Digital Solutions and Machine Learning Can Improve Niche Market Reach

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SUMMARY

Digital solutions in marketing can help reach niche markets. Marketers have the greatest opportunity ever to address segments whose needs have not yet been met. Online segmentation techniques allow to better know their characteristics. The aim of this article is to investigate the segmentation and targeting possibilities of the Google Ads system, which helps to explore consumer patterns more deeply. Digital marketing solutions help marketers reach niche markets to maximise the effectiveness of their activities. The goal of this social constructivist research was to find an answer to the question of whether the segmentation and targeting options of the Google Ads advertising system can sufficiently ensure this. To this end, we examined the presence of the "target market category" label in 37 individuals using a face-to-face survey method. The occurrence of the labels and the actual interests often overlapped.

Keywords: Segmentation; digital marketing; machine learning; targeting; Google Ads
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INTRODUCTION

The emergence of Marketing 5.0 with modernization processes has had a significant impact on companies (Kotler et al., 2021), which has led to changes in consumer habits in addition to new technological achievements. This is confirmed by research conducted by GKID (2022), which shows that in 2021 the number of online orders in Hungary reached 68.9 million, which had a value of 1,2 trillion Hungarian forint (HUF). Contrary to expectations, the high number of orders and consumers has further increased market intensity and competition. Today, more than 15,000 online stores are fighting for the attention of consumers (Molnár, 2021), which they try to reach with a variety of marketing tools. Different channels and strategies can be found in digital form. By categorising outbound and inbound techniques, Bleoju et al. (2016) published a comparison table about which they mention that "digital marketing practitioners believe that the distinction between inbound and outbound is actually an artificial and meaningless one. They advocate the idea that no form of marketing fits into either of these artificial concepts and propose an overlap position between inbound and outbound, which they refer to as the grey area" (Bleoju et al., 2016, p. 5525). This idea is valid in the digital context, but inbound marketing techniques offer significant advantages over traditional outbound marketing techniques (Soco Sales Training, 2021), including more accurate measurement and stronger customer engagement, which is an important factor in lead generation (Halligan, 2021). Lead generation is also a high priority in customer acquisition, both marketing- and sales-related (Ehrlich, 2019; Decker, 2021; Sutton, 2021; Keenan, 2022). The importance of efficiency is also underscored by trends in customer acquisition costs: the cost per customer has increased by almost 60% in five years. In contrast, the results of a study of more than 700 companies operating in a subscription model showed that customer acquisition costs have increased by only 30% for those focusing on niche markets (Desai, 2019).

In this paper, we try to answer the following questions:

- How is it possible to target the right consumers in the Google Ads system?
- Which types of machine learning can help companies reach the target audience, and how?

To do so, we use an unconventional qualitative research methodology based on a review of the literature on segmentation and machine learning. This includes Google Ads, which uses tags identified by algorithms based on predefined product areas and segmentation criteria instead of and in addition to surveys.

LITERATURE REVIEW

The Digital Marketing Institute (2018) notes that machine learning and marketing go hand in hand these days. Doing one without the other is a mistake no company can afford to make if it wants to remain competitive". According to ECLAC (2016), the strategic pillar of production lies in data and digitised knowledge. Consumer databases and information gathered through automated marketing contribute significantly to the development of the digital economy. Customers' habits can be understood in greater detail as smart devices record users' every move. By analysing this data, it is possible to study the consumer's decision-making process, and based on this information, individual online stores can optimise their offers for everyone. In the field of online marketing, the importance of STP (segmentation, targeting and positioning) has increased. Kotler and Keller (2016, p. 267) state that "identifying and uniquely satisfying the right market segments are often the key to marketing success". In accordance with their theory "effective target marketing requires that marketers:

1. identify and profile distinct groups of buyers who differ in their needs and wants (market segmentation),
2. select one or more market segments to enter (market targeting),
3. for each target segment, establish, communicate, and deliver the right benefit(s) for the company's market offering (market positioning)" (Kotler & Keller, 2016, p. 267).

Customer segmentation is the process of grouping customers based on commonalities (Wang, 2022). The most popular segmentation criteria are geographic, sociodemographic, psychographic and behavioural (Haley, 1984).

It is interesting to note that in the digital marketplace, where we essentially have no personal presence of sellers, we can buy more personalised products and services than in traditional shop sales. An appropriate segmentation technique brings several benefits, such as identifying relevant trends, increasing the effectiveness of marketing activities, making the right decisions about promotions, better understanding the customer experience, and providing relevant products and services (Turkmen, 2022). Segmentation can be used to identify market needs that are not currently being met, and we believe the role of niche marketing has become more important. "For Internet-based companies, and especially those using Big Data tools, these technologies facilitate the development of specific products and services for specific market segments" (ECLAC, 2022, p. 38).

Although Haley (1984) defined the general expectations and targeting options associated with segmentation nearly 40 years ago, the most popular digital marketing ad managers adopted these options at different times and in different ways. Among these most popular ad managers, Google Ads (originally Google Adwords) was the first to use keywords as a setting option for optimal ad placement (Atkinson, 2014). The length of the search term affects consumer behaviour, so the keywords are also suitable for segmentation. In addition, the length of the search term also plays an important role for the company, as the search volume, competition, cost, and conversion rate depend on it (Barysevich, 2021). Earlier, one of the most effective ways to learn about consumers was through keyword research, which engaged both researchers and practitioners in the 2010s. Books such as Ron Jones' *Keyword Intelligence: Keyword Research for Search, Social, and Beyond* (2011) were written at this time. Today, its importance has faded into the background; it is mainly used in search engine optimization. The reason is that the Google Ads advertising platform has reached advertisers' target audiences in nine different ways, from demographic data to remarketing options, between 2000 and 2017. In this research, we will also explore these targeting options, for which we will first explore the knowledge of machine learning techniques and their application in segmentation.

As we mentioned, artificial intelligence (AI) and machine learning techniques help us in many areas, not the least of which is business management. Microsoft Research (2022) identified three themes in its research. Theory, Algorithm, Application in the field of machine learning. AI for science includes the categories of physics, biology, and sustainability; AI for industry contains supply chain applications.

Leonel's (2018) step-by-step infographic helps to understand how machine learning works. Supervised machine learning (SML) starts from categorized, pre-labelled inputs that must be augmented until it is able to separate the data without error, typically using statistical classification or regression calculations. The application areas of SML go beyond our expectations to help replace human activities (Kühl et al., 2022), image recognition (He et al., 2015) and speech recognition (Hinton et al., 2012). Kühl et al. (2022) carried out a study between real humans and SML to find which learns patterns faster. The laboratory study with 44 humans was followed by a study with three different SML algorithms. Their published results showed that the algorithms outperformed human recognition 50% of the time, albeit with slower performance. In their publication, Abdallah et al. (2022) justify the appreciation of machine learning techniques because they can effectively evaluate and identify anomalies that occur between "normal" activities, thus actively contributing to cyber-attack detection. Although in Leonel's (2018) presentation, cyberattack detection falls under the category of unsupervised machine learning, Abdallah et al. (2022) explain why this is also true for supervised techniques and explain the steps involved, including data collection capabilities. Supervised machine learning algorithms can also be structured in several ways. In the first case, the so-called IDS (intrusion detection system) identifies user actions based on whether they are considered different from usual. However, this requires the prior definition of huge data sets, which is not possible with conventional methods (Belavagi & Muniyal, 2016).

In unsupervised learning, on the other hand, uncategorized, unlabelled inputs are provided, and the algorithm determines the variables based on a criterion that serves as the basis for separation. In this case, clustering and anomaly detection models predominate (Leonel, 2018). Many studies have been conducted on both trends in the academic field, but their practical application also has a great importance. According to Peng et al. (2022), anomaly detection has become an important but difficult target of unsupervised methods due to unbalanced classes and expensive labelling methods. They proposed an extreme machine learning method with mutual estimation to track the anomalies. In their research, they used the dynamic kernel selection method to perform hierarchical clustering on unsupervised training data to generate clusters. Based on this information, we believe that it is difficult to map the essential difference between segmentation and cyberattack defence, as clustering is a fundamental necessity for both areas. Unsupervised learning is considered by Wang and Biljecki (2022) to be a key element of AI-assisted decision making. Since Unsupervised Machine Learning does not consider semantic relations, it is suitable for recognizing heterogeneous data in texts, images, sounds, or videos (Jain, 2010). According to our interpretation, the connection between Jain (2010) and Smith (1956) lies in the recognition of heterogeneity and its classification according to certain criteria. Moreover, according to El Bouchefry and de Souza (2020), UML itself determines the relevant outputs based on the properties of the data. Fidan and Erkan Yuksel (2022) used the effectiveness of different clustering methods in their study on COVID 19 and Price et al. (2022) in risk management (Song & Heo, 2022).

The ideas learned are presented in a summary in Table 1 that contains definitions, practical operation, goals, usage, and problem-solving possibilities.

Table 1

Supervised and Unsupervised Machine Learning comparison

	Supervised Learning	**Unsupervised Learning**
Definition	An activity in which the algorithm is taught to separate input data based on given criteria.	An activity in which the system itself finds the differences between input data.
Operation	Well-defined data is added to the system, and the system only maps the relationship between them. Data expansion continues until the connection is detected.	Operators leave the processing of the data provided to the system so that it can typically map relationships from a larger data set over a longer period, but also be able to make discoveries that the user had not thought of.
Goals	The “machines” produce not only statistical data, but also forecasts and statements.	The “machines” discover a new, previously unknown pattern and draw conclusions from it.
Usage	Risk analysis, revenue forecasting.	Recommendation system operation, anomaly mapping.
Problem solving possibilities	Spam filtering, image recognition, speech recognition.	Audience building, cross-buying mapping.

Source: Own editing

Among the numerous possible applications of the unsupervised machine learning technique, one of the most important from the marketing point of view is the formation of clusters, which can be interpreted as an essential element of segmentation. Both theorists (van Leeuwen & Koole, 2022) and practitioners (Das, 2020) are engaged in UML methods of data-driven segmentation. In the case of van Leeuwen, the research was conducted in the hospitality industry to create personalized advertising. Therefore, the authors emphasize the importance of research providing replicable results that can be applied by marketing departments and ultimately help generate profits. Tu et al. (2010) emphasized that segmentation is partly rule-based, which can be considered qualitative, and partly algorithm-based, which can be considered quantitative. Van Leeuwen and Koole (2022) pointed out in their research that without the right target and data input, any research is doomed to fail. Therefore, they conducted an algorithm-based segmentation of an audience based on 170,000 hotel guests to determine the lifetime value and the channel used for booking and to develop a strategy. Before running the UML algorithm, the number of clusters must be determined, which greatly affects the result. It is interesting to note that Google has outlined in its help which segmentation criteria can be used in the hospitality category and has only specified the use of its own data as the result requirement, unlike, for example, display networks where it has also listed 5 other categories (Google.com, 2022). For example, (Google.com, 2020) identified resellers in the medical market based on their income, number of patients, total number of prescriptions, and years of experience, and then stated that this is just a form of unsupervised machine learning because there are no predefined rules on how to group the data. The step-by-step article by Alzahrani (2021) helps to understand the solution of segmentation with unsupervised machine learning techniques. Consistent with van Leeuwen and Koole's (2022) statement, the first step was to describe the problem in the company, the second step was data exploration, the third step was data preparation, the fourth step was applying the model, and the fifth step was evaluating the results.

An interesting fact to read in on the website Data-flair (2019) is that "Google has declared itself a machine learning-first company." Given this, it is not surprising that Google is using the technology in a variety of services – speech recognition, image recognition, translation, personalized advertising – and in addition the company is also investing resources in the development of healthcare, robotics and quantum computing (Google AI, 2022). However, Google states on its official website that supervised learning offers more opportunities than unsupervised machine learning (Google Developers, 2022). Lawrence (2021) published a detailed guide on how business owners can use the data obtained in the Google Analytics program for segmentation with unsupervised machine learning techniques.

Even after an extensive and thorough search, it is not clear what type of method Google uses to segment consumers. However, based on the information we have, we assume that it uses predefined variables and constantly makes new inputs and refinements to tag consumers with a supervised machine learning technique that is linked to the targeting options of the Google Ads system, using different algorithms. In this, advertisers have several categories at their disposal to optimize the size and composition of their audience. These are as follows:

- Affinity segments: available based on a holistic picture of the consumer, based on their lifestyle, passions and habits.
- Life-events: Along major life milestones, such as a graduation, a move, or a marriage. They can be used to create a smaller segment because it affects fewer people and less frequently than general interest, but it is usually larger than in-market segments because reaching a milestone can trigger many purchases.
- In-Market Segments: a group of consumers who are considering buying a particular product or service.
- Detailed Demographics: segments based on common characteristics shared by a large portion of the population.
- Custom segments, custom intent segments, and remarketing segments are other methods that are not affected from the perspective of our research.

The full list of Vidhoarder.com (2022), including all segmentation options, reached 4,809 variables. The range of variables included in this study is much smaller. We are looking for the answer among the simpler targeting options to see if they are suitable to reach niche market, and at the same time we are looking for the answer to possible shortcomings in Google tagging. Thomas (2020), the author of Yieldify platform, has defined four categories for segmentation, three of which are compatible with Google's methodology: Demographic, Psychographic, Affinity, Behavioural, In-Market Segments.

In the other sections of our publication, we present the research method, results, and conclusion.

The goal of our analysis is to examine Google's segmentation and targeting options, their accuracy and applicability. Since artificial intelligence and various machine learning systems play a role in this, the paper also draws attention to the extent to which these ensure that the target audience and niche market for the various manufacturers and retailers are reached.

RESEARCH METHOD

Based on information from theorists and practitioners, we identified the segmentation variables and targeting criteria that sellers of predefined products and services intend to use in our target audience, whose are students at the University of Miskolc, Faculty of Economics. In total, we identified 41 such targeting options. In a face-to-face survey of 37 individuals, we asked the sample to confirm the presence or absence of tags for individuals by looking at Google ad preferences. In this research, respondents had to answer a dichotomous, closed-ended question about whether the area of interest indicated by each label really applies at the moment. We did not use a scaling technique in the survey. We addressed a typical shortcoming of research: the subjectivity of responses. We stated that an AI that tracks consumer activity could provide a more accurate picture than consumer opinion – since it can be interpreted as a form of observation – over many years.

In the second phase of our research, we examined how many of the predefined product and service categories identified had segmentation factors with the potential to create a niche market. In this case, we considered more than 80 interest- and hobby-based targets in Google Ads, as well as additional demographic targets.

RESULTS

In this section of the study, we present the proportion of the Google tagging system that displayed certain segmentation-related tags for the respondents, and then we also discuss how many segmentation groups can be filtered in the Google advertising system in order to sell a product of our choice

Table 2 contains the best data, sorted by median rate, and the worst, in terms of display ratio, among the 41 criteria examined in the survey, we conducted, as described in the research methodology section. The name can be seen in the "Designation" column, the category in the "Segment Type" column, the appearance rate in the "Appearance Rate" row, and the actual interest/performance ratio in the "Actual Rate" row.

Table 1

Appearance and actual rate of Google Tags on customers' ad settings

Additional information	Tags	Segment type	Appearance rate	Actual rate
Mostly appeared Google Tag	Age	Demographics	100%	100%
Mostly appeared Google Tag	Mobile phones	In-market segments	97.3%	41%
Mostly appeared Google Tag	Love Songs	Affinity	97.3%	100%
Mostly appeared Google Tag	Material status	Detailed demographics	97.3%	100%
Mostly appeared Google Tag	Gender	Demographics	97.3%	100%
Mostly appeared Google Tag	Movie lovers	Affinity	94.6%	100%
Google tag sorted by median	Starting a business soon	Life events	68%	27%
Google tag sorted by median	Video games	In-market segments	54%	46%
Google tag sorted by median	Laptop, Notebook	In-market segments	51%	62%
Google tag sorted by median	IOS phones	In-market segments	46%	62%
Google tag sorted by median	Android phones	In-market segments	38%	49%
Google tag sorted by median	Outdoor recreational equipment	In-market segments	35%	24%
Least appeared Google Tag	Movie streaming services	In-market segments	27%	89%
Least appeared Google Tag	Test preparation and tutoring	In-market segments	24%	3%
Least appeared Google Tag	Perfumes and fragrances	In-market segments	24%	65%
Least appeared Google Tag	Open online courses	In-market segments	22%	5%
Least appeared Google Tag	Swimwear	In-market segments	19%	8%
Least appeared Google Tag	Single	Detailed demographics	11%	41%

Source: Own editing

In our study, we collected data on demographics, detailed demographics, life events, partners, and market segments. As can be seen in Table 2, the appearance rate of the predefined 41 labels used for the segmentation of the target group is very different. The appearance rate of the label reached the maximum rate for age (accuracy was also reasonable, it can narrow consumers into age-based segments), followed by mobiles, music lovers, material status and gender with a frequency of 97.3%. These categories can be interpreted as different criteria that accurately reflect actual interest (or in the case of demographics, accuracy), with the exception of interest in cell phones, which, unlike the label, covers only 41% of actual interest. In the median of the 41 items the Market Segments category usually appears, showing little difference between the proportion of those with the label and those who are truly interested. An interesting finding is that in the case of IOS and Android devices, the overall real interest of respondents is above 100%, which is because a user has shown interest in both types. As for starting a business, which is the only item listed in the table as a life event, it is significantly overestimated by Google algorithms. Even among correctly labelled users, whose actual intention differs from 68%, only 27% intend to start a business in the next three years. Regarding the release rate of labels, the worst six elements among the university students surveyed mainly refer to the segment within the market. For the use of streaming services and the purchase of perfume, the target market is more difficult to reach with ads based on this information, as it represents a lower percentage than the actual prospects, only 27% and 24%, respectively, for this indicator.

The information collected by Google's machine learning technique appeared in the variables of the different criteria with varying accuracy compared to the actual interest. From this information, practitioners responsible for advertising can conclude that even with the most careful advertising settings the targeting options of the advertising system can easily lead to inaccurate results and reach people outside the target audience.

In Table 3, we looked for the answer to whether the combination of more than 80 segmentation criteria can be considered a suitable solution for creating niche markets, so that companies and entrepreneurs can keep customer acquisition costs lower, in line with modern trends. The table contains 10 predetermined categories of products/services, which are considered goods typically used by the respondents (university students). We examined the segment categories separately (In-Market Segments, Life events, Detailed Demographics, Affinity) and then determined the set of characteristics applicable to the formation of the niche market in an aggregated manner.

Table 2

Google Ads targeting possibilities to reach niche segments of university students

	In-Market Segments	**Life events**	**Detailed Demographics**	**Affinity**	**Niche segment targeting**
Premium laptops	1	2	2	3	8
Premium mobile phones	1	2	2	3	8
Premium perfumes	1	2	2	1	6
Sports equipments	1	2	2	1	6
Vehicles	1	2	2	1	6
Online classes	2	2	2	1	7
Music streaming	3	2	2	2	8
Video streaming	2	2	2	2	8
Cosmetic services (like beauty salons)	1	2	2	1	6
Restaurants and their services	1	2	2	1	6

Source: Own editing

As can be seen in Table 3, the number of attributes belonging to each product and service criterion varies between 1-3. By setting different criteria variables in the Google Ads system, the niche market belonging to the specified categories can have 6-8 attributes when creating an individual target group.

CONCLUSIONS

Marketers are under increasing pressure to make their sales activities as efficient as possible. One way to do this is to sell to consumer segments whose needs are not being met in the marketplace. Niche marketing is the solution to this problem and helps create a loyal customer base. The resurgence of segmentation has been ushered by online marketing, as Big Data and AI can be used to learn more about consumer habits. With the application of machine learning, targeting, reaching, and identifying niche markets has become attainable.

In our study, we examined the various labels of the Google Ads system. We did qualitative research where, instead of a consumer survey, we focused on the presence or absence of labels in Google's advertising settings, which are also freely available for consumers to view. In addition to display rate, we also used consumer survey data to provide some accuracy in the labelling methodology used by Google Ads. Ratings in the six most typical categories, the middle six categories sorted by median, and the six most atypical categories vary widely, and actual interest matches measured data does not match well with the Google Ads labels. This is likely due to shortcomings on the user side of the ad settings. Examining a larger sample and including more tags may provide a more accurate picture of effectiveness. The second phase of our study is based on the four segmentation categories mentioned in the literature review, namely in-market segments, affinity, detailed demographics, and life events. Among these variables, we explored how many options can be applied to narrow down the target audience for products and services that are typically of interest to the target audience (here, university students). Normally, their number is between 6-8, which of course can be further optimized by Google's additional factors not included in the research. The comparative analysis of the two tables can again be interpreted as a suggestion for practitioners to get an optimal picture of the category to set up ad targeting.

Limitations of the research:

- The number of respondents is relatively low; only 37 people were included in the qualitative research.
- The attributes asked during the research only contained the most characteristic features of the target group, so the majority of labels were not affected.
- The research can only be used when setting up the individual target audience and only affected the In-Market Segments, Life events, Detailed Demographics and Affinity factors. Additional targeting optimization options were not included in the research, such as remarketing options, use of keywords, etc.

Author's contribution

Zoltán Somosi was responsible for 60% of the overall work. He conceived and designed the study, collected the data, performed the analysis and wrote the paper.
Noémi Hajdú contributed 40 % to the study. She collected the data, performed the analysis; and also wrote and translate the paper.

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