Long-term Evolution of Search Visibility and Click-Through Performance in Romanian E-commerce: A Four-Year Longitudinal Analysis of Google Ads Data

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Abstract: *The integration of artificial intelligence into Google Ads bidding and delivery systems – through Smart Bidding strategies, the transition from Smart Shopping to Performance Max and the progressive generalization of fully automated campaign types – has coincided with a period of structural change in the broader digital advertising ecosystem, marked by privacy-related signal loss, the deprecation of third-party cookies and a substantial reshaping of consumer search behavior in the post-pandemic period. This paper analyzes the long-term evolution of search visibility and click-through performance in a Romanian e-commerce account over a 47-month observation window, using monthly aggregated Google Ads data on impressions and clicks. Results document a non-monotonic trajectory: an initial high-visibility phase with impressions exceeding two million per month and click-through rates above 2.2%, a peak-volume phase with the highest aggregate impressions in the dataset and a click-through rate stabilizing around 1.9%, and a sustained decline phase in which average monthly impressions fall to less than half of their previous peak while the click-through rate remains broadly stable. Seasonal patterns concentrated in the fourth quarter persist throughout the observation window. The findings illustrate, in a Romanian retail setting, the long-term consequences of operating in an algorithmically mediated and privacy-constrained advertising ecosystem, and they have implications for budget planning, performance benchmarking and the interpretation of long-term trends in digital advertising data.*

Keywords: Google Ads, search visibility, click-through rate, longitudinal analysis, artificial intelligence, e-commerce, digital advertising.

JEL: M31, M37, L81, O33.

1. Introduction

Over the past five years, the Google Ads ecosystem has undergone a sequence of structural transformations that have reshaped both the technical mechanics of paid search and the behavioral environment in which it operates. On the technical side, Smart Bidding strategies have become the default approach to setting bids in real time, Smart Shopping campaigns have been progressively replaced by Performance Max – a fully algorithmic campaign type that allocates spend across the Google network with minimal advertiser intervention – and the broader Google advertising stack has integrated an increasing number of machine-learning components. On the behavioral side, the COVID-19 pandemic accelerated digital adoption and reshaped consumer search behavior, while a sequence of privacy-related changes – including the introduction of Apple's App Tracking Transparency framework, the rollout of Google's Consent Mode and the planned (and repeatedly postponed) deprecation of third-party cookies – has progressively eroded the signal richness on which ad delivery algorithms depend.

For an individual advertiser, the joint effect of these structural changes is not directly observable from a single campaign report. It manifests instead as a long-term pattern in aggregate metrics such as monthly impressions, monthly clicks and click-through rate (CTR). Documenting these patterns is therefore a methodologically distinct exercise from analyzing single-campaign performance: it requires a longitudinal perspective on data that spans several years of operation and several technological and behavioral regimes. As I show in an analysis of Google Ads campaigns Hoțoi (2024) from a Romanian online retailer over a 30-month interval, such longitudinal data can reveal both the structural impact of the pandemic on consumer behavior and the operational consequences of the digital ecosystem's evolution.

The present study contributes to this line of inquiry by analyzing a 47-month dataset of monthly aggregated Google Ads data from a single Romanian e-commerce retailer (henceforth referred to as "the retailer"). The data cover the period in which AI-driven bidding became the operational default in Google Ads, in which Performance Max was introduced and generalized, and in which several privacy-related changes affected the signal infrastructure of digital advertising. The research aims are: (i) to document the long-term evolution of monthly impressions, clicks and CTR for a Romanian e-commerce account; (ii) to identify the main phases of this evolution and their associated performance profiles; (iii) to discuss the relationship between the observed patterns and the broader technological and behavioral context in which they emerged; and (iv) to derive practical implications for performance benchmarking and budget planning in small and medium e-commerce businesses.

The research is exploratory and empirical, based on secondary data exported from Google Ads at a monthly aggregation level and analyzed descriptively. The remainder of the paper is structured as follows: Section 2 reviews the literature on AI in paid search, on longitudinal analysis of advertising performance and on search behavior analytics in applied research; Section 3 presents the data and methodology; Section 4 reports and discusses the results; Section 5 concludes with managerial implications, limitations and directions for future research.

2. Literature review

2.1. Artificial intelligence and the evolution of paid search

The integration of artificial intelligence into paid search advertising has followed a trajectory that mirrors the broader transformation of marketing analyzed by Davenport et al. (2020). The authors argue that AI is reshaping marketing strategy across three dimensions: the nature of the tasks performed, the structures used to support those tasks and the engagement model with customers. Within paid search, this transformation has manifested as the progressive replacement of manual bidding with Smart Bidding (Target CPA, Target ROAS, Maximize Conversions, Maximize Conversion Value), and as the introduction of fully algorithmic campaign types such as Smart Shopping (launched in 2018) and Performance Max (introduced in 2022 and gradually replacing Smart Shopping by 2023).

Huang and Rust (2021) propose a strategic framework in which AI in marketing operates on mechanical, thinking and feeling levels, and locate algorithmic bidding systems primarily at the thinking layer, where AI optimizes for explicit objectives over large volumes of structured signals. Vlačić et al. (2021), in a systematic review of AI in marketing, identify advertising and customer relationship management as the most mature application areas, while Kumar et al. (2019) emphasize personalization at scale as the most consequential outcome of AI adoption. Choi et al. (2020) document, in a broader context of programmatic advertising markets, how such systems internalize bidding decisions and reduce the operational role of the human advertiser.

The technological foundations on which these systems operate were anticipated, in part, by earlier work on cloud-based infrastructure and AI-powered tools for business use. Olteanu (2016) analyzed Facebook Graph as one of the first widely available AI-powered search tools, while Olteanu (2014) examined the emergence of dedicated tools for monitoring social networks in business sectors. These tools, in turn, rely on the cloud-based data infrastructure discussed by Olteanu (2013a) and on the principles of reliable web service continuity examined by Olteanu (2010) – preconditions that remain operationally critical for any longitudinal analysis of digital advertising performance, since they determine the consistency of the data on which such analysis depends.

2.2. Longitudinal analysis of paid search performance

The empirical literature on the longitudinal performance of paid search campaigns is comparatively limited, in part because long time series of consistent advertiser-level data are difficult to obtain. Yang and Ghose (2010), in an early study of the relationship between organic and sponsored search advertising, document substantial temporal heterogeneity in click-through behavior and in the interaction between paid and organic results. Blake, Nosko and Tadelis (2015), in a large-scale field experiment on eBay, find that the incremental effect of paid search advertising varies significantly across user segments and over time, with implications for the long-term evaluation of paid search investments. Berman (2018) shows that the choice of attribution model can substantially affect the apparent performance of a paid search account over time, particularly when the campaign mix evolves across the observation window.

Two recent structural shocks have made longitudinal analysis of digital advertising performance particularly relevant. First, the COVID-19 pandemic produced a sudden and large reshaping of consumer behavior, with documented effects on the role of digital channels in purchasing decisions (Sheth, 2020; Hoekstra and Leeflang, 2020). In the Romanian context, Hoțoi (2024) shows that the pandemic accelerated the digital adoption of consumers and increased the role of paid search campaigns in conversion-generating purchase journeys, with measurable effects on key performance indicators over an extended observation window. Second, a sequence of privacy-related changes – including Apple's App Tracking Transparency framework, Google's Consent Mode v2 and the progressive deprecation of third-party cookies – has reshaped the signal infrastructure on which ad delivery and measurement systems rely, with consequences for the interpretation of long-term trends in advertiser-level data.

2.3. Search behavior analytics in applied empirical research

Beyond paid search proper, the use of online search and behavioral data sources for empirical analysis has become a methodological staple in a wide range of applied studies. Olteanu (2013b) discussed early on the range of digital techniques through which online consumer behavior can be shaped, anticipating much of the contemporary discussion on algorithmic content delivery. Bazac et al. (2023) show that the online referential value of urban historical parks can be assessed through digital marketing indicators in order to support sustainable management decisions, while Marin et al. (2025) propose a software-based assessment framework that analyzes online search behavior to support the integration of scientific heritage sites into their urban environment. In adjacent applied domains, Grecu et al. (2020) document the role of mega-events in the development of structural tourism capabilities, drawing on audience-related data, while Drăghici et al. (2022) illustrate the broader methodological importance of longitudinal demographic and behavioral data in understanding the dynamics of specific populations. Chaffey and Ellis-Chadwick (2022), in a foundational textbook on digital marketing, position the longitudinal analysis of search visibility and CTR among the core analytical practices for managerial decision-making in digital advertising.

3. Research methodology

The research is quantitative, exploratory and descriptive, based on secondary data exported from the Google Ads account of a Romanian online retailer operating in the discount and promotional e-commerce segment. To preserve the anonymity of the retailer, the exact identity of the account, the specific calendar dates of the observation window and the absolute level of advertising spend are not disclosed. The observation window is reported as a 47-month period covering both the post-pandemic recovery and the progressive integration of AI-driven bidding and delivery systems into Google Ads.

The data source is a monthly aggregated report from Google Ads, containing for each calendar month two performance indicators: the number of impressions delivered and the number of clicks received. From these two indicators, the monthly click-through rate (CTR) was computed as the ratio of clicks to impressions, expressed as a percentage. The dataset thus contains three time series – monthly impressions, monthly clicks and monthly CTR – over 47 calendar months, of which 44 record non-zero activity. The three months with zero activity, which occur consecutively at the start of the observation window, are interpreted as a period during which the account was either inactive or running campaigns with no impression delivery; they are excluded from the calculation of averages but retained when characterizing the overall structure of the time series.

The analysis is performed at three levels of aggregation: the entire observation window, individual annual periods (covering 12 consecutive months, except for the first and last annual periods, which are partial) and individual months. The objective of this multi-level analysis is to separate three components of the observed time series: a long-term trend across the four-year window, a recurring seasonal pattern centered on the fourth quarter, and month-to-month variation that may reflect specific operational or contextual events. The methodological approach is descriptive and comparative, in line with the longitudinal secondary-data design used by Hoțoi (2024) and consistent with the framework of online behavior analytics articulated by Marin et al. (2025). No attempt is made to estimate causal effects, since the data do not contain the controls or counterfactual structure required for such estimation; the analysis is limited to documenting and interpreting the observed patterns.

4. Results and discussion

4.1. Overall structure of the time series

Over the 47-month observation window, the account recorded a cumulative total of 1,246,015 clicks and 61,195,794 impressions, corresponding to an overall click-through rate of 2.04%. The activity covers 44 months, with three consecutive months of zero delivery at the start of the window. The monthly distribution of impressions is highly heterogeneous: at the upper end, the most active months recorded volumes above two million impressions, while at the lower end, the least active months recorded fewer than 300,000 impressions – a ratio of approximately ten to one between the highest and the lowest monthly levels of search visibility. The monthly CTR is comparatively more stable, ranging between 1.56% and 2.89% across the entire window, with the great majority of months falling between 1.7% and 2.2%.

4.2. Long-term trend: three phases of search visibility

The annual aggregation of the data reveals a clearly non-monotonic long-term trajectory, with three distinguishable phases. The first phase corresponds to the early portion of the observation window, when the account averaged approximately 2.1 million impressions per month over the seven active months recorded in that period, with an annual CTR of approximately 2.23%. This phase is characterized by relatively high search visibility, an above-average CTR, and click volumes consistent with active growth in the account.

The second phase spans the following two full annual periods, in which the account recorded its peak aggregate volumes: more than 18 million impressions in the first full year and more than 21 million impressions in the second full year, corresponding to monthly averages of approximately 1.5 and 1.8 million impressions respectively. The annual CTR in this phase declined modestly to between 1.95% and 2.15%, but the absolute click volumes reached their highest levels in the dataset – consistent with a mature account operating at scale within the algorithmically mediated Google Ads ecosystem. This phase corresponds, in the broader market context, to the progressive generalization of Smart Bidding strategies and to the introduction of Performance Max, as well as to the post-pandemic normalization of consumer search behavior discussed by Sheth (2020) and Hoekstra and Leeflang (2020).

The third phase, covering the most recent full annual period and the partial period at the end of the window, displays a sustained and substantial decline. Monthly impressions fell to an average of approximately 960,000 in the third year – less than half of their previous peak – and to an average of approximately 430,000 in the partial fourth year, while the annual CTR remained broadly stable between 1.81% and 1.90%. The stability of the CTR alongside the sharp decline in volume indicates that the contraction operates primarily on the supply side of impressions, rather than on the click responsiveness of the audience: the algorithm continues to deliver impressions at approximately the same rate of click conversion, but to a substantially smaller volume of users. This pattern is consistent with the cumulative effect of the privacy-related changes discussed in the literature (Yang and Ghose, 2010; Berman, 2018) and with a hypothesis of intensified competition for high-value impressions within a contracting addressable audience.

4.3. Seasonal pattern: Q4 concentration

Superimposed on the long-term trend, a recurring seasonal pattern is visible throughout the observation window. The fourth quarter, and in particular the months of November and December, systematically records higher click and impression volumes than the rest of the year, consistent with the well-documented importance of Black Friday and end-of-year promotional periods in Romanian e-commerce. In the highest-volume year, November alone recorded approximately 70,000 clicks and more than 3.2 million impressions, with a CTR of 2.17% – substantially above the surrounding monthly levels. In the preceding year, November recorded its own local peak at approximately 52,000 clicks and a CTR of 2.89%, the highest single-month value in the dataset.

The persistence of this seasonal pattern across all phases of the long-term trend has practical implications. First, performance comparisons that do not account for seasonality are highly sensitive to the choice of reference period, with potentially misleading conclusions about year-over-year evolution. Second, the maintenance of clear seasonal peaks even in the contraction phase suggests that the structural factors responsible for the long-term decline – algorithmic, competitive or privacy-related – do not eliminate the underlying seasonality of consumer demand. As Hoțoi (2024) notes in a comparable Romanian setting, the seasonality of digital marketing campaigns has remained robust even through the structural shocks of the pandemic and post-pandemic period.

4.4. CTR stability and the algorithmic interpretation

The relative stability of the monthly CTR across the observation window – moving between approximately 1.7% and 2.2% for the great majority of months, with isolated peaks above 2.8% in seasonal high-points – is, in itself, a finding worth highlighting. Within an algorithmically mediated bidding and delivery ecosystem, the CTR can be interpreted as a joint product of three factors: the quality of the match between the ad and the user (largely controlled by the algorithm), the relevance and competitiveness of the ad creative (controlled by the advertiser) and the propensity of the user to click (a function of the user's intent and the broader behavioral context). The fact that this composite indicator remains broadly stable while the absolute volume of impressions varies by an order of magnitude suggests that the contraction of search visibility operates primarily through changes in the volume of addressable users, rather than through a degradation in match quality.

This pattern is consistent with the broader frameworks proposed by Davenport et al. (2020), Huang and Rust (2021) and Vlačić et al. (2021), in which AI-driven advertising systems are designed to optimize the marginal value of impressions and tend to defend per-impression performance metrics even as macro-level conditions deteriorate. It also echoes the observation by Olteanu (2013b) that digital influencing techniques operate through targeted matching rather than through volume alone – an observation made more than a decade before AI-driven bidding became the operational default. For a contemporary advertiser, the implication is that long-term performance benchmarks should be constructed at the level of volume metrics (impressions, clicks) as well as at the level of rate metrics (CTR), since the two can evolve in substantially different ways within the same account.

5. Conclusions

This paper has analyzed the long-term evolution of search visibility and click-through performance in a Romanian e-commerce account over a 47-month observation window, using monthly aggregated Google Ads data on impressions and clicks. Four findings emerge from the analysis.

First, the long-term trajectory of search visibility is markedly non-monotonic and can be characterized as three phases: an early high-visibility phase, a peak-volume phase corresponding to the maturation of AI-driven bidding and the introduction of Performance Max, and a sustained decline phase in which monthly impressions fall to less than half of their previous peak. Second, the monthly CTR remains broadly stable across the entire observation window, indicating that the contraction in search visibility operates primarily on the supply side of impressions rather than on the click responsiveness of the audience. Third, the seasonal concentration of activity in the fourth quarter – consistent with the importance of Black Friday and end-of-year promotional periods – persists robustly across all phases of the long-term trend. Fourth, the joint pattern of declining volumes and stable CTR is consistent with the cumulative effects of privacy-related signal loss and intensified competition for a contracting addressable audience, within a broadly stable algorithmic matching environment.

These findings have implications for both research and practice. For practice, they argue against the use of volume metrics alone as benchmarks of long-term performance, since substantial declines in impressions and clicks can occur in the absence of any degradation in per-impression efficiency. They also support the construction of performance dashboards that combine rate and volume indicators, with explicit attention to seasonality, in order to provide a sound basis for budget planning and target setting. For research, the findings extend to a Romanian e-commerce setting the broader patterns documented in the literature on AI-driven advertising (Davenport et al., 2020; Huang and Rust, 2021; Vlačić et al., 2021), on longitudinal advertising performance (Yang and Ghose, 2010; Blake et al., 2015; Berman, 2018) and on the post-pandemic evolution of consumer behavior (Sheth, 2020; Hoekstra and Leeflang, 2020), and they complement the Romanian longitudinal evidence developed by Hoțoi (2024).

The study has several limitations. First, it is based on a single account in the discount e-commerce segment, which limits the generalizability of the quantitative findings; future work should compare long-term patterns across multiple accounts and verticals. Second, the available data are limited to impressions and clicks, with no information on cost, on conversion outcomes or on the campaign-type composition of the account; consequently, the analysis cannot decompose the observed trends into their algorithmic, competitive and behavioral components. Third, the analysis is descriptive rather than causal: it documents patterns and discusses plausible interpretations, but does not estimate the marginal effect of specific changes in the Google Ads ecosystem (such as the transition from Smart Shopping to Performance Max or the rollout of Consent Mode v2). Future research could address these limitations by combining monthly Google Ads data with cost and conversion data, by using quasi-experimental designs around well-defined platform changes, and by comparing the long-term patterns across accounts operating with different campaign-type mixes.

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