pp. 203–213, Jan. 2022.

[36] B. Bach et al., “Dashboard design patterns,” *IEEE Trans. Vis. Comp. Graph.*, 29, no. 1, pp. 342–352, Jan. 2022.
[37] O. M. Yigitbasioglu and O. Velcu, “A review of dashboards in performance management: Implications for design and research,” *Int. J. Accounting Inf. Syst.*, vol. 13, no. 1, pp. 41–59, 2012.

HENRIQUE L. S. GINO received the master’s degree in computer science from the University of São Paulo, São Paulo, Brazil, in 2025. He is currently a Data Scientist with experience in machine learning engineering, especially applied to search algorithms, Big Data analysis, recommendation systems, and advertising selection. His research interests include information visualization and retrieval, with a focus on the e-commerce domain.

JEAN R. PONCIANO is currently an Assistant Professor with the Mathematics and Computer Science Institute - University of São Paulo, São Paulo, Brazil. His research interests include information visualization, visual analytics, network science, and data streams. He is also a Program Committee Member for relevant conferences, including IEEE Vis, EuroVis, and ASONAM, and as an external reviewer for other relevant venues, such as IEEE TRANSACTIONS ON VISUALIZATION AND COMPUTER GRAPHICS, *Compter Graphics Forum*, *Computers & Graphics*.

CLAUDIO D. G. LINHARES received the B.Sc., M.Sc., and Ph.D. degrees in computer science from the Federal University of Uberlandia, Uberlândia, Brazil, in 2012, 2016, and 2020, respectively. He also completed a Postdoctoral Fellowship with ICMC, University of São Paulo, São Paulo, Brazil, in 2023. He is currently a Senior Lecturer with the Department of Computer Science and Media Technology, Linnaeus University, Växjö, Sweden. His research interests include information visualization and network visualization, with a particular focus on the healthcare domain and urban data.

AGMA JUCI MACHADO TRAINA (Member, IEEE) received the B.Sc. and M.Sc. degrees in computer science and the Ph.D. degree in computational applied physics from the University of São Paulo, São Paulo, Brazil, in 1983, 1987, and 1991, respectively. Since 2008, she has been a Full Professor with the Mathematics and Computer Science Institute - University of São Paulo. Her research interests include indexing and retrieval of complex data by content, similarity queries, data visualization, visual data mining, as well as image and video processing.

Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES) - ROR identifier: 00x0ma614