AI Driven Smart Shopping vs. Manual Search Campaigns in E commerce: An Attribution Based Performance Analysis

~ *Ph.D. Student* **Anca Hoțoi** *(The Bucharest University of Economic Studies, Romania) ORCID: https://orcid.org/0000 0002 0834 5295*

E-mail: ancahotoi@gmail.com

Abstract: *: Paid advertising platforms have changed a great deal once machine learning moved into the bidding stack, and Google Ads is now the obvious case in point. I look at how AI driven Smart Shopping campaigns compare with manually managed Search campaigns from a Romanian online wine retailer, and I ask, in particular, what last click attribution misses when the two types of campaigns run in parallel. The dataset combines three Google Analytics reports covering six concurrently running campaigns, plus an assisted conversion analysis on a 30 day lookback window. Four indicators carry most of the weight: CTR, CPC, ecommerce conversion rate and ROAS. What I find is uneven. Smart Shopping pulls in most of the clicks and most of the assisted touches, yet records the lowest last click conversion rate; manual Search campaigns, targeting users already close to buying, score the opposite way. Within this Google Ads account, from my digital marketing agency (Performance Target), approximately 47.6% of all conversions are identified as assisted conversions rather than last click interactions. From a strategic standpoint, this substantial share indicates that relying solely on last click reporting provides an incomplete picture, making it an unreliable foundation for budget allocation decisions. To address these complexities, this paper concludes with practical insights from my agency, for small e commerce retailers on how to effectively balance AI driven and manual campaigns. Specifically, it outlines strategies to avoid over investing in branded search while ensuring that top of funnel campaigns which actively generate the initial customer demand are not inadvertently starved of budget.*

Keywords: Google Ads, Smart Shopping, artificial intelligence, attribution modeling, e commerce, consumer behavior, digital marketing.

JEL: M31, M37, L81, O33

1. Introduction

Something important has changed in how paid advertising runs. The decision layer of platforms like Google Ads is now largely automated: when a query enters the auction, what gets shown, to whom, at what bid a model decides, often in milliseconds. Smart Shopping (and now Performance Max) is the textbook case. The advertiser uploads a feed, picks a goal, sets a budget, and the rest is handed over. Davenport et al. (2020) place this shift at the center of their account of how AI is rewriting marketing, and I agree with their framing: tasks, supporting structures, and the engagement model are all being reorganized, and digital advertising sits right at the leading edge.

The pandemic poured fuel on this fire. Hoțoi (2024), working with Google Ads data from a Romanian online shop, shows that consumer behavior shifted, the share of online purchases grew, and paid campaigns took on a heavier role in conversion. Once the dust settled, retailers were facing a harder market, more competition, costlier acquisition, and bidding systems that were no longer optional adds on but the default one.

Comparing AI driven campaigns with manually managed ones is not, however, clean exercise. The standard move line up last clicks conversions and last click ROAS by campaign type gives an unfair advantage to whatever sits closest to the final purchase. Branded search wins; non branded Shopping does not, even when it brought the customer in the first place. Berman (2018) makes this point formally: last click attribution can misallocate budgets in ways that are not small. And because Smart Shopping was built precisely to reach users who do not yet know the brand, much of its contribution shows up as an assist rather than as the final click.

My study works through this measurement problem with campaign level data from a real Romanian client, from my agency, online wine retailer (I call it "the retailer") that ran AI driven Smart Shopping in parallel with manually managed Search and Shopping campaigns. Four aims drive the analysis: comparing AI driven and manually managed campaigns on CTR, CPC, CR and ROAS; measuring assisted conversions per campaign type on a 30 day window; gauging how badly last click attribution underplays AI driven campaigns; and drawing practical implications for budget allocation and attribution policy in the SME e commerce segment.

Methodologically the work is empirical and exploratory. It rests on secondary data pulled from Google Analytics and Google Ads, and the analysis is descriptive and comparative no causal claims. Section 2 covers the literature on AI in digital advertising, on attribution and on consumer behavior online. Section 3 sets out the data and methodology. Section 4 walks through the results. Section 5 closes with managerial implications, limitations and a few directions worth pursuing.

2. Literature review

2.1. The integration of artificial intelligence in digital advertising

AI in marketing went, over roughly a decade, from a niche capability to part of the basic infrastructure. Davenport et al. (2020) describe the shift along three axes what tasks AI takes on, what data and analytics structures support those tasks, and how customers are engaged. Huang and Rust (2021) layer onto this a different framework, distinguishing mechanical, thinking and feeling AI; algorithmic bidding lives mostly in the second of these, where structured signals are optimized against explicit targets. Google's Smart Bidding family (Target ROAS, Target CPA, Maximize Conversions, Maximize Conversion Value) fits the description neatly: real time bid setting on the basis of context.

These tools were anticipated, in some respects, well before they became routine. Olteanu (2016) wrote about Facebook Graph at a point when AI powered search was barely commercial and saw in it a way of supporting data driven decisions in marketing and customer acquisition. Olteanu (2014), a couple of years earlier, surveyed the first dedicated tools for monitoring social networks in a business setting. A decade later, what those early papers pointed at algorithmic surfacing of relevant audiences and signals is the ordinary mode of operation across every major ad platform. Vlačić et al. (2021), in a careful systematic review, identify advertising and CRM as the two domains where AI adoption has gone furthest, while Kumar et al. (2019) put personalization at scale at the center of the story.

None of this works without a particular kind of infrastructure underneath: cloud based processing, continuous web availability, reliable data pipelines. Olteanu (2013a) discussed migrating applications to the cloud and the open questions it raised reliability, portability, vendor lock in. Olteanu (2010), earlier still, focused on prevention, backup and restoration procedures for web servers, which sounds almost quaint now but was a concrete obstacle at the time. Advertisers today take all this for granted; it remains, even so, the operational backbone of every AI driven campaign.

2.2. Consumer behavior in online environments

Any account of why an AI driven campaign performs the way it does has to begin with the behavior it is trying to shape. Olteanu (2013b) argued early, in our view that online consumer behavior can be influenced through a wide set of digital techniques, and most of what is now called personalization, retargeting or algorithmic content delivery is a continuation of that line of thinking. The intervening decade made digital environments the dominant locus of pre purchase information search, particularly for product categories where buyers want to read before they buy.

Then came COVID 19. Sheth (2020) and Hoekstra and Leeflang (2020) both document a real, structural movement of consumers toward digital channels not a temporary blip. Hoțoi (2024) makes the same point for Romania, with Google Ads data running from April 2022 to September 2024: conversion rates and the weight of paid traffic in revenue both shifted in measurable ways. Dwivedi et al. (2021), in a long collaborative agenda piece, place these developments inside a wider conversation about AI enabled marketing.

Beyond e-commerce, online search behavior has become something of a standard data source for empirical work in unrelated fields. Bazac et al. (2023) use digital marketing indicators to assess the online referential value of urban historical parks, with management implications attached; Marin et al. (2025) propose a software based assessment that examines online search behavior to study how scientific heritage sites integrate into their urban surroundings. The same logic read public search data to learn something about a population has been applied to tourism (Grecu et al., 2020) and to demographic patterns in protected areas (Drăghici et al., 2022). I borrow that logic and apply it to a strictly commercial setting.

2.3. Smart Bidding, Smart Shopping and the limits of last click attribution

Smart Shopping, launched in 2018 and gradually folded into Performance Max from 2022 onward, was the first widely used Google Ads campaign type to hand over both bidding and placement to the algorithm. It runs across Search, Shopping, Display, YouTube and Gmail; the input is essentially a product feed and a goal; the output is conversion value, optimized within a budget. Choi et al. (2020), reviewing programmatic display markets, describe the same phenomenon in broader terms bidding decisions move inside the platform, advertisers lose much of their operational role. Chaffey and Ellis Chadwick (2022), in their textbook treatment, document how these tools have been absorbed into everyday agency practice.

Attribution choices then decide what these campaigns appear to be worth. Berman (2018) shows, in a formal model of online advertising attribution, that last click systematically over rewards channels at the bottom of the funnel branded search, direct and under rewards everything further upstream. Kannan, Reinartz and Verhoef (2016), reviewing the multichannel attribution literature, come to a similar conclusion: change the attribution model and the same conversion data tells you a different story about which channels are working. Anderl et al. (2016) put forward a graph based methodology for mapping customer journeys across channels and warn, in plain terms, that reading last click conversions as a measure of channel value is a mistake.

For AI driven Smart Shopping the problem is sharper than for most other campaign types. These campaigns are designed to find new audiences across the funnel, so much of their contribution arrives as an assist rather than as the closing click. Google Analytics surfaces this through its assisted conversion reports, which separate last click (or direct) conversions from assisting touchpoints within a configurable window. Hoțoi (2024), looking at a different Romanian e commerce account, makes the same observation: the default reports that most advertisers consult routinely undersell what AI driven campaigns deliver up the funnel.

3. Research methodology

The work is quantitative and exploratory. The source is the Google Analytics account of a Romanian online wine retailer a small business selling, exclusively online, both Romanian and imported wines.

Three reports formed the data backbone: an All Traffic report (aggregate acquisition, behavior and ecommerce metrics across all sources); a Google Ads Campaigns report (the same metrics broken out by individual campaign); and an Assisted Conversions report (last click and assisted conversions per Google Ads campaign on a 30 day lookback). I anonymize the observation period as an 84 day window during the post pandemic recovery; specific dates have been withheld to protect the retailer.

Four indicators carry the comparison. CTR is clicks divided by impressions. CPC is the average cost per click. Ecommerce conversion rate (CR) is transactions divided by sessions. ROAS is campaign revenue divided by campaign cost. The four together cover demand generation, cost efficiency and revenue. For the assisted conversion analysis I use the assisted to last click ratio as a quick way of reading each campaign's upper funnel weight.

Campaigns were sorted into three categories based on how much of their operation is automated: AI driven Smart Shopping, where bidding and placement are both handed to Google; manually managed Search and Shopping campaigns, where the advertiser keeps control; and brand protection and display campaigns, kept in the dataset for completeness. The approach is descriptive and comparative, on the model of the secondary data work done by Hoțoi (2024) in a similar Romanian setting.

4. Results and discussion

4.1. Campaign level performance

Over the 84 day window, the Google Ads account delivered 18,767 clicks at a total cost of RON 7,460.17 an average CPC of RON 0.40. Paid Google traffic accounted for 58.90% of website users and 56.86% of sessions; it produced 194 transactions (44.19% of the site total) and revenue of RON 82,875 (36.28% of total revenue). On paid Google traffic the ecommerce conversion rate landed at 0.99%, against 1.28% for the site as a whole.

Once broken down by campaign, the picture turns heterogeneous fast. The AI driven Smart Shopping campaign brought in 11,176 clicks 59.55% of all paid clicks at a CPC of RON 0.31, the second lowest in the account. It produced 77 transactions and RON 25,940 in revenue, which works out to a last click ROAS of about 7.5 and a conversion rate of 0.69%. The manually managed Search campaign focused on the retailer's core category ("PT - Magazin de vinuri") generated 5,538 clicks under half the Smart Shopping volume at a higher CPC of RON 0.54; but it converted at 1.18% and returned RON 32,160 on 69 transactions, for a ROAS of 10.8.

Two further manually managed campaigns a standard Shopping campaign and a brand protection Search campaign recorded much higher ROAS values (50.9 and 48.2 respectively) and higher conversion rates (1.50% and 2.98%). The volumes, though, were small: 767 and 673 clicks. These figures match what you would expect from campaigns that catch users already close to buying: direct brand searches and product name searches. A display awareness campaign at the upper end of the funnel pushed 397 clicks at a CPC of RON 1.26 and produced no last click conversions at all another example, if any were needed, of where last click measurement quietly breaks down.

4.2. Assisted conversions and the underestimation of AI driven campaigns

Looking at the 30 day assisted conversions window changes the picture. Across all Google Ads campaigns, the account recorded 103 assisted conversions worth RON 43,221, against 149 last click (or direct) conversions worth RON 61,234. The aggregate assisted to last click ratio was 0.69 well above the site wide 0.53 reported by Google Analytics and assisted interactions accounted for 47.59% of all conversion paths attributable to Google Ads.

Pulling the assisted conversions apart by campaign clarifies what is happening. Smart Shopping logged 36 assisted conversions (value RON 13,282) against 66 last click conversions (value RON 22,935). Its assisted to last click ratio of 0.55 says, in effect, that for every two purchases credited to it at last click, it contributed to one further purchase as an assist. The brand protection campaign moved in the opposite direction: 27 assisted against 17 last click, a ratio of 1.59. The reading is intuitive once spelled out branded search is capturing, at the final click, demand that other touchpoints generated earlier. Smart Shopping is one plausible source.

This lines up with the predictions of Berman (2018), Kannan et al. (2016) and Anderl et al. (2016): last click rewards lower funnel campaigns and penalizes the ones that fed them. A 47.6% share of assisted conversions, observed in a single SME account, is the same order of magnitude as what Hoțoi (2024) reports for another Romanian e commerce setting. The implication, I think, is hard to escape: for small online retailers, a non trivial chunk of the value generated by Google Ads is invisible in the default report.

4.3. Practical implications for budget allocation

Three implications follow, all practical. First, judging AI driven Smart Shopping campaigns on last click ROAS alone is a way of systematically underestimating them. A naive rule shift money from the lowest last click ROAS campaign to the highest would, in this account, defund Smart Shopping. The same Smart Shopping that brings in most of the clicks and a substantial volume of assists.

Second, the high last click ROAS of the brand protection campaign should not be read as the marginal return on an extra euro spent there. Brand demand is itself manufactured upstream, mostly by other campaigns. Cutting upstream spend to feed the brand protection campaign would, in time, leave the brand protection campaign with less brand demand to catch.

Third and this is where the analysis is really about strategy rather than measurement the choice of attribution model is itself a budget decision. Davenport et al. (2020) and Huang and Rust (2021), both writing more broadly about AI in marketing, make the same point in slightly different words: bringing AI in means revising the metrics, not just installing the tools.

5. Conclusions

I have analyzed the comparative performance of AI driven Smart Shopping and manually managed Search campaigns in Google Ads, using data from a Romanian online wine retailer over an 84 day post pandemic window. Four findings stand out.

AI driven Smart Shopping campaigns generate substantially more clicks than manually managed campaigns, at a lower CPC, but record lower last click conversion rates consistent with their prospecting role. Manually managed campaigns aimed at high intent queries convert at higher rates and post higher ROAS, but on a much smaller volume of clicks. Around 47.6% of Google Ads conversions in this account were assisted rather than last click, which tells us that the default reporting underplays AI driven prospecting campaigns. And finally, the brand protection campaign's high assisted to last click ratio suggests that part of the demand it captures at the last click was produced, plausibly, by Smart Shopping further upstream.

For practice, the takeaway is that last click ROAS should not be the sole metric for evaluating mixed Google Ads accounts; attribution models that credit upper funnel work are the saner basis for budget decisions. For research, our findings extend to a Romanian SME setting the broader patterns described in the AI in marketing literature (Davenport et al., 2020; Huang and Rust, 2021; Vlačić et al., 2021) and in the multichannel attribution literature (Berman, 2018; Kannan et al., 2016; Anderl et al., 2016), in continuation of the kind of analysis Hoțoi (2024) did for a different e commerce account.

The study has its limits. It rests on a single account in one product category wine retail which restricts how far the quantitative findings can be generalized. The 84 day window is short; it does not let us see seasonality or the long run learning curve of AI driven campaigns. The analysis is descriptive and comparative, not causal: i documented the associations, i do not establish that Smart Shopping caused the assists observed downstream. Future work could lengthen the window, pool multiple accounts across categories, and bring quasi experimental designs (geo experiments, incrementality tests) to the question of causal contribution. The migration from Smart Shopping to Performance Max which hands even more decision making to the algorithm and gives the advertiser even less visibility is the obvious next case to study.

REFERENCES

1. Anderl, E., Becker, I., von Wangenheim, F. and Schumann, J. H. (2016) 'Mapping the customer journey: Lessons learned from graph based online attribution modeling', International Journal of Research in Marketing, 33(3), pp. 457-474. https://doi.org/10.1016/j.ijresmar.2016.03.001.
2. Bazac, T., Marin, S., Olteanu, C. and Hoțoi, A. (2023) 'Sustainable management decisions for urban historical parks: A case study based on online referential values of Carol I Park in Bucharest, Romania', Sustainability, 15(19), 14456. https://doi.org/10.3390/su151914456.
3. Berman, R. (2018) 'Beyond the last touch: Attribution in online advertising', Marketing Science, 37(5), pp. 771-792. https://doi.org/10.1287/mksc.2018.1104.
4. Chaffey, D. and Ellis Chadwick, F. (2022) Digital Marketing: Strategy, Implementation and Practice, 8th edition. Harlow: Pearson Education.
5. Choi, H., Mela, C. F., Balseiro, S. R. and Leary, A. (2020) 'Online display advertising markets: A literature review and future directions', Information Systems Research, 31(2), pp. 556-575. https://doi.org/10.1287/isre.2019.0902.
6. Davenport, T., Guha, A., Grewal, D. and Bressgott, T. (2020) 'How artificial intelligence will change the future of marketing', Journal of the Academy of Marketing Science, 48(1), pp. 24-42. https://doi.org/10.1007/s11747 019 00696 0.
7. Drăghici, C. C., Grecu, A., Olteanu, C., Paru, A., Gruia, A. K. and Dascălu, V. G. (2022) 'Specificity of the demographic dynamics in the Danube Delta', in The Danube River Delta, pp. 175-202.
8. Dwivedi, Y. K., Ismagilova, E., Hughes, D. L., Carlson, J., Filieri, R., Jacobson, J., Jain, V., Karjaluoto, H., Kefi, H., Krishen, A. S., Kumar, V., Rahman, M. M., Raman, R., Rauschnabel, P. A., Rowley, J., Salo, J., Tran, G. A. and Wang, Y. (2021) 'Setting the future of digital and social media marketing research: Perspectives and research propositions', International Journal of Information Management, 59, 102168.

https://doi.org/10.1016/j.ijinfomgt.2020.102168.

9. Grecu, A., Gruia, K. A., Ducman, A., Rădoi, I. and Olteanu, C. (2020) 'Mega events and structural tourism capabilities development - Cluj Napoca, Sibiu, Constanța Năvodari, as case studies', Public Recreation and Landscape Protection, 1(1), pp. 291-295.
10. Hoekstra, J. C. and Leeflang, P. S. H. (2020) 'Marketing in the era of COVID 19', Italian Journal of Marketing, 2020(4), pp. 249-260. https://doi.org/10.1007/s43039 020 00016 3.
11. Hoțoi, A. L. (2024) 'Exploring the impact of digital technologies on consumer behavior in the post pandemic era', Annals of "Dunărea de Jos" University of Galați, Fascicle I. Economics and Applied Informatics, 30(3), pp. 408-417. https://doi.org/10.35219/eai15840409469.
12. Huang, M. H. and Rust, R. T. (2021) 'A strategic framework for artificial intelligence in marketing', Journal of the Academy of Marketing Science, 49(1), pp. 30-50. https://doi.org/10.1007/s11747 020 00749 9.
13. Kannan, P. K., Reinartz, W. and Verhoef, P. C. (2016) 'The path to purchase and attribution modeling: Introduction to special section', International Journal of Research in Marketing, 33(3), pp. 449-456. https://doi.org/10.1016/j.ijresmar.2016.07.001.
14. Kumar, V., Rajan, B., Venkatesan, R. and Lecinski, J. (2019) 'Understanding the role of artificial intelligence in personalized engagement marketing', California Management Review, 61(4), pp. 135-155. https://doi.org/10.1177/0008125619859317.
15. Marin, S., Peptenatu, D., Bazac, T., Hoțoi, A. and Olteanu, C. (2025) 'Applying a software based assessment framework for integrating the patrimony of the Astronomical Institute of the Romanian Academy within its urban environment', Romanian Astronomical Journal, 35(1-2), pp. 59-79. https://doi.org/10.59277/RoAJ.2025.1 2.04.
16. Olteanu, C. C. (2010) 'Prevent, backup and restore procedures for a web server', LESIJ - Lex ET Scientia International Journal, 17(1), pp. 483-489.
17. Olteanu, C. C. (2013a) 'Porting your applications and saving data in cloud as reliable entity', Manager Journal, 18(1), pp. 140-145.
18. Olteanu, C. C. (2013b) 'Influencing average internet consumer's online behavior. Fact. Fiction. Right. Wrong.', Manager Journal, 17(1), pp. 302-306.
19. Olteanu, C. C. (2014) 'New tools to monitor social networks in business sector', Manager Journal, 19(1), pp. 151-157.
20. Olteanu, C. C. (2016) 'New ways to improve business management. Facebook Graph, a search tool that uses artificial intelligence', Manager Journal, 24(1), pp. 199-203.
21. Sheth, J. (2020) 'Impact of Covid 19 on consumer behavior: Will the old habits return or die?', Journal of Business Research, 117, pp. 280-283. https://doi.org/10.1016/j.jbusres.2020.05.059.
22. Vlačić, B., Corbo, L., Costa e Silva, S. and Dabić, M. (2021) 'The evolving role of artificial intelligence in marketing: A review and research agenda', Journal of Business Research, 128, pp. 187-203. https://doi.org/10.1016/j.jbusres.2021.01.055.