Algorithmic Audience Targeting in Meta Ads Remarketing Campaigns: A Demographic Analysis of AI-Driven Delivery in a Romanian Aesthetic Medicine Clinic

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Abstract: *Within the Meta advertising ecosystem (Facebook and Instagram), audience targeting decisions are increasingly delegated to machine-learning systems that determine, in real time, which users see an ad and at what frequency. This paper analyzes the demographic distribution of algorithmically delivered impressions in a remarketing campaign run by a Romanian private aesthetic medicine clinic, a real client from my digital marketing agency (Performance Target) over a 122-day observation window. Using ad-set-level data exported from Meta Ads Manager, with breakdowns by age and gender, the study examines how a single remarketing campaign – nominally addressed to the entire pool of website and profile visitors – is in practice distributed across demographic segments by the platform's delivery algorithm. Results show a very strong gender skew (94.9% of the budget delivered to women) and a clear age concentration: women aged 35 to 54 receive 58.3% of total spend, and women aged 35 to 64 receive 76.5%. The cost per thousand impressions (CPM) ranges between 13.18 and 17.70 RON depending on segment, while the campaign maintains a low average frequency of 1.10 to 1.14 over the entire window, indicating that the algorithm continuously identifies new audience members rather than over-exposing the same users. The findings illustrate, in a healthcare service setting, the dynamics of algorithmic ad delivery documented in the broader literature on AI-driven advertising, with implications for managerial control over targeting, for advertiser accountability and for the design of marketing strategies in regulated service sectors.*

Keywords*:* Meta Ads, algorithmic targeting, artificial intelligence, social media advertising, remarketing, demographic analysis, healthcare marketing.

JEL: M31, M37, I11, O33.

1. Introduction

The Meta advertising ecosystem – encompassing Facebook, Instagram and Messenger – has become one of the most consequential venues for digital advertising in Europe, both because of the scale of its audience and because of the depth of algorithmic decision-making that governs its delivery. Within a Meta Ads campaign, the advertiser specifies a high-level objective (awareness, traffic, engagement, leads, sales) and a broad audience definition, after which the platform's machine-learning systems decide, in real time, which users see the ad, in which placement, at what bid and at what frequency. As Davenport et al. (2020) and Huang and Rust (2021) note, this delegation of decision-making to AI systems is the dominant trend in contemporary marketing and is most visible in social media advertising, where the platform's data advantage is largest.

For small and medium businesses, this paradigm offers obvious benefits in terms of operational simplicity, but it also raises questions about the actual demographic distribution of the audience reached and about the alignment between the advertiser's stated intent and the algorithm's realized delivery. Olteanu (2016) anticipated this discussion when he analyzed Facebook Graph as one of the first widely available AI-powered search and targeting tools, while Appel et al. (2020) and Dwivedi et al. (2021) more recently position social media advertising at the center of the AI-driven marketing research agenda.

The post-pandemic period has further intensified the relevance of these questions. As Hoțoi (2024) shows in an analysis of digital campaigns from a Romanian online retailer, the COVID-19 pandemic reshaped consumer behavior, expanded the share of digital channels in purchasing decisions and increased the role of paid social media in business communication. In service sectors that combine high information asymmetry with a strong reliance on personal recommendation – such as private healthcare and aesthetic medicine – social media advertising has become a primary acquisition channel, but the patterns of algorithmic delivery in these sectors remain underdocumented in the academic literature.

The present study addresses this gap through a case study of a Romanian private aesthetic medicine clinic (henceforth referred to as "the clinic"), focusing on a remarketing campaign run on Meta Ads over a 122-day observation window. The research aims are: (i) to document the demographic distribution – by age and gender – of impressions delivered by the Meta Ads algorithm within a single remarketing campaign; (ii) to compare the cost per thousand impressions (CPM) across demographic segments; (iii) to assess the evolution of delivery efficiency over the observation period; and (iv) to discuss the managerial and methodological implications of algorithmic ad delivery in regulated service sectors.

The research is exploratory and empirical, based on secondary data exported from Meta Ads Manager and analyzed descriptively. The remainder of the paper is structured as follows: Section 2 reviews the literature on AI in social media advertising, on algorithmic ad delivery and on audience 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 in social media advertising

The integration of artificial intelligence into social media advertising is one of the most advanced manifestations of the broader AI-in-marketing trend documented by Davenport et al. (2020), who argue that AI is reshaping marketing strategy across the dimensions of tasks performed, supporting structures and customer engagement. Huang and Rust (2021) propose a strategic framework in which AI operates on mechanical, thinking and feeling levels, and locate algorithmic ad delivery 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 two most mature application areas, while Kumar et al. (2019) emphasize personalization at scale as the most consequential outcome of AI adoption.

The dynamics of these systems were anticipated, in the social media context, well before AI-driven ad delivery became the industry default. Olteanu (2016) analyzed Facebook Graph as one of the first widely available AI-powered search tools for business use, highlighting its potential for data-informed customer acquisition. Olteanu (2014) had previously examined the emergence of dedicated tools for monitoring social networks in business sectors, anticipating the audience-analytics infrastructure that is now embedded in major advertising platforms. These tools, in turn, rely on the cloud-based data infrastructure and continuous service availability discussed by Olteanu (2013a, 2010) – preconditions that are now largely taken for granted but remain operationally critical.

More recent reviews of social media marketing position AI-driven delivery and personalization at the center of the research agenda. Appel et al. (2020) identify the algorithmic mediation of audience targeting as one of the defining features of the contemporary social media environment, while Dwivedi et al. (2021), in a multi-author research agenda, call for empirical work that documents the actual patterns of algorithmic ad delivery across different markets and sectors. The present study contributes to this agenda by providing such empirical evidence from a Romanian healthcare service setting.

2.2. Algorithmic ad delivery and demographic targeting

A growing body of literature documents that, even when advertisers specify a broad and demographically inclusive target audience, platform algorithms in practice deliver impressions to demographically skewed subsets of that audience. Ali et al. (2019), in an empirical analysis of Facebook ad delivery, show that the platform's optimization systems can produce significant skews in the demographic distribution of impressions, even for ads with identical bid configurations, content and nominal audience definitions. Lambrecht and Tucker (2019), in a complementary study of advertising for STEM careers, document similar patterns and discuss the implications for advertiser intent and accountability. These findings raise the question – relevant to the present study – of how much of the demographic distribution observed in a campaign reflects the advertiser's decision and how much reflects the platform's optimization.

From a consumer-behavior perspective, the influence of algorithmically delivered content on online decision-making has been a long-standing topic of inquiry. 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. Lee, Hosanagar and Nair (2018) document, in a large-scale study of social media advertising content, that engagement patterns vary systematically across content types and audience segments, while Voorveld et al. (2018) compare engagement across social media platforms and confirm the role of platform-specific algorithms in shaping consumer responses.

2.3. Audience analytics in applied empirical research

Beyond the immediate context of paid advertising, the use of digital data sources for audience and behavioral analytics has become a methodological staple in a wide range of applied empirical studies. 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 the field of tourism, Grecu et al. (2020) document the role of mega-events in the development of structural tourism capabilities, in studies that mobilize audience and visitor data to support strategic decisions. Drăghici et al. (2022), studying demographic dynamics in the Danube Delta, illustrate the broader importance of disaggregated demographic data for understanding the behavior of specific populations – a methodological orientation that translates naturally to the analysis of demographically segmented ad delivery.

Within the Romanian e-commerce context, Hoțoi (2024) shows how Google Ads campaign data can be analyzed quantitatively to understand the impact of digital technologies on consumer behavior in the post-pandemic period, with implications that extend beyond e-commerce to other digitally mediated service sectors. The present study draws on this general methodological orientation, applying it to a Meta Ads campaign in the aesthetic medicine sector.

3. Research methodology

The research is quantitative, exploratory and descriptive, based on secondary data exported from the Meta Ads Manager account of a Romanian private aesthetic medicine clinic. The clinic is a small and medium business operating in a major Romanian city and running, during the observation period, a single active Meta Ads campaign of the remarketing type, addressed to users who had previously interacted with the clinic's Facebook page, Instagram profile or website.

The data source is an ad-set-level report exported from Meta Ads Manager for an observation window of 122 calendar days, with breakdowns by day, age group and gender, and the metrics: reach, impressions, frequency, amount spent and attribution setting. To preserve the anonymity of the clinic, the observation window is reported only as a 122-day period; specific dates are not disclosed. The campaign ran with a 1-day click attribution setting and a daily ad-set budget.

Three categories of indicators were used in the analysis: (i) volume indicators – impressions, reach (cumulated across daily reports rather than as unique reach) and amount spent; (ii) efficiency indicators – cost per thousand impressions (CPM), computed as amount spent divided by impressions and multiplied by 1,000, and frequency, computed as impressions divided by reach; and (iii) distribution indicators – the share of total spend and total impressions attributable to each demographic segment, expressed as a percentage. The analysis was performed at three levels of aggregation: the entire campaign, individual demographic segments (age × gender), and monthly evolution.

The methodological approach is descriptive and comparative, in line with the secondary-data design used by Hoțoi (2024) in a comparable Romanian setting and with the software-based assessment logic discussed by Marin et al. (2025) in a different applied domain. The analysis does not attempt to establish causal effects of demographic targeting on conversion outcomes, since conversion data was not available for the observation window; the focus is strictly on the demographic distribution of algorithmically delivered impressions.

4. Results and discussion

4.1. Overall campaign performance

Over the 122-day observation window, the remarketing campaign delivered 173,217 impressions and reached a cumulated audience of 154,612 users (counted across daily reports), at a total cost of 2,578.72 RON. The campaign was active on 81 out of 122 calendar days, with an average daily spend of approximately 31.84 RON on active days. The overall cost per thousand impressions was 14.89 RON, while the average frequency stood at 1.12, indicating that the typical user exposed to the campaign saw it slightly more than once during the observation window.

The low frequency value is methodologically informative: in a remarketing context, where the eligible audience is by definition finite (only users who previously interacted with the clinic's digital properties), a frequency close to 1.0 over four months indicates that the algorithm continuously identifies new audience members rather than over-exposing the same individuals. This is consistent with the design of Meta's delivery system, which is documented in the literature as optimizing for incremental reach within the available eligible audience (Appel et al., 2020; Dwivedi et al., 2021).

4.2. Gender distribution of algorithmic delivery

The most striking feature of the demographic distribution is the gender skew. Out of 2,578.72 RON in total spend, 2,448.21 RON (94.94%) were delivered to users classified as female, 116.90 RON (4.53%) to users classified as male and 13.61 RON (0.53%) to users with unspecified gender. The corresponding impression shares are 163,576 (94.4%), 8,872 (5.1%) and 769 (0.5%) respectively. The CPM is broadly similar across genders – 14.97 RON for women, 13.18 RON for men and 17.70 RON for unspecified – which indicates that the gender skew in spend reflects the algorithm's decision to deliver more impressions to women, rather than a difference in per-impression cost across genders.

This pattern is consistent with the findings of Ali et al. (2019) and Lambrecht and Tucker (2019), who document that platform algorithms can produce strong gender skews in delivery even for nominally inclusive audiences. In the present case, the skew is plausibly compatible with the substantive content of the campaign – aesthetic medicine services are traditionally marketed predominantly to women – but the magnitude of the skew (more than 20:1 in spend) and the fact that it emerges from algorithmic optimization rather than from an explicit advertiser exclusion is worth documenting. As Olteanu (2013b) noted in a more general discussion of online consumer behavior, the techniques through which digital environments shape behavior often operate beneath the level of explicit advertiser intent.

4.3. Age distribution and segment concentration

The age distribution displays a clear central tendency around the 35–54 bracket. The 45–54 segment receives the largest share of spend (34.16%, 880.90 RON) and impressions (33.02%, 57,189 impressions), followed by the 35–44 segment (26.58% spend, 25.88% impressions). The two adjacent segments – 25–34 and 55–64 – together account for an additional 30.80% of spend, while the youngest (18–24) and oldest (65+) segments together account for less than 9% of total spend. The CPM is also higher in the 35–44 and 45–54 segments (15.29 and 15.40 RON respectively) than in the 18–24 and 65+ segments (13.26 and 13.62 RON), suggesting that competition for impressions is more intense in the middle-age brackets that the algorithm has identified as the campaign's primary audience.

When the analysis is performed at the age × gender level, the concentration becomes even more visible. The single most served segment – women aged 45–54 – receives 32.62% of total spend (841.25 RON), followed by women aged 35–44 (25.64%, 661.09 RON) and women aged 55–64 (18.22%, 469.94 RON). Cumulatively, women aged 35 to 54 absorb 58.3% of the total budget, and women aged 35 to 64 absorb 76.5%. The dominance of these segments is consistent with the demographic profile of aesthetic medicine consumers documented in the healthcare marketing literature, but it is the algorithm – not an explicit advertiser configuration – that produces this concentration within a nominally inclusive remarketing audience.

These findings echo, in a different applied domain, the methodological orientation of studies that mobilize disaggregated demographic data to understand the behavior of specific populations (Drăghici et al., 2022) and the framework of online audience analytics developed by Bazac et al. (2023) and Marin et al. (2025) in other contexts. They confirm that algorithmically delivered ad impressions, even within a single nominally homogeneous campaign, follow patterns that closely mirror the underlying demographics of the served service category.

4.4. Temporal evolution and learning effects

The monthly distribution of spend shows a marked upward trend over the observation period. Spend increased from 453.15 RON in the first observed month (delivered on 14 active days) and 300.86 RON in the second month (8 active days) to 828.37 RON in the third month (29 active days) and 910.62 RON in the fourth month (28 active days). Part of this increase reflects the higher number of active days, but the daily spend rate also increased, from approximately 32 RON per active day in the first months to over 32 RON per active day in the third and fourth months.

More informative is the trajectory of CPM, which rose from 14.29 RON in the first month to 16.58 RON in the third month, before falling to 14.04 RON in the fourth month. This pattern is consistent with the expected learning curve of an algorithmic delivery system: initial efficiency is high while the algorithm exploits the most accessible audience, efficiency degrades as the available audience is consumed and competition intensifies, and efficiency partially recovers as the algorithm refines its identification of valuable users. The recovery of CPM in the fourth month, combined with the stable frequency of 1.12, suggests that the algorithm continued to find new addressable users throughout the observation window. The methodological implications of such learning curves for the evaluation of AI-driven campaigns are consistent with the broader framework proposed by Huang and Rust (2021) and Davenport et al. (2020).

5. Conclusions

This paper has analyzed the demographic distribution of algorithmically delivered impressions in a Meta Ads remarketing campaign run by a Romanian private aesthetic medicine clinic over a 122-day observation window. Four findings emerge from the analysis. First, even within a nominally inclusive remarketing audience, the platform's delivery algorithm produces a very strong demographic concentration: 94.9% of the budget is delivered to women, and 58.3% of the budget is delivered to women aged 35 to 54. Second, the cost per thousand impressions varies modestly across demographic segments, with the highest values in the age brackets that the algorithm identifies as the campaign's primary audience, indicating intensified competition for those impressions. Third, the campaign maintains a low average frequency of 1.12 over the entire window, suggesting that the algorithm continuously identifies new audience members rather than over-exposing the same users. Fourth, the monthly evolution of CPM is consistent with the expected learning curve of an algorithmic delivery system, with an initial efficiency phase, an intermediate competition phase and a partial efficiency recovery.

These findings have implications for both research and practice. For practice, they document the magnitude of demographic concentration that can emerge from algorithmic delivery within a nominally inclusive audience, and they argue for closer advertiser attention to the realized demographic distribution of campaigns – not merely to the configured one. For research, they confirm in a Romanian healthcare service setting the broader patterns identified in the literature on algorithmic ad delivery (Ali et al., 2019; Lambrecht and Tucker, 2019) and on AI in marketing (Davenport et al., 2020; Huang and Rust, 2021; Vlačić et al., 2021), and they extend to this sector the type of digital-data analysis advanced by Hoțoi (2024), Bazac et al. (2023) and Marin et al. (2025) in adjacent applied domains.

The study has several limitations. First, it is based on a single campaign in a single clinic, which limits the generalizability of the quantitative findings; future work should compare delivery patterns across multiple clinics, multiple service sectors and multiple campaign objectives. Second, the observation window of 122 days is relatively short and does not allow for the observation of annual seasonality or of structural shifts in the delivery algorithm. Third, conversion data were not available, which means that the analysis documents the demographic distribution of impressions but does not establish whether the served segments are also the most valuable in terms of business outcomes. Future research could address this limitation by combining ad-set-level Meta Ads data with conversion data from CRM systems, by using lift-based incrementality measurement, or by comparing demographic distributions across different campaign objectives (awareness, engagement, leads, conversions) within the same advertiser account. The continuing evolution of Meta's delivery algorithms – including the gradual generalization of Advantage+ campaign types that internalize an even larger share of targeting decisions – provides a natural next step for this line of research.

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