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DATA-DRIVEN ADVERTISING: THE EFFECTIVENESS OF DYNAMIC PRODUCT ADS (DPAs)

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YÜKSEK LİSANS TEZİ

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Hazırladığım bu Yüksek Lisans Tezinin tamamen kendi çalışmam olduğunu ve başka çalışmalardan yaptığım alıntıların kaynaklarını kurallara uygun biçimde tez içerisinde belirttiğimi onaylıyorum.

YAĞMUR EYİLMEZ

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Yukarıdaki imzaların adı geçen öğretim üyelerine ait olduğunu onaylarım.

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ABSTRACT

EYİLMEZ, YAĞMUR. *DATA-DRIVEN ADVERTISING: THE EFFECTIVENESS OF DYNAMIC PRODUCT ADS (DPAs)*, MA, İstanbul, 2021.

Dynamic Product Ads (DPAs) are data-driven online advertising forms for mostly remarketing purposes or detect consumers who are interested in that category of product. Both large-scale and small-scale businesses can use DPA in their advertising strategy as it reduces the time spent on the production of ads and targeting process, besides providing the highest level of personalization in today's technology. The primary purpose of the DPAs is to drive consumers to purchase, and some of its features, such as the easiness of the buying process and the high level of personalization, are possible effects to trigger impulsive buying behavior. This study examines the effectiveness of DPAs comparing to manually optimized ads on Facebook and Instagram for a small-scale business in the light of impulsive buying theory. The data contains online advertising campaigns from a small-scale business with a niche product in an extended period. The key findings of this research revealed that for niche products, manually optimized ads on Instagram are more effective on purchase, and dynamic product ads are more effective on reach and driving consumers to the website. There is no significant effect of DPA on impulse buying.

Keywords: dynamic product ads (DPAs), personalized ads, impulse buying, data-driven advertising, AI, machine learning

ÖZET

EYİLMEZ, YAĞMUR. *VERİ GÜDÜMLÜ REKLAMCILIK: DİNAMİK ÜRÜN REKLAMLARININ(DPAs) ETKİNLİNLİĞİ*, MA, İstanbul, 2021.

Dinamik ürün reklamları, yapay zeka temelli ve veri güdümlü, tüketicilerin ilgi alanlarına ve geçmiş tüketim alışkanlıklarına göre hazırlanan reklamlardır. Dinamik ürün reklamları günümüzün en ileri hedefleme gücüne sahiptir. Ayrıca reklam üretim maliyeti ve zaman kaybını önemli derece azalttığı için küçük ve büyük ölçekli tüm işletmelere uygun olabilir. Dinamik ürün reklamlarının en büyük kullanım yararları yüksek kişiselleştirme ve kolay süreci ile tüketiciyi satın alıma yönlendirmek ki bu özellikler dürtüsel satın almayı tetikleyebilecek faktörler. Bu tezin en temel amacı, dürtüsel satın alma teorisi ışığında Facebook ve Instagram'daki dinamik ürün reklamlarının manuel olarak optimizasyon yapılan reklamlara göre niş ürün grubuna sahip bir küçük işletme için ne kadar efektif olduğunu incelemek. Elimizdeki veri, kişiselleştirilmiş niş ürünler satan küçük ölçekli bir işletmenin Facebook ve Instagram'da yaptığı reklam kampanyalarının verileridir. Bu tezde kullanılan yöntem, uzun zaman aralığında oluşmuş çevrimiçi reklam verilerinin incelenmesiyle oluşmuştur. Toplanan veri nicel yaklaşımla incelenmiştir. Araştırmanın temel bulguları, niş ürünler için Instagram manuel optimize edilmiş reklamların daha etkin olduğu ve Facebook dinamik ürün reklamlarının erişim ve tıklanma üzerinde etkin olduğu yönünde. Dinamik ürün reklamlarının dürtüsel satın alım üzerinde yetkin bir etkisi görülmemiştir.

Anahtar Kelimeler: dinamik ürün reklamları, dürtüsel satın alım, kişiselleştirme, veri temelli reklamcılık, sosyal medya reklamları, yapay zeka, makine öğrenmesi

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1. INTRODUCTION

E-commerce sales are increasing over the last years worldwide, not just purchasing products but also purchasing travel and food services, payment and money transfers, etc. According to the report of eMarketer, the growth of e-commerce retail sales was 16.5% in May 2020 and has increased just in 6 months to 27.6% in Dec 2020 (eMarketer, 2021). In recent years, the growth in e-commerce is attributed to the increase in internet and smartphone usage (Noor, Awan, and Zahid, 2019). This raise is creating a highly growing amount of personal data that can be processed. After AI and machine learning developments, consumers' data can be implemented beneficially in many fields, especially marketing and advertising. The developing technologies have become one of the essential marketing and advertising elements, although these phenomena are based on communication. With the ability to store, process, and relate data, understanding the consumer and creating insights has become much easier than before. The latest technologies have positively affected advertising at every stage. With the storage and processing of big data, targeting is way more accurate and detailed before. Marketers and companies are no longer see the consumers as groups and categorize them, but they see individuals with their interests, actions, and buying behaviors. They offer their service, product, or content depending on their interest, search history, or the product checked before. Digital advertising's future is more likely to be highly personalized relies on the rise of available, detailed, and definitive consumer data (Lee and Cho, 2020). The evaluation of social media channels and advertising has a significant impact on the personalization process either. It has a non-negligible effect on consumer's buying behavior. According to the recent survey of Adweek, 60% of millennials and %40 overall adults claim that they purchased a product they saw on Facebook (Adweek, 2021).

Due to these developments, social media platforms have begun to develop ad models with much higher targeting and personalization capability. They provide the most appropriate content to the users by using artificial intelligence and machine learning. Dynamic Product Ad (DPA) is one of the data-driven ad models that simplify the whole process. Facebook was one of the earliest ones that started to serve dynamic ads. Most of the small and large-scale e-commerce companies are taking advantage of the product since 2015.

After Instagram has joined the Facebook group, DPA has also started to be implemented in Instagram.

The primary purpose of this thesis is to measure the effectiveness of Dynamic Product Ads compared to manually optimized ads from Facebook and Instagram in a certain period. The data has been collected from a small-scale e-commerce company that utilizes DPA and manually optimized ads. We analyzed some metrics from online advertisements and DPA's. The effects and contributions of DPA were observed after it was started to be used by the brand. The selected measurements are the most efficient criteria for small-scale businesses that focus on the three main segments; awareness, efficiency, and profit. The paper's findings offer valuable insights about the performance and effectiveness of DPA for e-commerce companies and small businesses that are exploring and comparing especially personalized social media advertising models. There are not so many research studies about dynamic product ads and retargeting products in academia. Researchers that examine this issue have focused on the customer reaction to the personalized ads (Frick, 2018), the placement of the ad, or the comparison of the platforms (Semerádová and Weinlich, 2020). This research is developed to fill the research gap in the field as DPA performance compared to the manually optimized ads with or without the same goal, especially on Instagram that has never been examined before.

2. LITERATURE REVIEW

The purpose of this chapter is to provide the literature perspective relevant to the research of this thesis. It begins with the impulse buying theory in the literature and an overview of niche product marketing. Next is creativity in advertising and social media advertising, followed by data-driven advertising. Lastly, personalization in online advertising and the overview of dynamic product ads have been examined. After which, the chapter ends with the research questions and hypotheses.

2.1 IMPULSE BUYING THEORY

Impulse buying is a concept of consumer behavior. It is one of the different kinds of consumer decision-making processes. The concept has been discussed from different perspectives over the years. Impulse buying is defined by Stern as shopping behavior that has not been planned in advance (1962). He categorizes the concept into four subconcepts: pure impulse buying, reminder impulse buying, suggestion impulse buying, and planned impulse buying. The instant novelty or escape purchase is pure impulse buying. Reminder impulse buying is remembering the need when a customer sees a product. Suggestion impulse buying appears when a consumer sees a product that has never been seen before and realizes the need for the product. The difference between reminder and suggestion impulse buying is the previous experience with the product. Lastly, planned impulse buying, which appears when a customer has the plan to buy a certain product, however with the anticipation and motivation to purchase by special discounts or coupons. Another definition adds the comparison of the situations. Kollet and Willet (1967) define it as an unintended purchase that was the outcome of a comparison of alternative purchase motivations with actual results. Rook (1987) brings a different perspective to the process and states that it is the situation in which a consumer buys a product in a moment of sudden, forceful, and continual impulsiveness. This may trigger emotional conflicts and can be accepted as an undesirable feel of being out of control (Rook, 1987). After this, the unplanned actions have been observed and discussed that while all impulse buyings might be recognized as not planned, but not all unplanned buyings might be accepted as impulsive (Koski, 2004). These developments and analyzes into details of impulsive consumer behavior brought more a more extended definition.

Currently, it is explained as “immediate, irresistible, hedonically complex buying behavior in which the pace of the impulse buying decision inhibits any rational, mindful analyzing of alternatives or future effects” (Sharma et al., 2010, p. 277). The extended definition narrows the perspective of impulse buying behavior in order to differentiate it easily.

With the developments of Web 2.0 and e-commerce, impulse buying has emerged online impulse buying. Online impulse buying is described as quick and abrupt online buying without pre-shopping motivations (Piron, 1991). After the rise of internet usage and e-commerce, online impulse buying has become an issue to study. There are opposite opinions about impulsive behavior in online purchasing. As online purchasing is based on seeking information and searching about products, impulsiveness has not been supported in the process by many researchers (Kacen, 2003; Verhagen and van Dolen, 2011; McCabe and Nowlis, 2003). On the other hand, as online purchasing is a much easier and faster process than physical buying, it also has a wider range of products and fewer limitations, impulse buying is supported in online shopping (Chan et al., 2017; Greenfield, 1999). There are many external and internal stimuli that trigger user’s impulsive behaviors such as personal characteristics (hedonic needs and impulsiveness), online store features (user friendliness, interactivity), marketing promotions (e.g., bonus and discounts), product features (e.g., type and price) (Chan, Cheung, Lee, 2017) and buying options (e.g., credit card options). According to the literature review analysis of Chan, Cheung and Lee (2017), most of the stimuli that have been discussed are user characteristics, marketing promotions, and website features, although there is not enough knowledge about context-specific stimuli that increases impulsive behavior.

With the developments of social media advertising technology, there are more relevant ads are reaching to right consumers, and this might be another powerful stimulus for impulsive buying. Platform characteristics of social media, the level of personalization of the ad, the creativity, and the entertainment level of the ad might be additional triggers for impulse buying. To increase consumers’ impulsive purchases, personalization is a tool that serves content-specific stimuli for users and is used by retailers (Dawson and Kim, 2010), and it is an essential factor for marketers (de Kervenoael, Aykac, & Palmer, 2009).

As DPA's level of personalization is one of the best in today’s technology, it can be a strong stimulus. According to a research about personalization effect on impulsive buying, although perceived reliability and informativeness moderately intercede the personalization to practical clickthrough motivation connection, particularly perceived entertainment and creativity completely intercede the personalization to hedonic clickthrough motivation connection (Setyani et al., 2019). The lack of entertainment and creativity might be disadvantageous for DPA ads to trigger impulsive buying. The importance of social media should be considered in DPA ads and manually set up ads. Instagram is the most effective platform for impulse buying, following by Facebook, Pinterest and Twitter (Setyani et al., 2019). Moreover, the performance of Instagram and Facebook creates a great interest for them on advertisers. But for both online and offline shopping, social networks trigger consumers for impulse buying at a high level (Setyani et al., 2019).

2.2 NICHE PRODUCTS MARKETING

Finding niche markets and makes them achieve success is always an issue in marketing. 4Ps (Promotion, price, place, product) of the marketing mix have different dynamics than usual when it comes to niche products. Understanding the core elements of the communication and marketing tactics for a niche product is essential, especially for small businesses. For this, firstly, the concept must be mastered.

There are several definitions and explanations of niche in marketing literature. One of the descriptive ones is from Keller and Kotler (2015); a niche is a more narrowly described consumer group seeking a unique combination of benefits within a segment. According to Michaelson (1988), niche marketing is discovering small consumer groups who need service within a segment. Another definition is positioning into small-scale, beneficial, similar market segments which are disregarded or overlooked by others (Dalgic and Leeuw, 1994). Phillips and Peterson (2001) state that "niche marketing is a marketing strategy that utilizes product distinction to impress a focused group of customers" (Phillips and Peterson, 2001, p. 1). According to Keller and Kotler (2015), marketers generally splits segments into subsegments to determine niches. If personalized socks are divided into sub-segments according to this definition, they can be listed as follows: *Clothes* > *Socks* > *Personalized Socks*. According to Shani and Chalasani (1992), the mechanism and the differentiator of niche product marketing is that the marketer begins with some consumers' needs and evenly expands a more extensive customer base. Kotler (2003) states that there are five features of niche markets. The first one is that the consumers have an unlike and evident group of needs. The second one is the willingness to pay more to satisfy their needs in the best way. Thirdly, the niche market does not catch competitor companies' attention. Another feature is specialization helps niche marketers to benefit more in certain economies. Lastly, size, gain, and the possibility of growth are the features that a niche market has.

There are several points that are mentioned as essential factors to be successful in niche marketing. One of the most critical points is differentiation. Kotler (1991; 2003) claims that specialization is the most significant point to efficient niche marketing. This specialization can be seen in some conditions, such as customer-size specialist, vertical-level specialist, specific-customer specialist, geographic specialist, product-line specialist, product-feature specialist, or quality-price specialist. According to Toften and Hammervoll's (2009) study, their findings show that it seems highly important to establish the strategic approach on competitive advantage by values consumers and enforce differentiation, including intangible as well as actual use criteria. Another essential point to be successful in niche marketing is strong customer relations. A long-term and robust relationship provides an advantageous position in the competition (Dalgic & Leeuw 1994; Toften & Hammervoll 2009). Strong relationships help to create word of mouth, which is a treasure for niche markets. Using them is to create awareness about the brand is increases the reputation (Dalgic and Leeuw, 1994). In their study, Toften and Hammervoll (2009) also highlight a couple of essentials to success in a niche market. These are the capability to modify quick and the probability to sustain some adjustability, having knowledge about the relevant market and products inherently applies to niche firms too, and as final entering fast growing markets, and for minimizing risk, targeting more than only one product market (Toften and Hammervoll, 2009).

Unfortunately, there is a shortage of niche product advertising and purchase intention studies in the field. A study indicates an effect in the context of using social media for boosting niche products, although which have been identified to be specifically promising, it persists comparably undiscovered in the literature (Dellarocas, Gao, and Narayan, 2010).

According to another study about niche products, social media platforms can advertise conversations about niche products and enables both current and potential enthusiasts to learn about products that are not available offline or in traditional media by facilitating mass interaction and engagement among consumers. (Phang, Zhang and Sutanto, 2013). They also indicate that greater degrees of user participation in content production was shown to boost consumption purposes in terms of users demonstrating their preferences to buy a product (Phang, Zhang, and Sutanto, 2013). Dalgic and Leeuw (1994) underline the importance of data-driven marketing for niche products. Today's database forms able to maintain advertisers with a cheaper, useful marketing tool in comparison. This database can list predictions and customer qualities and it is especially for decision making. Consumer databases should be connected to other marketing information systems and business intelligence systems in order to be a respondent to the marketplace (Dalgic and Leeuw, 1994). In addition, social media channels have an impressive amount of users in their database and their targeting options are more detailed than traditional advertising. It is more effortless and cheaper than many other ways. Advertising on social media sites is more affordable and more targeted for small businesses as well, although the major advertisers on social media platforms are the most successful companies such as Walmart, P&G, and Microsoft (Jones, Borgman, and Ulusoy, 2015).

2.3 CREATIVITY IN ADVERTISING

In the advertising field, one of the most discussed and tried to be solved terms is creativity. It seems like the key to the success of the ad. The visual, the text, and the channel should be served in a creative way to impress and persuade audiences both online and or traditional advertising. It is also important to acknowledge for advertisers that why creativity is crucial or how crucial for an ad to be successful. Most of the study proves the positive effect of creative advertising on the consumer buying journey. Based on years of ad analysis, Campbell (2011) states that by great advertising creativity, the biggest and most valuable brands from the world get positive financial effects. In their experimental study, Smith et al. (2007) found that creative advertisements drive the audience to process the ad and develop the attitude toward the ad and ensure that the positive effect transfers to the brand. According to a study about the effect of creativity on the memorability of ads, creative advertisements (by participants evaluation) are more likely to be recognized properly rather than less creative ads (Shen et al., 2020). They also add that creative advertisements are harder to forget than less creative ads (Shen et al., 2020). Sheinin, Varki, and Ashley (2011) supported these statements and proved that creativity has a positive impact on attitude toward the brand. More surprisingly, even when customers are not interested in a product, advertising creativity may still have major impacts (Yang and Smith, 2009). But what is this *creativity* and can an ad be creative?

Creativity is mainly explained as in these terms; creative thinking, ability, problem-solving, imagination, or innovation (El-Murad and West, 2004). Creativity is a highly wide concept that can be adapted in every field. There are several explanations of creativity in advertising. According to Haberland and Dacin (1992), advertising creativity is the degree of the ad's originality and unexpectedness. Another explanation of the creativity of advertising is the progress of generating and improving the idea of advertising (El-Murad and West, 2004). To be more specific, they define ad creativity as the art of building a new and meaningful connection between things that were irrelevant before in a manner that is relevant, realistic, and tasteful, but which somehow shows the product in a new light (El-Murad and West, 2004). Furthermore, advertising creativity is highly significant as it is related to the primary human need to consume something original, new, unusual, and inventive (Haberland & Dacin, 1992).

There are several pieces of research about what factors affect creativity in advertising campaigns. Diversity and relevance are known as leading features that affect advertising creativity; while divergence relates to elements that are new, different, or unusual, relevance associated to elements in such terms meaningful, appropriate, practical, or valuable to the audience (Smith et al., 2007). According to their study, originality, flexibility, synthesis, elaboration, and artistic value are related to divergence and must be evaluated (Smith et al., 2007). A study shows that with actual online reviews and with their lab research, creative, informative ads with more interaction get more views, and users tend to share those kinds of ads more (Moldovan, Steinhart, and Lehmann, 2019). Also, users see this as a perception of social status elevation (Moldovan, Steinhart, and Lehmann, 2019).

The success of the creative ads also mostly depends on those two factors. Most of the researches that examine the consumers' attitude among social media ads, getting information about a product or service that relates to the customer's needs or interests creates a positive attitude towards the ad and increase the possibility to buy the product (Alalwan, 2018) as it helps to make consumers a beneficial purchase (Lee and Hong, 2016). Another factor is the high level of ad creativity that can maintain a hedonic value to consumers, which develops positive attitudes (Lee and Hong, 2016). The main predictor of purchase intention is confirmed as hedonic motivation (Alalwan, 2018). Organizations can design and improve their advertisements in a progressively innovative and creative approach (Alalwan, 2018). Young and Smith (2009) suggest that strategies that can decrease resistance to persuasion and make consumers more open-minded have a significant influence on the intentions of consumers' advertising display and brand purchase. One of the parameters of success in advertising campaigns after social media is becoming viral. As people like the ad or content, they start to share it with their relatives and it reaches so many people. Creativity is one of the most efficient factors to becoming viral. Researches about viral advertisements mostly underline these concepts that are more powerful to circulate the ad; entertaining, funny, surprising, intriguing, enjoyable, and unique (Campo et al. 2013; Cruz and Fill 2008; Porter and Golan 2006; Berger and Milkman 2012; Golan and Zaidner 2008; Kaplan and Haenlein 2011; Petrescu and Korgaonkar 2011; Phelps et al. 2004). We can say that making people laugh or be surprised can be a success factor of creativity. In addition, according to the findings of Dobele et al. (2007), positive or negative emotions combined with surprise are used in successful viral advertising campaigns. The findings from another study suggest that the dominance of unexpectedness over expectedness is seen in the ads with positive feelings (Ang and Low, 2000). Likewise, Berger and Milkman (2012) state that triggering emotions, both positive and negative, motivates virality. We can understand that making people feel emotions by ads is also efficient to see the ads as worth sharing.

2.4 SOCIAL MEDIA ADVERTISING

Nowadays, social media advertising is one of the most trendy advertising methods. Most companies and brands transpose their marketing budget to social media advertising within integrated marketing communication, especially when outdoor advertising decreases because of the Covid-19 lockdowns. Apparently, as proof of pandemic, the growth of 16.3% compared to the previous year attributes social media to approximately 30% (29.6%) of all internet advertising revenues (IAB, 2021). In Turkey, the rate of social media spending in total digital media spending is 27% (Deloitte, 2020). With the growth and developments of social media, platforms improve their marketing strategies and advertising models every day. To discover the new forms of social media advertising, understanding social media and its structure are crucial.

There are many different definitions among social media and social media advertising. To begin with social media, one of the most fundamental explanations is Internet-based technology that is emphasizing create or share user-generated content (Kaplan & Haenlein, 2010). Commonly, social media are mentioned by platform features, either defining the message directionality (Kent, 2010) or utilizing specific tools such as Facebook or Twitter to illustrate the types of interplay (Howard & Parks, 2012) as mentioned by Carr and Hayes (2015). Carr and Hayes (2015) also broaden the term and come with a definition that involves all the aspects. Social media refers to online platforms which authorize users to involve in opportunistic and careful self-presentation, in the present or asynchronously, that acquire value from user-generated content with broad and narrow audiences and the perception of interplay with others (Carr and Hayes, 2015).

According to the American Marketing Association, social media marketing refers to promoting business products or services by using social media platforms (AMA, 2021). Social media advertising is one of the tools for promotion. Media platforms create their own premium advertising types, which are manually sold from media owners through in-house or external sales teams. Programmatic advertising is explained as automated actions of buying and selling digital ad stock by connecting publishers with advertisers to deliver ads to the most suitable target at the most appropriate time and place (IAB UK, 2018). Manually sold premium type ads are mainly used for launch campaigns, seasonal ads, or extensive communication. Programmatic ads are continuous ads that help to keep the extensive campaigns alive and keep the brand visible. They also can be used purchase-oriented. Programmatic ads use user data to target the right consumer at the right time and place with the right price. There are three categories for marketers to get data: first, second and third-party data. First-party data is collected by a company that has online and offline information. Second-party data is typically first part data brought from another source or partnership. Third-party data is generated and aggregated from other platforms or marketing databases. Programmatic advertisement investments are increasing every year globally. In 2020, the total ad spend on programmatic advertising was 129.1 billion dollars and it is expected to be 155 billion dollars at the end of 2021 (Statista, 2021). Programmatic advertising is highly popular because of its high level of adaptability, automation, and cost benefits compared to traditional advertising buys (Shehu et al., 2020). One of the major issues in online programmatic advertising is that managers' lack of control over where their ads display and this leads to appearances on non-premium websites (user-generated content websites, gaming sites, content aggregators, online forums) and cause brand safety problems (Shehu et al.,2020). The benefit of social media channels in this situation is the certainty of where the ad is going to be viewed. It will be within the borders of the platform so that advertisers can feel safer.

According to Rodger and Thorson (2017), one of the advantages of social media is strengthening the human factor that draws the most attention to recognizing the consumers' reaction and their online content that suits an advertising strategy which consists. Users can participate in an ongoing advertising campaign and relate to it. This creates the most beneficial point of social media advertising: WOM (word of mouth). The ad or content can have a much more return than spent, spread to more users, and have more impact on the user. That is why one of the primary purposes of social media advertising is persuading users to share the brand image and achieve free promotion (Dehghani and Tumer, 2015). It also helps both customers and marketers by profiting from the comments and information that others post on social media (Cha, 2009). Online commerce allows consumers to locate niche and hard-to-find products from worldwide, and consumption groups deliver forums for consumers to share reviews and suggestions of products (Solomon, 2013). In addition, users can interact with brands way more accessible, which affects the brand's perception and position in the user's mind. The internet and social media alter how consumers connect with companies and with each other (Solomon, 2013). Another advantage of social media marketing is that it can be measured instantly (Reena and Udita, 2020). This allows marketers and advertisers to observe results constantly and make instant changes.

Due to people spend more time online, the benefits are followed by possible problems, including privacy violation and the disruption of traditional social interactions (Solomon, 2013). Trust is argued as a fundamental concept that affects the success of e-commerce (McCole, 2002; Papadopoulou et al., 2001; Ratnasingham, 1998) and the success of consumer-retailer communication (Anderson and Narus, 1990; Doney and Cannon, 1997; Ganesan, 1994; Morgan and Hunt, 1994). A user's viral intent to an advertisement on a social networking site is negatively affected by privacy concerns (Lee and Hong, 2016). Especially data privacy concerns are one of the most significant issues nowadays, and companies and social media platforms come with the developments, such as IOS 14 update. From now on, users should allow applications and social networks to follow their behavior online. Otherwise, companies cannot benefit from personal data. When consumers believe that the online sellers are reliable, responsible, and trustworthy, they are more willing to buy products online (Chuchinprakarn, 2005). Another disadvantage of social media advertisements is that they hinder the entertainment experience. When a user's primary motivation to visit social media platforms is entertainment, seeing unrelatable ads might be disturbing. That is why the content of advertising has an effect on this issue.

What users are looking for in social media advertising is also a key question. There are some critical points that define social media advertising as successful or help to make it work. Many of the studies claim that informativeness and entertainment are the most effective factors in a social media ad (Kim, Kim and Park, 2010). On the other hand, Muntinga et al. (2011) discuss that the primary motive to use social media platforms is a desire for enjoyment, relaxation, and spending time. Additionally, social media platforms have different offerings to entertain consumers depends on mostly the executional manner of the advertisement, such as interactivity, the appeal of the message and direct virtual experience which are expected from consumers in social media ad content (Zhang and Mao, 2016). Another main reason to use social media platforms is seeking and exchanging information (Muntinga et al., 2011). As social media ad content demonstrates an appropriate medium for such goal by its format which maintains both execution of personal contacts and besides product information mostly provided as pictures and videos, consumers intentionally looking for it (Dao et al., 2014; Hamouda, 2018). The honesty, believability and accuracy of the perceived advertising content are described as the credibility of advertising. (MacKenzie and Lutz, 1989). As social media advertising presents the comments and sharings on existing social connections and in the content, it is seen as reliable and trustworthy by users (Chu and Kim, 2011).

2.5 DATA-DRIVEN ADVERTISING

With every action, when we open our computers and get into the internet, our behaviors and actions are constantly saved and stored. Our digital footprints allow companies and marketers to understand how someone, as an individual, consumes and interacts with the products, services, and contents. This process can be called data-driven marketing. Cho and Lee (2018) suggested that data-driven marketing may be defined as the process of gathering, relating, and analyzing customer data to improve and optimize alternative marketing actions continue.

Since the beginning of the 20th century, sellers have collected information that provides a better solution to the customers, and that information lets sellers market their service or product better. Before the 1960s, data-driven marketing was based on mailing lists with addresses and phone numbers that permit direct marketing (Petrison, Blattberg, and Wang, 1997). As nearly all advances in business since the integration of computers to the direct-marketing field have been based on computer technology, it can be seen as the milestone of the data-based marketing history (Petrison, Blattberg, and Wang, 1997). After the computer has been involved in the process, data has started to be stored. Still, with the development of programming, the binding between consumer information has raised the value and benefit of the data. Most of the demographics and, in addition, purchases have begun to be available for companies by credit cards. The second milestone of data-based marketing is the internet. The internet has allowed companies to attain information without being physically in the store or market. Nevertheless, it has facilitated sharing, which is crucial for internal usage and operating the data. Internal departments and employees such as marketers and external groups such as advisors have reached the information with sharing. After the internet, the change has been raised, and improvements have brought us to today, which data can be stored, shared, and processed for marketing purposes.

Data mining, machine learning which is an extensive domain that enables computers to learn with no purposely programming (Shah et al., 2020), knowledge management, and artificial intelligence have started to involve the marketing process from different parts of media channels to advertising. During these days, data mining techniques and knowledge management systems are improving to utilize the knowledge for digital media to amplify and create a valuable marketing intelligence environment (Mulhern, 2013). Many professionals believe that data-driven marketing and advertising technologies can help to improve the process and make it easier for the consumer and company end. There are significant benefits of new technologies to the field. One of them is to reach consumers at the most appropriate time and channel, which is one of the most fundamental topics for marketers. According to Shah, regardless of deep concerns that need to be solved before AI can be adopted in every field, it benefits society, marketers and consumers, and in general by enabling advertiser's capability to build and spread value at the appropriate time to the appropriate people (Shah et al., 2020). With machine learning and big data, understanding consumer behavior and creating insights from it is easier. It helps to see the bigger picture to understand the need of the consumer. Using big data to catch simultaneous buyer insights might increase their understanding level of any unsatisfied consumer needs. Then, companies can convert those insights into actions and increase the efficiency of digital advertising while improving the organization's dynamic ability (Erevelles et al., 2016). Big data and data-driven advertising alter the process and capture the customer's interest from their internet history to improve relevancy. This usage of data also enables AI to forecast consumers' needs according to their interests. It is another incredible advantage of new technologies for companies to decrease human power and using time efficiently in another area. According to the CMO of IBM Watson Advertising Randi Stypes, contrary to programmatic advertising that implements transactions, AI advertising is able to notice patterns, learn in some time, and predict that allowing marketers to make faster and more precise decisions depends on the consumer's aim (Forbes, 2020). He adds that, unfortunately, less than 25% of worldwide businesses take advantage of AI's potential completely, demonstrating the raised chance to utilize the technology within marketing and media (Forbes, 2020).

2.6 PERSONALIZATION IN ONLINE ADVERTISING

The definition of personalization differs on the goal. Personalization represents different things to different people from various fields (Fan and Poole, 2006). Fan and Poole (2006) have divided the definitions of personalization according to the work or study fields, and two of them are related to personalization in social media. According to Riecken (2008), in the marketing and advertising field, personalization is by maintaining a valuable one-to-one relationship, understanding each individual's demands and working efficiently towards that goal, and briefly addressing each individual's need in a given context, achieving loyal customers. On the other hand, to define it as more technology and information-centric, it can be said that the combination of technology usage and consumer information to adjust e-commerce interactions between a business and all consumers is personalization (Personalization Consortium, 2003). When we look at advertising personalization, it might be explained as the firm-initiated modification of ad content regarding consumers' choices (Arora et al., 2008). Therefore, the rise of the relevancy of ads by personalization is related to the directness of firms' customer preferences prediction (Frick, 2018).

As personal data are collected day by day, personalization in advertising is developing and increasing. Personalization in marketing and advertising has become an important subject to explore the effects and discuss the contributions. In the literature, it has been discussed in many research studies. Some of them focus on the positive impact of the customer journey (Setyani et al., 2019). Others have underlined the adverse effects of personalization on customers because of the privacy issues and the sense of being watched (Van Doorn and Hoekstra, 2013). For the negative part, according to Van Doorn and Hoekstra (2013), when the ad is more intrusive, the positive effect is weaker; also, a high match of an advertisement with the customers' need can drive higher purchases. Still, it can also lead to higher intrusiveness recognition, resulting in the opposite effect of providing more relevant messages to consumers (Van Doorn and Hoekstra, 2013). Consumers might understand the high match of the ad as proof that their personal information has been used by advertisers, which can be felt like a loss of control. (Edwards et al., 2002). On the positive side, online behavior tracking allows marketers, companies, and advertisers to drive related content, service, or product to the consumers individually. Personalized advertising delivers more targeted and appropriate information to satisfy users' needs (Chen and Hsieh, 2012; Deuze, 2016; Liu Thompkins, 2019). We see that customers are resistant and annoyed by non-relatable ad predictions of brands, such as advertising featuring a product they are not interested in (Arora et al., 2008). Personalized ads also aid in reducing the overwhelming data (Liang et al., 2006). Personalization of advertising positively impacts consumers as they offer highly relatable content to them, also beneficial for brands to communicate with consumers in the right way (Frick, 2018). According to Julie Bernard's research, 88% of Millennials and Z generation members wants advertising creatives to reflect their activities, places, and interests (Belaval Diaz, 2018). Another surprising finding is that Millennials and Gen Z participants want to see an offer to act immediately or keep for later (Belaval Diaz, 2018). Lambrecht and Tucker (2013) point out if the dynamic retargeting ads' placement of the websites is effective on the power of the ad, they suggest that dynamic retargeting ads have positive power among buying the product when consumers have checked out a review website and searching related websites.

Personalization in marketing and advertising has switched incredibly with the internet and individual tracking. The most critical contribution of the internet is to facilitate target consumers. Businesses are using personalized advertisements to powerfully affect the behaviors of users on social networking sites (Montgomery and Smith, 2009). Now, the targeting options are highly advanced to target individuals, even one by one. Being more related or consumer-focused is one of the most efficient reasons behind the other factors by far, to turn their face and invest in data-driven marketing and advertising according to 52.7% of the international panelists (Braveman, 2015). As the targeting technology improves by especially big data, machine learning and AI, there will be no doubts that the level of personalization will be incredibly specific.

2.7 DYNAMIC PRODUCT ADS (DPAs)

Dynamic Product Ads (DPAs) and Dynamic Search Ads (DSAs) facilitate advertisers by showing ads explicitly created for them to connect with possible customers (Semerádová and Weinlich, 2020). As it can be seen in Fig. 1, Dynamic Product Ads are assembled programmatically to track the behavior of separate users, and they use this for doing special advertising practices by products they've already seen in the company's product catalog. They follow users by the user's ID on social media channels. Facebook provides a pixel code to set up in the website and SDK to the app to track customers. After this process, the company owner uploads the product catalog, including the product prices, number of products, or location.

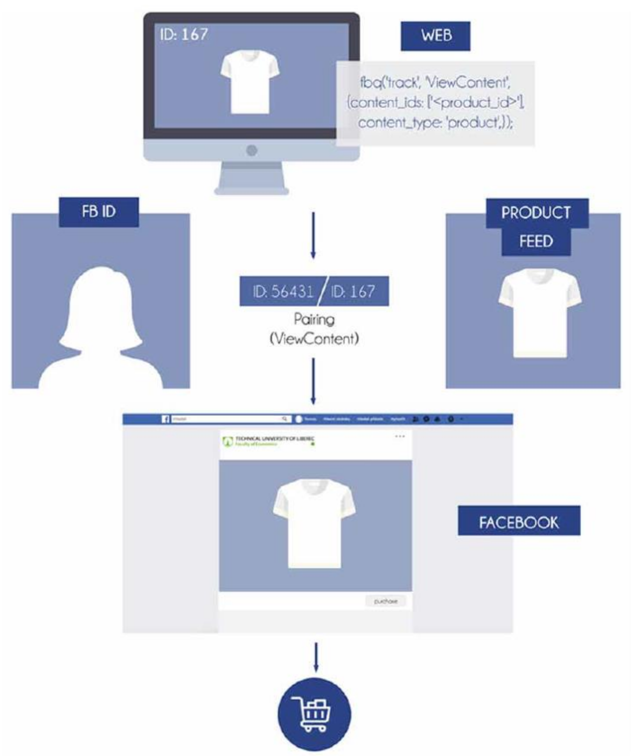

Fig 2.1 The Delivery Mechanism of Facebook Dynamic Ads

Source: Semerádová & Weinlich, 2020

Dynamic ads display content based on the previous activities of consumers from particular merchandise, which is called retargeting, or it uses the similarities that a customer has been interested in before with the current service or product, which is called social targeting. In retargeting, consumers' searching action is used to interpret users' desires and target them with personalized ads on external websites (Flick, 2018; Bleier and Eisenbeiss, 2015; Lambrecht and Tucker, 2013). On the other hand, consumers are aimed by the advertisers, by the usage of their social connections' to interpret their desires, and these desires are made clear in the ad text to foster consumers' identification with the advertised product in social advertising (Tucker, 2016). This application can be seen in Dynamic Product Ads and Dynamic Retargeting Ads. The difference between dynamic product ads and dynamic retargeting ads is the online channel they are displayed. Dynamic product ads are displayed in social networks and social media channels such as Facebook or Linkedin. On the other hand, dynamic retargeting ads are placed on other websites as banner ads. The social media influence and effect emerge from this difference. Social media channels maintain the environment of an ad, although it might seem as the context for social media advertising (Voorveld et al., 2018).

Also, dynamic product ads can target consumers who have visited similar websites by their internet history, not just the company's site. The company can reach new customers with custom and lookalike audience options. In retargeting, the consumer must visit the company's website before. Dynamic product ads are reaching users who are familiar with the brand or product types. That is why before reaching the seller, at the most critical step of the buying process, marketing automation tools interact with customers (Semerádová and Weinlich, 2020). Retargeting is an essential tool to achieve the purchase, especially for new and niche markets. Approximately 92% of users who visit a website are not ready to purchase a product or service yet (Episerver, 2020). That is why reminding the brand and the product, encourage users to revisit the website should be the primary goal.

There are several benefits of dynamic product ads. One of them is personalization. According to Kim and Han (2014), the results show that personalized advertisement designed to take into account customer needs, preferences, interests has decreased the irritation and discomfort of the customers. Dynamic Ads might be among the models that may cause minor irritation as they display the products according to the user's recent actions and intents. More detailed personalization allows companies to fit consumers' preferences more relatively and, in addition, drop consumers' search budgets by more precise suggestions. However, it increases the risk of choice misclassification, driving negative returns to ads (Frick, 2018).

One of the other benefits of Dynamic Product Ads is the ads' shorter production time and effort. The advertising production process is now data-based, independent of human experience and initiative (Lee and Cho, 2020). The creative part is the most time-consuming process of advertising for a starter and also experienced companies. The Dynamic Ads aims to remind the consumer of their incomplete purchase process and make them buy the item. As the ad's purpose does not require any appealing subject or catchy phrase rather than the product the customer has already been interested in, the production process of Dynamic Ads is automized. Standard template visual, copy text, and the owner provide other information, and the system automatically creates each content by AI. Once the product catalog has been uploaded and the campaign has been set, it continues with up-to-date price and stock information, always finding the right people for each product as long as the determined time (Facebook, 2021).

Another one is detailed customer targeting based on their behavior. Dynamic Ads enable to exclude customers that have purchased a product from the company before. It eliminates them from the ads and helps to allocate the spending efficiently on ad spend. This increases the efficiency of the targeting. In addition, if related products are sold, Facebook provides cross-sell and up-sell to past customers. This means it can be offered the upgrade version of the product and associated products from other categories that fit the customer's current choice. This orientation is helping to increase sales and lifetime values.

Lastly, Facebook allows cross-channel advertising. Dynamic ads can be published on every Facebook company platform, such as Instagram or Messenger. Cross-channel advertising saves advertisers a so much time, and brands can reach different users with different intentions. This allows to extend the target, and additionally, the frequency of the ad can be separated even.

Those features, benefits, and negative points have developed questions about the long-term effectiveness of dynamic ads at customers and advertisers or company owners

2.8 RESEARCH QUESTIONS & HYPOTHESES

Research questions of the current study are given below.

Research question 1: Do dynamic product ads have a significant impact on purchase comparing to manually set up ads?

Research question 2: Do dynamic product ads have a significant impact on leading consumers to a website comparing to manually set up ads?

Research question 3: Do consumers purchase more during or before the special days?

Research question 4: Do manually optimized ads have a significant impact on reach than dynamic product ads?

Research question 5: Do consumers purchase more during weekends?

Research question 6: Does mobile a more appropriate device than tablet or desktop for generating more clicks?

Research question 7: Does Instagram a more appropriate platform than Facebook for dynamic product ads to increase sales amount?

According to the research questions, the following hypotheses are developed.

Hypothesis 1: Dynamic ads have a positive effect on driving to purchase.

Hypothesis 2: Dynamic ads have a positive effect on the number of clicks.

Hypothesis 3: Special days have a positive effect on the number of purchases.

Hypothesis 4: Dynamic product ads have a positive impact on reach.

Hypothesis 5: Weekends have a positive effect on purchases.

Hypothesis 6: Ads for tablet devices have a positive effect on clicks.

Hypothesis 7: Facebook has a positive impact on reaching consumers for DPA.

Hypothesis 8: Instagram has a positive impact on clicks for manually optimized ads.

Hypothesis 9: Instagram has a positive impact on purchases for manually optimized ads.

3. METHODOLOGY

3.1 DATA & DATA SOURCE

The data belongs to a small Turkish brand based in Istanbul that designs personalized socks and other items such as masks and bags with consumers' photographs, especially their pets. The brand was established in 2019, and since the beginning, it has been conducting its communication on social media platforms, especially on Instagram and Facebook. The data was obtained from the Facebook Ad Manager. There were not any other traditional or online advertising campaigns during certain periods that Facebook and Instagram campaigns were live.

The data captures the daily social media advertising of the brand from 01 January 2020 to 30 April 2021 on Instagram and Facebook. It is time-series data which is a sequence of observations of the defined variable at a uniform interval over some time in successive order (Shrestha and Bhatta, 2018). There are manually optimized ad and DPA results that we examine how they perform on purchase, click and reach. There is 486 days total with 43 episodic ad campaigns, which contain special days such as Valentine's Day or New Year’s Eve. The majority of the ads were posted on Instagram, which contributes to the literature among media channels. In 463 days, there were ads on Instagram and in 305 days, there were ads on Facebook. Also, the total time period there has been manually set up ads and dynamic ads are different. The majority of the ads belong to manually set up ads.

The data includes the number of reaches (the number of users who have seen the content), impressions (the total number of people your content is visible to), the number of clicks the ad received, cost per click, and total purchases from ads. It is seen that there is a big gap in manual and DPAs’ link clicks and the total number of reaches. There are 410 purchases from DPA ads and 483 purchases from manually set up ads. In total, the number of sold items is 893. The distribution of purchases over time is shown in Figure 2. There is a peak in purchase revealed from DPA and that rise equalizes the big difference between the two model’s number of purchases. Besides, there is additional information that can provide valuable insights. The data includes the information of placement of the ad in the part of the platform, which are *story, feed, explore page, marketplace, and right column*. For both Instagram and Facebook, the first four placement exists. Only the right column is special for Facebook. Stories are the contents that can be visible for up to one day and locates on the top of the screen. Feed is the main page for both platforms; the content of the social connections for the user are displayed in this area. Explore page is for finding other related content from creators based on the interest. The marketplace is where users can see the business's official pages and can shop their products. Lastly, the right column is the area in the right part of the desktop feed page. The device of the ad has shown to users can be differentiated as mobile, desktop, or tablet.

3.2 RESEARCH METHOD AND DESIGN

Due to aim of this study, which is understanding how effective DPAs comparing to manually optimized ads on purchase, click and reach, cause and effect research design, is the appropriate design for this study. Cause-effect research occurs when one phenomenon is the cause of the other in the relationship between two phenomena. (Salkind, 2010). It can be explained in other words as a particular independent variable (the cause) has an effect on the dependent variable of interest (the effect). To understand if there is a relationship between the independent variables, in this case, DPA model and manually optimized model or social media platforms and dependent variables, in this case, reach, click and purchase, cause and effect method is the most appropriate approach for this thesis.

This research is quantitively situated. Objectivity is fundamental in quantitative research. Gathering countable measures of variables and implications from a sample of the population is especially appropriate for quantitative research. For collecting data, organized actions and formal instruments are adopted by quantitative research and they collect data empirically and methodically. In this thesis, data were collected by the brand. The analysis of numerical data is implemented by statistical techniques, usually using software for example SPSS, R or Stata (Queirós, Faria, and Almeida, 2017). To analyze the data, we used SAS Studio 3.8 (Enterprise Edition) program which is software for advanced statistical analysis, business intelligence, data management and visualization.

The study aims to draw a wide image of how DPA performs comparing to manually optimized ads and which factors affect their performance; thus this type of research needs to take inputs from an advertiser who uses both models in which these needs are met by quantitative research method. As quantitative research allows for insightful comparison of the objects under study here, this method for this specific master thesis has been chosen.

3.3 ANALYSIS

First of all, to understand if there is a relationship with variables and how they are related, we applied correlation analysis. The factors that affect the performance of the ad are examined and found how effective and related they are by correlation. Then, we used the autoregressive (AR) model to estimate the effects of the variables. The autoregressive model can be seen as mainly a linear regression of the values in the present series against one or older data in the same series. AR model is highly flexible in that it can process many types of time series and this is one of the reasons to use this model.

There are also distributed lag models which are examined for this study. ADL and PDL might be used for the analysis under some other circumstances. PDL (Polynomial Distributed Lag) is mainly used to find if there is a delay in the exposure action and the time observed (Gasparrini, Armstrong and Kenward, 2010). Autoregressive distributed lag (ADL) model takes adequate numbers of lags to capture the effectiveness of the ads (Kiygi-Calli et al., 2021; Shrestha and Bhatta, 2018; Kiygi-Calli et al., 2017; Kiygi-Calli et al., 2012) and it is applicable for both non-stationary time series as well as for times series with mixed order of integration. The reason why distributed models were not used for this study is that dynamic product ads get instant actions from users and their observations' effects cannot be seen in the upcoming days.

Three main values were selected as the dependent variable to examine, which are reach, click and purchase. This might be a representation of the steps of the consumer buying process and it can be detected if there is an impulse buying effect on the purchase. That is why we did not examine CPC or other variables as they would not be relatable with the consumer buying journey and we would not see if there is a relation with impulse buying behavior. Those variables are mentioned in descriptive statistics and correlation results to show the wider picture of the ad models' performance. Independent variables are calendar effect (days of the week, months of the year, special days and lag of it), Facebook and Instagram ad models separated as DPAs and manually optimized ads, the device (mobile, tablet or desktop) which the ad displayed and lastly, the place of the advertisement on the platform.

We did examine the trend specifically for the dependent variables in the data. From Figure 3.1, we can conclude that there is no significant trend in the data.

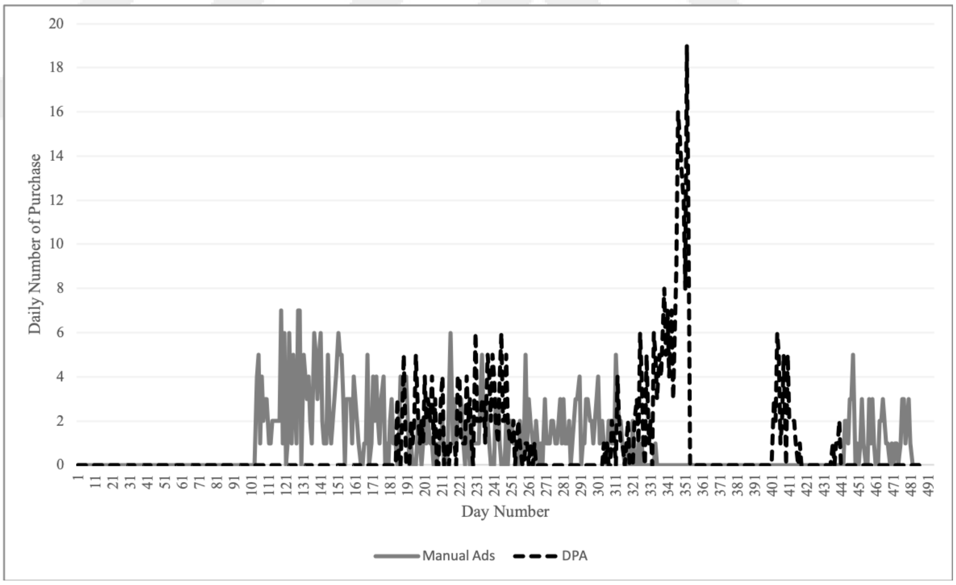

Fig 3.1 Daily Amount of Purchases Generated by Ads

We also checked the seasonality to detect any trends or patterns. Seasonality is a type of sequence in high-frequency data such as yearly, quarterly, monthly, weekly, or daily (Kiygi-Calli et al., 2021; Shrestha and Bhatta, 2018; Kiygi-Calli et al., 2017; Kiygi-Calli et al., 2012). The beginning of months is a perfect example of seasonality. Since most people's salaries are paid at the beginning of the month in Turkey, shopping increases during these times. Special days are the days celebrated by a certain type of people with mostly exchanging gifts such as Father's Day or Valentine's Day.

We treat the day as the observation unit, so we deal with reach indicated by R_t where the subscript t denotes the day. It also applied to the click and purchase.

The equations for each dependent variable situated;

$$R_t = \theta + \overbrace{\sum_{i=1}^{7} \lambda_i R_{t-i}}^{Autoregressive\ Terms} + \overbrace{\sum_{j=1}^{11} \gamma_j M_{j,t}}^{Months} + \overbrace{\sum_{k=1}^{6} \mu_k D_{k,t}}^{Days} + \overbrace{\sum_{m=0}^{7} \phi_m S_{t-m}}^{Special\ Day} + \overbrace{\sum_{n=1}^{4} \eta_n A_{n,t}}^{Advertising\ Model} + \overbrace{\sum_{q=1}^{5} \sigma_q L_{q,t}}^{Placement\ of\ Ad} + \overbrace{\sum_{r=1}^{2} \rho_r T_{r,t}}^{Device} + \varepsilon_t \tag{3.1}$$

$$C_t = \theta + \overbrace{\sum_{i=1}^{7} \lambda_i C_{t-i}}^{Autoregressive\ Terms} + \overbrace{\sum_{j=1}^{11} \gamma_j M_{j,t}}^{Months} + \overbrace{\sum_{k=1}^{6} \mu_k D_{k,t}}^{Days} + \overbrace{\sum_{m=0}^{7} \phi_m S_{t-m}}^{Special\ Day} + \overbrace{\sum_{n=1}^{4} \eta_n A_{n,t}}^{Advertising\ Model} + \overbrace{\sum_{q=1}^{5} \sigma_q L_{q,t}}^{Placement\ of\ Ad} + \overbrace{\sum_{r=1}^{2} \rho_r T_{r,t}}^{Device} + \varepsilon_t \tag{3.2}$$

$$P_t = \theta + \overbrace{\sum_{i=1}^{7} \lambda_i P_{t-i}}^{Autoregressive\ Terms} + \overbrace{\sum_{j=1}^{11} \gamma_j M_{j,t}}^{Months} + \overbrace{\sum_{k=1}^{6} \mu_k D_{k,t}}^{Days} + \overbrace{\sum_{m=0}^{7} \phi_m S_{t-m}}^{Special\ Day} + \overbrace{\sum_{n=1}^{4} \eta_n A_{n,t}}^{Advertising\ Model} + \overbrace{\sum_{q=1}^{5} \sigma_q L_{q,t}}^{Placement\ of\ Ad} + \overbrace{\sum_{r=1}^{2} \rho_r T_{r,t}}^{Device} + \varepsilon_t \tag{3.3}$$

where R_t is the total reach, C_t is the total click and P_t is the total purchase. Independent variables are $D_{k,t}$is a dummy for days of a week, $M_{j,t}$ is a dummy for months in the year, $A_{n,t}$ is a dummy for advertising model, $L_{q,t}$ is a dummy for placement of the ad, and $T_{r,t}$ is a dummy for the device type. The sums of the days of the week k=1 start from Monday and the months of the year j=1 start with January are added to the equation. ε_t is white noise. Lags of special days up to 7 days are included in the equation as a sum. We wanted to see how consumers react to ads a week before the special days and added all the days until a week. We also added autoregressive terms of the dependent variables as $\lambda_i R_{t-i}$. Autoregressive terms of R are the predictors of the total reach. It includes up to seven days apart. Autoregressive terms for C is $\lambda_i C_{t-i}$ and for P is $\lambda_i P_{t-i}$

4. RESULTS

4.1 DESCRIPTIVE STATISTICS RESULTS

As it can be seen from the Table 4.1, descriptive statistics include mean, standart deviation, sum of the variables, minimum value of the variable and the maximum value of the variable.

Descriptive Statistics						
Variable	**N**	**Mean**	**Std Dev**	**Sum**	**Minimum**	**Maximum**
Reach	486	25,022	23,042	12,160,818	0	111,379
Click	486	181.9	165.4	88,421	0	654
Purchase	486	1.84	2.48	893	0	19

Table 4.1 Descriptive Statistics for Reach, Click, and Purchase

According to the results, 25,002 people saw the brand's ads on a daily average of 486 days. 12,160,818 people saw the brand's ads in 486 days. It is important to underline that the brand did not give advertisements on social media every day. The standard deviation of reach is 23,042 which explains the missing ad days. The ads got almost 182 clicks on a daily average and the standard deviation is 165.4 which also explains the missing days. On the contrary, there were almost 2 purchases daily from the ads and the standard deviation of purchases is 2.48. This might be caused by the increased amount of purchase in December due to New Year's Eve season. The highest number of purchases in a day is 19. Additionally, the daily mean of cost per click is almost 1 Turkish Lira and the standard deviation is 1.4 Turkish Lira. This might be caused by the inconsistency of the ads and the optimization problem. The frequency of manually optimized ads and dynamic product ads have differences. Manually set up ads are displayed 10.5 times a day on average and the standard deviation is 10.1 which may also be caused by the missing days. DPAs are displayed 2.2 times in a day on average which is quite lower than manually set up ads. It has 4.2 standard deviation which shows that this might be related to the purchase peak on December due to New Year's Eve. It can be seen in Figure 4.1, Figure 4.2 and Figure 4.3 that the change in the number of reaches, click and purchase over time. There are three peaks in reach and click, which are in similar time periods; on the other hand, the purchase has one peak point which is December 2020, and there are no other visible significant ups and/or downs.

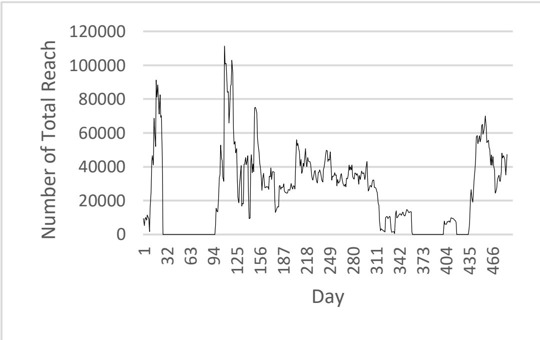

Fig 4.1 Total Daily Reach Among Time

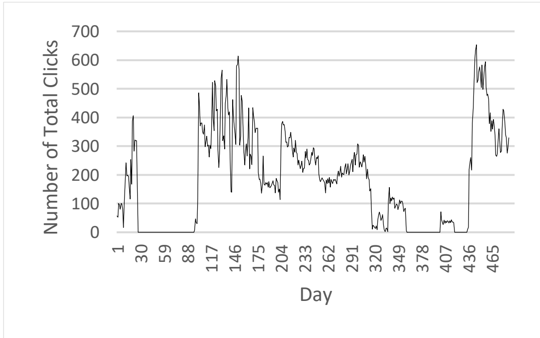

Fig 4.2 Total Daily Clicks Among Time

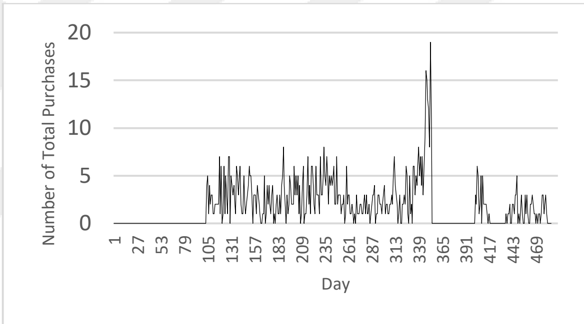

Fig 4.3 Total Daily Purchases Among Time

Instagram, Facebook, mobile, tablet, desktop, marketplace, right column, explore page, feed page and story page variables are dummy variables that is why the means are in between 0 and 1. Between the platforms, Instagram has a higher mean of 0.7 comparing to Facebook which is displayed less with 0.6 means. Among devices, tablet and mobile are more used than a desktop with a 0.7 mean against 0.6. In the place of the ad, story and feed has the highest mean with 0.7 and followed by explore page with 0.6. The story has 0.42, the feed page has 0.44 and explore page has 0.47 standard deviation which again may be related to missing days. On the other hand, the right column and marketplace have a lower displayed average compared to others but their standard deviation is higher than others with 0.49.

4.2 CORRELATION RESULTS

A Pearson correlation coefficient was conducted to measure the direction and the strength of the tendency to vary together of variables which are the total number of reach, click, CPC and purchase. As it can be seen in Table 4.2, there is a strong positive correlation (+0.8) between total reach and the number of clicks that an ad gets. There is a weaker positive correlation between total reach and number of purchases (+0.22) and also the number of clicks and number of purchases (+0.25). There is no correlation between reach, purchase, clicks and the daily sum of cost per click (CPC) and daily average CPC results. Daily average CPC has negatively correlated with total reach (-0.06) and the number of clicks (-0.1); however the results are not efficient to suggest a correlation. Taken together, the results suggest that when the number of users who sees the ad increase, the number of clicks that the ad gets will also increase. In addition, when the reach and the number of clicks increases, the buying from the ad might increase. On the other hand, the changes in the CPC results do not relate to the number of users who see the ads or clicks them.

Table 4.2 Pearson Correlation Coefficients for Reach, Click, Purchase and CPC

Pearson Correlation Coefficients, N = 486 Prob > |r| under H0: Rho=0					
	Reach	**Click**	**Purchase**	**CPC**	**AVE _CPC**
Reach	1.00000	0.84595 <.0001	0.22161 <.0001	0.07696 0.0901	-0.06634 0.1442
Click	0.84595 <.0001	1.00000	0.25195 <.0001	0.02758 0.5441	-0.10739 0.0179
Purchase	0.22161 <.0001	0.25195 <.0001	1.00000	0.12083 0.0077	0.15496 0.0006
CPC	0.07696 0.0901	0.02758 0.5441	0.12083 0.0077	1.00000	0.73264 <.0001
Ave_ CPC	-0.06634 0.1442	-0.10739 0.0179	0.15496 0.0006	0.73264 <.0001	1.00000

4.3 AUTOREGRESSIVE MODEL RESULTS

The analysis is conducted for three main parameters of advertisements which are reach, click and purchase. These parameters can represent the three levels of the consumer buying process as awareness, consideration and action. The results can be seen in the tables (see Tables 4.3, 4.4, 4.5).

4.3.1 Reach

The autoregressive model is estimated to understand which factor has an effect on total reach. To achieve parsimony, the final model is obtained by deleting non-significant variables with t-values less than one (Kiygi-Calli et al., 2017). We delete all of the regressors when their associated t-values are smaller than 1 in absolute value (Calli et al., 2012). According to the estimation results of Equation 1, the Mean Square Error is 42,195,820 and the adjusted R-square was 0.9256 which states that the data fit the model.

First of all, all days of the week are significant with a significant level of 0.05. This result shows us that different days have different effects on reach. The benchmark of the analysis for the day is Saturday and all the other days have a negative effect on reach comparing to Saturday.

In months, January, February and March have not significant effect on reach however May, June, July, August, September, October and November have a significant effect on reach and April has an almost significant effect on reach. Although they have a negative impact on the reach comparing to December, it can be seen that these months have an important effect on how many people see the ad.

The results suggest that a special day is not a significant predictor of reach. Special days such as Valentine's Day do not affect the number of users who see the ad on the current day. However, some of the lag variables of the special days are significant. A week before the special day (p Value = 0.0880) is almost significant. These results suggest that the number of users who see ads seven days before the special day might increase the number of reaches.

The device which the ad has shown has an effect on the reach with a significant level of 0.05. Comparing to our benchmark variable (mobile), the tablet is a significant predictor and has a significant impact on reach. However, the desktop is an insignificant factor and it might be unnecessary to advertise on a desktop for reaching users.
The placement of the ad on the platform has an impact on reach. Marketplace (p Value = 0.0054) and Right Column (p Value = 0.0358) are significant. Those placements affect the number of users who see the ads and showing the ads in those placements might be beneficial for the brand.

Lastly, manually optimized ads in Instagram (p Value = 0.0342) are a significant predictor for reach however Facebook (p Value = 0.2171) manually optimized ads are not significant predictors for reach. It might be beneficial to continue to broadcast ads on Instagram to reach users. For DPA, DPA ad on Facebook (p Value = 0.0187) is a significant predictor comparing to Instagram DPA. DPAs on Facebook have an effect on the number of people who see the advertisement.

Table 4.3 Estimation Results of Equation 1

Parameter Estimates			
Parameter Name	**Parameter**	**Estimate***	**p-value**
Intercept	θ	2869(948.1160)	0.0026
First-order Lag	λ_1	0.7315(0.0304)	<.0001
	λ_5	0.2378(0.0447)	<.0001
	λ_6	0.2455(0.0433)	<.0001
Days	μ_1	-3208(1134)	0.0049
	μ_2	-3469(1128)	0.0022
	μ_3	-4190(1132)	0.0002
	μ_4	-4249(1137)	0.0002
	μ_5	-2652(1127)	0.0191
	μ_7	-2171(1129)	0.0551

Months	γ_4	-2272(1363)	0.0962
	γ_5	-8592(1924)	<.0001
	γ_6	14439(2186)	<.0001
	γ_7	13999(2270)	<.0001
	γ_8	13615(2245)	<.0001
	γ_9	13615(2243)	<.0001
	γ_{10}	13917(2243)	<.0001
	γ_{11}	13033(2652)	<.0001
Special Day	ϕ_2	2063(1544)	0.1823
	ϕ_7	-2667(1560)	0.0880
Advertising Model	η_1	-5628(2386)	0.0187
	η_2	5163(2431)	0.0342
	η_3	1985(1606)	0.2171
Device	ρ_2	8419(2683)	0.0018
Placement of Ad	σ_1	4374(1563)	0.0054
	σ_2	3307(1570)	0.0358

*Standard errors can be found in parentheses with estimated values

4.3.2 Click

The autoregressive model is estimated to understand which factor has an effect on the total number of daily clicks over time. To achieve parsimony, the final model is obtained by deleting non-significant variables with t-values less than one (Kiygi-Calli et al., 2017). We delete all of the regressors when their associated t-values are smaller than 1 in absolute value (Calli et al., 2012). According to estimation results of Equation 2, Mean Square Error was 2,403 and the adjusted R-square was 0.9170 which states that the data fit the model.

The results show that Monday and Wednesday are significant predictors for click with a significant level of 0.05. Sunday (p-Value= 0.0963) is almost significant. This result suggests that different days have different effects on the number of clicks. The benchmark of the analysis is Saturday and Monday, Wednesday and Sunday have a negative effect on clicks comparing to Saturday. This suggests that most of the users click the ads on Saturday but days generally have an effect on the number of clicks.

In months March and May have not significant effect on the number of clicks. However January, April, June, July, August, September, October and November have a significant effect on the number of clicks. February (p-Value= 0.0849) has almost significant effect on click. Although they have a negative impact on the click comparing to December, it can be seen that these months have an important effect on how many people clicks on the ad.

The results suggest that a special day was not a significant predictor of reach. Special days such as Valentine’s Day do not affect the number of users who see the ad on the current day. In addition, the days before the special day have not also a significant effect on the number of clicks. We examine till a week before the special day ane any of the variables are significant.

The device which the ad has shown has an effect on the clicks that the ad gets. Comparing to our benchmark variable which is mobile, tablet (p Value = 0.0036) is a significant predictor and has an effect on the number of clicks. However, the desktop is an insignificant factor and it might be unnecessary to advertise on a desktop for driving users to go to the website.

The placement of the ad on the platform has an impact on clicks. As in the reach, Marketplace (p Value = 0.0164) and Right Column (p Value = 0.0439) are significant with a significant level of 0.05. Those placements affect the number of users who also click the ads and showing the ads in those areas might be beneficial for the brand to drive consumers to their product or website.

Lastly, manually optimized ads in Instagram (p Value = 0.0101) are a significant predictor for the number of clicks and Facebook (p Value = 0.0666) is an almost significant predictor for the number of clicks. The results suggest that they have an effect on the number of people who click the ad. It might be beneficial to continue using those ad formats for reaching users. For DPA, DPA ad on Facebook (p Value = 0.0067) is a significant predictor comparing to Instagram DPA. DPAs on Facebook have a positive effect on the number of people who click the advertisement comparing to manually optimized Facebook ads.

Table 4.4 Estimation Results of Equation 2

Parameter Estimates			
Parameter Name	**Parameter**	**Estimate**	**p-Value**
Intercept	θ	25.7149(7.3106)	0.0005
First-order Lag	λ_1	0.7553(0.0463)	<.0001
	λ_2	-0.0956(0.0584)	0.1024
	λ_3	0.0768(0.0438)	0.0802
Days	μ_1	-26.4291(7.3172)	0.0003
	μ_2	-11.2885(7.3765)	0.1266
	μ_3	-21.2292(7.3014)	0.0038
	μ_4	-11.8101(7.3323)	0.1079
	μ_7	-12.1450(7.2888)	0.0963
Months	γ_1	-33.2537(9.2583)	0.0004
	γ_2	-14.8380(8.5928)	0.0849
	γ_4	-38.7867(10.8032)	0.0004
	γ_5	-21.6646(14.5242)	0.1365
	γ_6	-74.1213(15.8559)	<.0001
	γ_7	-93.7236(16.7568)	<.0001
	γ_8	-82.0268(16.4169)	<.0001
	γ_9	103.1339(17.0106)	<.0001
	γ_{10}	-90.3816(16.6749)	<.0001
	γ_{11}	-98.6073(19.3703)	<.0001
Special Day	ϕ_1	16.0140(11.5800)	0.1674
Advertising Model	η_1	-51.1100(18.7631)	0.0067
	η_2	47.5275(18.4050)	0.0101
	η_3	-22.1686(12.0579)	0.0666
Device	ρ_2	61.8897(21.1320)	0.0036
Placement of Ad	σ_1	26.9629(11.1938)	0.0164
	σ_2	23.6508(11.7018)	0.0439

4.3.3 Purchase

The autoregressive model was conducted to understand which factor has an effect on the total number of daily purchases. To achieve parsimony, the final model is obtained by deleting non-significant variables with t-values less than one (Kiygi-Calli et al., 2017). We delete all of the regressors when their associated t-values are smaller than 1 in absolute value (Calli et al., 2012). According to estimation results of Equation 3, Mean Square Error was 2.8 and the adjusted R-square was 0.5577 which states that the data is fit to the model.

The results present that Wednesday (p Value = 0.0169) is significant which means those different days have different effects on number of purchases. The benchmark of the days is Saturday and all the other days have a negative effect on purchases comparing to Saturday. This suggests that most of the users purchase the product on Saturday but Wednesday have also effect on the number of purchases.

In months, May and August have not significant effects on the number of purchases. However January, February, March, April, June, July, September, October and November have significant effects on the number of purchases. Although they have a negative impact on purchase comparing to December, it can be seen that these months have an important effect on how many people purchase.

The results suggest that special day is not a significant predictor of reach. Special days such as Valentine's Day do not affect the number of purchases. However, one day before the special day (p Value = 0.0026) is a significant predictor. These results suggest that the number of users who purchase the product is higher a day before the special day than the number of purchases on the special day.

The device which the ad has shown has an effect on the number of purchases that the ad gets. Comparing to the mobile, tablet (p Value = <.0001) is a significant predictor and has a higher impact on the number of purchases. However again, the desktop is an insignificant factor and it might be unnecessary to advertise on a desktop for driving users to purchase the products.

The placement of the ad on the platform has an impact on also the number of purchases. Right Column (p Value = 0.0707) is almost significant however Marketplace or other placements are not significant for purchase. Right Column affects the number of the purchase and showing the ads in this area might be beneficial for the brand to drive consumers to buy the products.

Lastly, manually optimized ads on Instagram (p Value = <.0001) are a significant predictor for purchase. The results suggest that they have an effect on the number of people who buy the product. Opposite of the estimation results of Equations 1 and 2, only in purchase Instagram manually set up ads has a positive impact on the number of purchases. It might be beneficial to continue using this ad format for leading consumers to buying. For DPA models, neither on Instagram nor on Facebook, dynamic product ads are significant predictors.

Table 4.5 Estimation Results of Equation 3

Parameter Estimates			
Parameter Name	**Parameter**	**Estimate**	**p-Value**
Intercept	θ	2.1392(0.4103)	<.0001
First-order Lag	λ_1	0.3154(0.0449)	<.0001
	λ_2	0.0884(0.0475)	0.0633
	λ_3	0.0903(0.0461)	0.0506
	λ_5	0.0689(0.0461)	0.1355
	λ_6	0.0711(0.0479)	0.1384
	λ_7	0.1897(0.0454)	<.0001
Days	μ_3	0.5396(0.2250)	0.0169
	μ_7	0.2973(0.2261)	0.1892
Months	γ_1	2.1058(0.4255)	<.0001
	γ_2	2.1300(0.4366)	<.0001
	γ_3	1.8809(0.4240)	<.0001
	γ_4	1.5149(0.3629)	<.0001

	γ_6	1.3969(0.3846)	0.0003
	γ_7	0.8389(0.3755)	0.0260
	γ_9	1.2688(0.3845)	0.0010
	γ_{10}	1.6082(0.3960)	<.0001
	γ_{11}	0.8373(0.3804)	0.0282
Special Day	ϕ_1	1.2018(0.3975)	0.0026
Advertising Model	η_2	1.8083(0.4286)	<.0001
Device	ρ_2	2.895(0.6607)	<.0001
Placement of Ad	σ_2	0.7464(0.5503)	0.1756
	σ_5	0.5296(0.2903)	0.0707

5. DISCUSSION AND CONCLUSION

5.1 DISCUSSION

This study provides beneficial insights about social media advertising models for niche product brands and the usage of the DPA advertising model. It also examines the additional factors like social media platforms, devices and the placement that advertising displayed which affect the performance of the ads. It can be seen the difference between platform performances among DPA and manually set up ads and the most effective devices that affect the performance of the ads.

The findings indicate that DPA does have a significant positive impact on the performance of reach and click by a niche product brand. Manually optimized ads are significant for both platforms for reach and click and only Instagram for purchase. However, similarly to the initial hypothesis (Hypothesis 7), Facebook DPA has a significant effect on reach and click and Instagram has no significant effect on any of the estimates. The results show that Facebook is significant than Instagram when it is compared for DPAs. As stated in Semeradova and Weinlich (2020), the placement choice has a critical impact on the performance of Facebook ads for both DPA and manually optimized ads. Our findings confirm that Right Column is a significant predictor for all the dependent variables and Marketplace is significant for reach and click. In addition, it can be concluded that for both manually set up ads and dynamic product ads, different days and months have different effects on the dependent variables, which highlights the seasonality and special days. As socks are mostly for cold weather and seem by consumers as a great option of gift, December is a great period of success for the brand since it is winter and there is New Year’s Eve celebration. The most attractive feature of the socks of this brand is their personalized style. Consumers can put photos of their pets, friends or loved ones and most of the communication of the brand is based on this. This may assist consumers in positioning the product as a gift. In addition, the tablet is the most effective device for all three dependent variables and targeting tablet devices more may help to increase the rates.

As it has been discussed in the literature, personalization is a tool to increase impulsive purchase (Dawson and Kim, 2010). Impulse buying might be triggered by the DPA because of its features. The high level of personalization of the DPA and the easiness of the process may influence the users and lead them to buy the product. DPA on Facebook has a positive effect on clicks. This can be seen as a sign of impulse buying however contrary to the literature when we examine the purchase results, and we found that there is no significant effect of DPA on purchase on both social media channels, Facebook and Instagram. It can be claimed that DPA has no significant effect on impulse buying behavior. The type of the product and personalization feature of the product might be the cause of this solution; that is why examining other types of products' DPA results might improve the study.

Answers on the research questions and hypotheses in order to determine the research findings:

Research Question 1: Do dynamic product ads have a higher impact on purchase comparing to manually set up ads?
Answer: There is no significant effect of DPA ads on purchases.

Research Question 2: Do dynamic product ads have a significant impact on clicks comparing to manually set up ads?
Answer: Yes. Not Instagram but Facebook dynamic ads have a significant impact on clicks and it is more effective comparing to manually set up ads.

Research Question 3: Do consumers purchase more during or before the special days?
Answer: Yes. It can be seen that purchases and clicks have been affected one day before the special day.

Research Question 4: Do manually optimized ads have a significant impact on reach more than dynamic product ads?
Answer: No. Facebook dynamic product ads have a significant influence on reach than manually optimized Instagram and Facebook ads. However, it should be considered that

Facebook and Instagram have an effect on reach although only Facebook DPA has an effect.

Research Question 5: Do consumers purchase more during weekends?
Answer: Yes. Saturday has a significant effect on the purchase.

Research Question 6: Does mobile an appropriate device than tablet or desktop for generating more clicks?
Answer: Mobile was a benchmark for the analysis and tablet is a significant predictor however desktop is not significant for clicks.

Research Question 7: Does Instagram a more appropriate platform than Facebook for dynamic product ads to increase sales amount?
Answer: No. Facebook dynamic product ads have a significant impact on reach and click however both platforms are not significantly effective on purchase.

According to our results, accepted and not accepted hypotheses can be found in the table below (Table 5.1).

Table 5.1 Status of Hypotheses

	Reach	Click	Purchase
Accepted	H4: Dynamic product ads have a positive impact on reach	H2:Dynamic product ads have a positive effect on the number of clicks	H3:Special days have a positive effect on the number of purchase.
	H7: Facebook has a positive impact on reaching consumers for DPA.	H6: Ads for tablet devices have a positive effect on clicks.	H5: Weekends have a positive effect on purchase
		H8: Instagram has a positive impact on clicks for manually optimized ads.	H9: Instagram has a positive impact on purchases for manually optimized ads.
Not Accepted			H1: Dynamic product ads have a positive effect on driving to purchase.

5.2 CONCLUSION

This research aims to examine the long-term effectiveness of Dynamic Product Ads and compare it with manually optimized ads on reach, click and purchase for a niche brand. Based on the quantitative analysis of the reach, click and purchase data of the given ads for 486 days in total, it can be concluded that there is a significant difference between DPAs and manually set up ads in these three dependent variables for a new niche product brand. Facebook DPA has an impact on the reach and clicks however Instagram DPA does not affect any of them. Facebook and Instagram manually set up ads have an effect on reach and click however they are less effective than DPA and only Instagram has an impact on purchase. As purchase has not been affected by the DPA model, we can say that DPA has no significant effect on impulsive buying from social media. This might be caused by the type of the product, the personalization part of the product or the level of awareness of the brand. The founder of the brand was consulted to get an expert opinion. The owner of the brand adds that the view and interaction rates of the brand's organic content on TikTok are impressively high and have a great effect on the awareness of the brand and the sales rates. Tiktok is a popular platform especially among small businesses that need to find consumers who might be interested. This might be an indicator that the brand needs more awareness campaigns and reaching more users in this stage of its evolution. Niche product brands that need more awareness should consider the campaigns that generate more reach to give consumer trust and advertising models with the aim of purchase; in this case, DPA might help them to achieve this goal. According to Semerádová and Weinlich (2020), manually optimized ads better perform at the stages of awareness and consideration in Facebook, similar to our findings. Their findings indicate that in the conversion stage, DPAs are more effective than manually optimized ads, opposite to our findings, which might be caused by the type of the product. Although there are different successful cases on Facebook that show the benefits of AI-based advertising, niche products might need more creative content to attract consumers and motivation of driving them to the last stage, purchase.

This study can be improved by analyzing DPA and manually optimized data for different brands from different sectors like FMCG companies or small businesses with mainstream products. In addition, getting data from a longer period might also increase the accuracy and help to see the wider picture of the ad performances.

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CURRICULUM VITAE

Personal Information

Name/Surname : Yağmur Eyilmez

Education

Undergraduate Education : Bahcesehir University Advertising

Graduate Education : Kadir Has University Business Intelligence and Analytics

Foreign Language Skills : Turkish and English

Work Experience

Name of Employer and Dates of Employment: Genart Media 2020

APPENDIX A

SAS Studio 3.8 codes are given below.

```
MEANS
proc means data=dpa.data_02072021;
var Total_Reach
Total_Click
Total_Purchase
Total_CPC
Ave_Total_CPC
;
run;

CORRELATION
Proc corr data=dpa.data_02072021;
var Total_Reach
Total_Click
Total_Purchase
Total_CPC
Ave_Total_CPC
;
run;

CORRELATION2
Proc corr data=dpa.data_02072021;
var Instagram
Facebook
Mobile
Tablet
Desktop
Marketplace
Right_Column
Explore_Page
Feed_Page
Story_Page
Sum_of_Freqency_Standard
Sum_of_Frequency_DPA
Total_Impression
;
run;

PDLREG REACH
proc pdlreg data=dpa.data_02072021;
model total_reach= Total_reach_T1 /*Total_reach_T2 Total_reach_T3
Total_reach_T4*/ Total_reach_T5 Total_reach_T6
/*Total_reach_T7 */
Monday Tuesday Wednesday--friday Sunday /*January--March*/ April--November
```

```
/*Special_Day Special_Day_T1*/ Special_Day_T2 /*Special_Day_T3*/
Special_Day_T7
/*Instagram_DPA*/
/*Instagram_DPA_T1*/ /*Instagram_DPA_T2 Instagram_DPA_T3*/
/*Instagram_DPA_T7*/
Facebook_DPA /*Facebook_DPA_T1 Facebook_DPA_T2 Facebook_DPA_T3*/
/*Facebook_DPA_T7*/
Intagram_Standard Intagram_Standard_T1
/*Intagram_Standard_T2 Intagram_Standard_T3*/ Intagram_Standard_T7
Facebok_Standard Facebok_Standard_T1 /*Facebok_Standard_T2
Facebok_Standard_T3*/
/*Facebok_Standard_T7*/
/*mobile*/ tablet /*desktop*/
Marketplace    /*Feed_Page Story_Page*/
Right_Column
/*Explore_Page*/
;
output out=dpa.reg_output;
run;

PRDLREG PURCHASE
proc pdlreg data=dpa.data_02072021;
model total_purchase= Total_purchase_T1 Total_purchase_T2 Total_purchase_T3
/*Total_purchase_T4*/ Total_purchase_T5 Total_purchase_T6
Total_purchase_T7
/*Monday Tuesday*/ Wednesday /*Thursday--friday*/ Sunday January--April June--
July
September--November
/*Special_Day*/ Special_Day_T1 /*Special_Day_T2*/ /*Special_Day_T3*/
/*Special_Day_T7*/
/*Instagram_DPA*/
/*Instagram_DPA_T1 Instagram_DPA_T2 Instagram_DPA_T3 Instagram_DPA_T7*/
/*Facebook_DPA Facebook_DPA_T1 Facebook_DPA_T2 Facebook_DPA_T3
Facebook_DPA_T7*/
Intagram_Standard /*Intagram_Standard_T1
Intagram_Standard_T2 Intagram_Standard_T3 Intagram_Standard_T7*/
/*Facebok_Standard*/ /*Facebok_Standard_T1 Facebok_Standard_T2
Facebok_Standard_T3
Facebok_Standard_T7*/
/*mobile*/ tablet /*desktop*/
/*Marketplace Feed_Page*/ Story_Page
Right_Column
/*Explore_Page*/
;
output out=dpa.reg_output1;
run;

PDLREG CLICK
```

```
proc pdlreg data=dpa.data_02072021;
model total_Click= Total_Click_T1 Total_Click_T2 Total_Click_T3
/*Total_Click_T7*/
Monday Tuesday Wednesday--Thursday /*friday*/ Sunday January--February April--
November
/*Special_Day*/ Special_Day_T1 /*Special_Day_T2 Special_Day_T3*/
/*Special_Day_T7*/
/*Instagram_DPA*/
Facebook_DPA
Intagram_Standard
Facebok_Standard
/*mobile*/ tablet /*desktop*/
Marketplace    /*Feed_Page Story_Page*/
Right_Column
/*Explore_Page*/
;
output out=dpa.reg_output2;
run;

PDLREG REACH2
proc pdlreg data=dpa.data_02072021;
model total_reach= Total_reach_T1 /*Total_reach_T2 Total_reach_T3
Total_reach_T4*/ Total_reach_T5 Total_reach_T6
/*Total_reach_T7 */
Monday Tuesday Wednesday--friday Sunday /*January--March*/ April--November
/*Special_Day Special_Day_T1*/ Special_Day_T2 /*Special_Day_T3*/
Special_Day_T7
/*Instagram_DPA*/
/*Instagram_DPA_T1*/ /*Instagram_DPA_T2 Instagram_DPA_T3*/
/*Instagram_DPA_T7*/
Facebook_DPA /*Facebook_DPA_T1 Facebook_DPA_T2 Facebook_DPA_T3*/
/*Facebook_DPA_T7*/
Intagram_Standard /*Intagram_Standard_T1*/
/*Intagram_Standard_T2 Intagram_Standard_T3*/ /*Intagram_Standard_T7*/
Facebok_Standard /*Facebok_Standard_T1*/ /*Facebok_Standard_T2
Facebok_Standard_T3*/
/*Facebok_Standard_T7*/
/*mobile*/ tablet /*desktop*/
Marketplace    /*Feed_Page Story_Page*/
Right_Column
/*Explore_Page*/
;
output out=dpa.reg_output3;
run;
```