



**THE EFFECT OF TRUST AND PERSONALIZATION IN PROGRAMMATIC
ADVERTISING ON CONSUMERS' PURCHASE INTENTION**

Burçin SÜRÜCÜ

Master Thesis

Advisor: Assist. Prof. Hale Fulya YÜKSEL

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T.C.
AFYON KOCATEPE UNIVERSITY
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MASTER THESIS

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PURCHASE INTENTION**

by
Burçin SÜRÜCÜ

Advisor
Assist. Prof. Hale Fulya YÜKSEL

AFYONKARAHİSAR 2021

OATH TEXT

I hereby declare that this master's thesis titled **“The Effect of Trust and Personalization in Programmatic Advertising on Consumers' Purchase Intention”** has been written by myself according to academic rules and ethical conduct. I also declare that all materials benefited in this thesis consist of the mentioned resources in the reference list. I verify all these with my honor.

.../.../.....

Burçin SÜRÜCÜ



**DECISION OF THESIS JURY AND APPROVAL OF INSTITUTE
DIRECTORATE**

TEZ JÜRİSİ KARARI VE ENSTİTÜ ONAYI

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İmza

Tez Danışmanı	: Dr. Öğr. Üyesi Hale Fulya YÜKSEL
Jüri Üyeleri	: Prof. Dr. Erkan AKAR
	: Prof. Dr. Aydın KAYABAŞI

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**Prof. Dr. Elbeyi PELİT
MÜDÜR**

ABSTRACT

THE EFFECT OF TRUST AND PERSONALIZATION IN PROGRAMMATIC ADVERTISING ON CONSUMERS' PURCHASE INTENTION

Burçin SÜRÜCÜ

AFYON KOCATEPE UNIVERSITY
INSTITUTE OF SOCIAL SCIENCES
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Advisor: Assist. Prof. Dr. Hale Fulya YÜKSEL

As a result of increased use of smartphones and computers, consumers / users create an excessive amount of data on the internet. Personal and behavioral data can be easily collected in the digital environment. Programmatic advertising, one of the artificial intelligence applications, also try to use this data in a useful way for marketing. Artificial intelligence technologies are adapted to programmatic advertising applications to improve the overall service provided. Thanks to programmatic advertising applications, personalized messages are shown to consumers. Although programmatic advertising has become an important subject in academic literature recently, it is a slowly progressing research area in terms of its effects on consumer behavior. In this study, the effects of programmatic advertising on consumers' purchase intention is examined as well as the effects of two factors in programmatic advertising –trust and personalization– on purchase intention. Furthermore, the differences in purchase intentions according to the demographic variables and other variables are also investigated. The data is obtained from 388 participants using an online questionnaire and SPSS and AMOS programs are used in the analysis of the collected data. As a result of the analyses, it is found that trust in programmatic advertising has a significant effect on purchase intention. On the other hand, it is determined that personalization in programmatic advertising does not have a significant effect on purchase intention. Additional analyses revealed different effects of demographic variables and perceptions of programmatic advertising practices on purchase intention. It is believed that the findings will both contribute to theoretical literature and provide insight to businesses that use programmatic advertising applications in marketing.

Keywords: Artificial Intelligence, Programmatic Advertising, Personalization, Trust, Purchase Intention.

ÖZET

PROGRAMATİK REKLAMCILIKTA GÜVEN VE KİŞİSELLEŞTİRMENİN TÜKETİCİLERİN SATIN ALMA NİYETİNE ETKİSİ

Burçin SÜRÜCÜ

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Danışman: Dr. Öğr. Üyesi Hale Fulya YÜKSEL

Akıllı telefon ve bilgisayar kullanımının artması sonucu tüketiciler / kullanıcılar internette aşırı miktarda veri oluşturmaktadırlar. Kişisel ve davranışsal veriler dijital ortamda kolaylıkla toplanabilmektedir. Yapay zeka uygulamalarından biri olan programatik reklamlar da bu verileri pazarlama açısından faydalı şekilde kullanmaya çalışmaktadır. Yapay zeka teknolojileri, sağlanan genel hizmeti geliştirmek için programatik reklam uygulamalarına uyarlanmaktadır. Programatik reklam uygulamaları sayesinde tüketicilere kişiselleştirilmiş mesajlar gösterilmektedir. Programatik reklamcılık, akademik literatürde yakın zamanda önemli bir konu haline gelmesine rağmen tüketici davranışına etkisi bakımından yavaş ilerleyen bir araştırma alanıdır. Bu çalışmada, programatik reklamcılığın tüketicilerin satın alma niyetine etkileri incelenirken aynı zamanda programatik reklamcılıktaki iki faktörün –güven ve kişiselleştirme-satın alma niyetine etkisi de incelenmiştir. Ayrıca, demografik verilere ve diğer değişkenlere göre satın alma niyetlerinde farklılaşma olup olmadığı da incelenmiştir. Veriler 388 katılımcıdan online anket yöntemi kullanılarak elde edilmiştir ve toplanan verilerin analizinde SPSS ve AMOS programları kullanılmıştır. Yapılan analizler sonucunda, programatik reklamcılıkta güven faktörünün satın alma niyeti üzerinde anlamlı etkisi olduğu bulunmuştur. Öte yandan, programatik reklamcılıkta kişiselleştirme faktörünün satın alma niyeti üzerinde anlamlı bir etkisi olmadığı tespit edilmiştir. İlave analizler, demografik değişkenler ve programatik reklamcılığa dair algıların satın alma niyetinde ne tür farklılıklara sebep olduğunu ortaya koymuştur. Elde edilen bulguların hem teorik literatüre katkı sağlayacağı hem de programatik reklamcılık uygulamalarını pazarlamada kullanan işletmelere öngörü kazandıracağına inanılmaktadır.

Anahtar Kelimeler: Yapay Zeka, Programatik Reklamcılık, Kişiselleştirme, Güven, Satın Alma Niyeti.

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TABLE OF CONTENTS

	<u>Page</u>
OATH TEXT	ii
DECISION OF THESIS JURY AND APPROVAL OF INSTITUTE DIRECTORATE	iii
ABSTRACT	iv
ÖZET.....	v
ACKNOWLEDGEMENTS	vi
TABLE OF CONTENTS	vii
LIST OF TABLES.....	ix
LIST OF FIGURES.....	x
LIST OF SYMBOLS AND ABBREVIATIONS.....	xi
INTRODUCTION	1

FIRST PART

ARTIFICIAL INTELLIGENCE AND PROGRAMMATIC ADVERTISING

1. DEFINITION AND SCOPE OF ARTIFICIAL INTELLIGENCE.....	4
1.1. COMPARISON OF HUMANS AND MACHINES	5
1.2. HISTORY OF ARTIFICIAL INTELLIGENCE	6
1.3. OPERATION OF ARTIFICIAL INTELLIGENCE	8
1.4. BENEFITS AND DRAWBACKS OF ARTIFICIAL INTELLIGENCE	11
1.5. USES OF ARTIFICIAL INTELLIGENCE	14
1.6. THE USE OF ARTIFICIAL INTELLIGENCE IN MARKETING.....	18
1.7. CONSUMERS' PERCEPTION OF ARTIFICIAL INTELLIGENCE	20
2. PROGRAMMATIC ADVERTISING	22
2.1. PROGRAMMATIC ADVERTISING ECOSYSTEM AND PROCESS.....	25
2.2. IMPORTANCE OF PROGRAMMATIC ADVERTISING	29
2.3. ADVANTAGES AND DISADVANTAGES OF PROGRAMMATIC ADVERTISING	34
2.3.1. Advantages of Programmatic Advertising	34
2.3.2. Disadvantages of Programmatic Advertising	35
2.4. CONSUMERS' PERCEPTION OF PROGRAMMATIC ADVERTISING	37

SECOND PART

TRUST, PERSONALIZATION AND PURCHASE INTENTION

1. TRUST.....	40
1.1. CONSUMERS' PERCEPTION OF ONLINE TRUST	40
1.2. CONSUMERS' TRUST IN PROGRAMMATIC ADVERTISING	42
2. PERSONALIZATION	44
2.1. PERSONALIZATION TYPES	44
2.2. CONSUMERS' PERCEPTION OF ONLINE PERSONALIZATION	47
2.3. PERSONALIZATION IN PROGRAMMATIC ADVERTISING	47
3. PURCHASE INTENTION	50
3.1. ONLINE PURCHASE INTENTION.....	51
3.2. PURCHASE INTENTION IN PROGRAMMATIC ADVERTISING	52

THIRD PART

THE EFFECT OF TRUST AND PERSONALIZATION IN PROGRAMMATIC ADVERTISING ON CONSUMERS' PURCHASE INTENTION

1. THE PURPOSE AND IMPORTANCE OF THE RESEARCH	54
2. RESEARCH HYPOTHESES AND RESEARCH MODEL.....	54
3. SCOPE AND LIMITATIONS OF THE RESEARCH	57
4. RESEARCH METHOD.....	57
4.1. DATA COLLECTION METHOD.....	57
4.2. POPULATION AND SAMPLE.....	58
4.3. DATA ANALYSIS	59
5. RESEARCH FINDINGS	59
5.1. DESCRIPTIVE STATISTICS	59
5.2. EXPLORATORY FACTOR ANALYSIS	62
5.3. CONFIRMATORY FACTOR ANALYSIS.....	65
5.4. ANALYSIS OF STRUCTURAL EQUATION MODEL AND HYPOTHESIS TESTING.....	68
5.5. ANALYSES OF DIFFERENCES IN PURCHASE INTENTION ACCORDING TO DEMOGRAPHIC AND OTHER VARIABLES	69
5.5.1. Purchase Intention Based on Gender	70
5.5.2. Purchase Intention Based on Age Groups.....	70
5.5.3. Purchase Intention Based on Education Level	71
5.5.4. Purchase Intention Based on Monthly Income.....	71
5.5.5. Purchase Intention Based on Marital Status	72
5.5.6. Purchase Intention Based on Occupation	73
5.5.7. Purchase Intention Based on Online Shopping Status.....	73
5.5.8. Purchase Intention Based on Frequency of Online Shopping.....	73
DISCUSSION, CONCLUSION AND SUGGESTIONS	75
REFERENCES	79
APPENDICES.....	92
CURRICULUM VITAE	99

LIST OF TABLES

	<u>Page</u>
Table 1. Contribution of Artificial Intelligence to Some Sectors and Usage Areas	14
Table 2. 5 Ps of Marketing AI by Paul Roetzer.....	20
Table 3. Aims of Using Programmatic Advertising	31
Table 4. Types of Personalization	45
Table 5. Distribution of Gender.....	60
Table 6. Distribution of Marital Status	60
Table 7. Distribution of Educational Level	60
Table 8. Distribution of Monthly Income.....	60
Table 9. Distribution of Age Groups	60
Table 10. Distribution of Occupation	60
Table 11. Online Shopping Status	61
Table 12. Distribution of Frequency of Online Shopping	61
Table 13. The State of Ownership of Digital Tools by Participants.....	61
Table 14. Participants' Approach to Programmatic Advertising.....	62
Table 15. Buying Products with Programmatic Advertising.....	62
Table 16. Data Suitability Test for Exploratory Factor Analysis	63
Table 17. Exploratory Factor Analysis Statistics	64
Table 18. EFA Factor Correlation Matrix	64
Table 19. The Goodness of Fit Values for Confirmatory Factor Analysis.....	65
Table 20. Goodness of Fit Statistics for the First Model.....	66
Table 21. The Goodness of Fit Statistics of Confirmatory Factor Analysis for the Modified Model	67
Table 22. CR, AVE and Factor Correlation Values of Modified Model.....	68
Table 23. The Goodness of Fit Statistics for Structural Equation Model.....	68
Table 24. Normality Test for PI_{avg} Variable	70
Table 25. Descriptive Statistics of PI_{avg} Variable	70
Table 26. Results of the T-Test for Gender Groups	70
Table 27. Result of the One-Way ANOVA Test for Age Groups	71
Table 28. Result of the One-Way ANOVA Test for Education Levels	71
Table 29. Result of the One-Way ANOVA Test for Monthly Income Groups.....	71
Table 30. Result of the Post Hoc Test for Monthly Income Groups	72
Table 31. Results of the T-Test for Marital Status Groups.....	73
Table 32. Result of the One-Way ANOVA Test for Occupation Groups	73
Table 33. Results of the T-Test for Online Shopping Status	73
Table 34. Result of the One-Way ANOVA Test for Frequency Online Shopping	74

LIST OF FIGURES

	<u>Page</u>
Figure 1. Subfields of Artificial Intelligence.....	9
Figure 2. First Known Deep Network	10
Figure 3. Expectations for AI’s Effect on Companies in Different Sectors	16
Figure 4. Reasons for Adopting for AI.....	17
Figure 5. The Level of AI Implementation in Organizations	17
Figure 6. Individuals’ Thoughts on Artificial Intelligence.....	21
Figure 7. Programmatic Advertising Ecosystem.....	27
Figure 8. Future Programmatic Ecosystem	29
Figure 9. Proportion of Programmatic Users for Display Campaigns	33
Figure 10. Programmatic Ad Spending	34
Figure 11. Benefits of Programmatic Advertising	35
Figure 12. Concerns about Programmatic Advertising	36
Figure 13. Research Model	55
Figure 14. CFA, Standardized Factor Loadings and Correlations of Measurement Model	66
Figure 15. CFA, Standardized Factor Loadings and Correlations of the Modified Model	67
Figure 16. Standardized Regression Coefficients of the Structural Model	69

LIST OF SYMBOLS AND ABBREVIATIONS

%: Percentage
&: and
AD: Advertising
ADS: Advertisements
AGFI: Adjusted Goodness of Fit Index
AI: Artificial Intelligence
AMOS: Analysis of Moment Structures
APPS: Applications
AVE: Average Variance Extracted
Avg: Average
CFA: Confirmatory Factor Analysis
CFI: Comparative Fit Index
CR: Composite Reliability
EFA: Exploratory Factor Analysis
GFI: Goodness of Fit Index
IAB: Interactive Advertising Bureau
IBM: International Business Machines
NFI: Normed Fit Index
OECD: Organization for Economic Co-operation and Development
PERS: Personalization
PI: Purchase Intention
PMP: Private Market Place
PwC: Price waterhouse Company
RMR: Root Mean Square Residuals
RMSEA: Root Mean Square Error of Approximation
SEM: Structural Equation Model
SMS: Short Messaging Service
SPSS: Statistical Package for the Social Sciences
TR: Trust
URL: Uniform Resource Loader

INTRODUCTION

As consumers are now spending a lot of time on the Internet, the digital data generated by their online activities is increasing rapidly. For marketing purposes, the use of artificial intelligence applications which utilizes this digital data is also increasing. With the advancement of technology, traditional advertising is leaving its place to programmatic advertising applications (Deng et al., 2019) which is one of the practices of artificial intelligence.

Companies want to make the consumer feel special by using the marketing solutions offered by the Internet in the most effective way in order to be in a better position than competitors. At the same time, they benefit from the advantages of the Internet in order to reach the right consumers, create a sense of trust and become the preferred brand of consumers. The Internet is the most frequently used source of information today. Consumers use this source of information to examine the products they need and to purchase when necessary (Önay, 2010: 179).

Since consumers spend most of their time on the Internet during the day, personalized messages that best suit the target audience can be delivered over the Internet. Consumers can get detailed information about the products or services they need with a single click, thanks to the personalized ads they encounter in digital environments. These personalized messages can be created using programmatic advertising. This study examines trust and personalization factors in programmatic advertising in terms of consumers' purchase intention. Trust is a major success factor in the online domain. In fact, on the Web trust often serves as the sole foundation on which consumers base their research and purchase decisions in lack of further information about firms (Bleier & Eisenbeiss, 2015). Orange (2014) found that in digital environments, consumers expect more transparent practices in protecting their personal data. Data-driven advertising models are widely used by marketers lately. Internet Advertising Bureau UK (2011) recommends that companies use certain icons, such as (3D Security, Visa) to ensure security of data. Such symbols affect the perception of trust.

Personalization is a another important factor in programmatic advertising. Wessel and Thies (2015) categorized levels of personalization (no personalization; in-advance; in-advance and continuous; in-advance, continuous and design) and concluded

that, different levels of personalization create different purchase intentions. The result of Wessel and Thies's (2015) study was that user-oriented personalization had a marked impact on purchase intention. Doorn & Hoekstra (2013), state that consumers with a high level of privacy concern perceive personalized advertisements as intrusive, so consumers are less likely to purchase.

Programmatic advertisements affect the purchase intention of consumers. There are few studies in the literature examining the relationship between programmatic advertising and purchasing. Zarouali et al. (2017) states that the effect of targeted advertisements on purchase intention is higher than that of non-targeted advertisements. With the development of technology, the effect of traditional purchasing methods is decreasing. Programmatic advertising applications are more practical and effective than traditional purchases (Saman, 2020). Lomas (2020) suggests that leaders who play a key role in programmatic (such as a CIO) should have a better command of management processes. Academic studies on programmatic advertising, which has become one of the important strategies of digital marketing and online advertising (Högström & Wallin, 2017) are still at the beginning level. In this research, it is believed that the findings will contribute to theoretical literature by explaining the effect of two important factors in programmatic advertising –trust and personalization- on consumers' purchase intention. Moreover, the findings will hopefully provide insight to businesses that use programmatic advertising applications in marketing.

This thesis consists of three main sections. In the first part, artificial intelligence and programmatic advertising are described in detail. The history, operation, benefits and drawbacks, and uses of artificial intelligence are explained and consumers' perception of artificial intelligence is stated. Moreover, the programmatic advertising ecosystem is described and the importance, advantages and disadvantages of programmatic advertising, are explained as well as consumer's perception of programmatic advertising.

In the second part, the main variables of the study are explained. These variables are; trust, personalization and purchase intention. The part starts with describing the definition of the trust and consumers' trust in programmatic advertising. Then, the definition of personalization, personalization types and personalization in programmatic advertising are mentioned. At the end of the second part, online purchase intention and purchase intention in programmatic advertising are explained.

In the last section, the research model is examined to explain the effect of consumers' perception of trust and personalization in programmatic advertising on their purchase intention. Structural equation modeling approach is used to analyze the relationships in the research model. T-test and One-Way ANOVA are conducted to investigate the differences in purchase intentions according to the demographic variables and other variables. Finally, research findings are interpreted and discussed with relevant literature. Suggestions are included for businesses and marketers and future research possibilities are stated.



FIRST PART

ARTIFICIAL INTELLIGENCE AND PROGRAMMATIC ADVERTISING

1. DEFINITION AND SCOPE OF ARTIFICIAL INTELLIGENCE

A large number of devices and systems have been combined with technological development to assist in difficult situations encountered in daily living activities. In these situations where the human mind and power are insufficient, it is necessary to focus on solving the problems to strengthen the existing system. The solutions of these problems have been accelerated by the development of the digital industrial revolution. The digital revolution has positively affected both the society and companies. Artificial intelligence (AI) might be one of the greatest inventions of the digital revolution (Makridakis, 2017).

Although the concept originated in the 1950s, it took time for it to adapt to our daily lives. The term Artificial Intelligence was introduced into the literature by John McCarty, a researcher at Stanford, in 1956 and defined as a sub-title of computer science (Rajaraman, 2014). According to Kaput (2016), artificial intelligence is defined as “*computerized systems that intake data to perform tasks of intelligent beings in a way that maximizes its chances of success*”. Artificial intelligence is one of the most significant system inventions in the current age of technology. Put simply by Demis Hassabis, founder and CEO of Google's AI company DeepMind, artificial intelligence is the “*science of making machines smart*” (Kamal, 2015).

Artificial intelligence aims to develop technology that can have knowledge at the human level and to make smart machines that can behave similar to human social intelligence behavior. Complex mathematical operations can be carried out by computers quite easily while forcing human intelligence. On the contrary, many issues that people can do without thinking about are complicated to be realized by computers. Artificial intelligence deals with difficult issues that require such knowledge and inference mechanisms (Yilmaz, 2004).

According to the Cybernetics Dictionary, artificial intelligence is “*a continually evolving and updated artificial system that simulates the solution of problems by human throughout his life*” (Kornienko et al., 2015). Artificial Intelligence is a study focusing on human intelligence and actions that are reproduced synthetically, where the design brings a level of rationality, which eventually may outsmart the human intellect, to aid

with specific and detailed tasks. Artificial intelligence imitates human intelligence. Artificial intelligence can be loaded with multiple actions and it can identify complex data. Artificial Intelligence applications has the necessary software to solve the problem. Artificial intelligence applications are constantly evolving of data search, learning and scanning. The term AI is generally used to refer to the field of science which proposes to supply machines with the capability of operating in actions such as reasoning, planning, learning, logic and perception. It surrounds the whole concept of a machine that is intelligent both in terms of operational and social outcomes (Perez et al., 2017: 8).

1.1. COMPARISON OF HUMANS AND MACHINES

There are some differences between humans and machines. The first difference is related to “acquiring goals”. Machines lack phenomenal consciousness, understanding, and insight. Machines do not fully possess human capabilities. Features such as conscience and morality possessed by humans are not found in machines. Machines operate only thanks to a specific algorithm and software. Since algorithms and software are made by humans, the knowledge of a machine is actually provided by the person who supplies the software to that machine. Artificial intelligence can excel in this area, but there will always be a lack of human emotions. As can be understood from here, artificial intelligence, no matter how superior the machines are, will be deprived of the features which predominate the human aspect (Müller, 2016: 5).

Some of the other differences between machines and humans are; machines are for complex operations, they're smarter and faster than humans, machines are safer in collecting and analyzing specific data and making a mistake in a machine can only happen with bad data and malicious humans (Sterne, 2017: 235). Another difference is that machines have a high ability to adapt to constantly changing environments and situations. The other important feature of machines is the constant development of the “perception” factor. Machines are more efficient than people in trust and automation. The error rate is lower on machines. The adaptation time to changes and innovations is longer in humans than machines. People’s time to acquire information is longer and more expensive than machines. Self-awareness and emotional factors are some of the key features that make people different from machines (Perez et al., 2017).

However, with evolving technological developments, machines are approaching the human thinking system. Computers can direct machines such as robots that perform certain physical human behaviors; and they can control brain systems that simulate the process of human thinking related to a particular area of expertise, such as data computation or medical diagnosis. With the differences provided by machines, there will be an increase in personal and practical applications in the field of artificial intelligence. In marketing perspective, successful applications are also available, and there has been financial return. For example, programmatic advertising and social media marketing, coupled with artificial intelligence, have become more comprehensive in the control of data analytics related to consumer purchase intentions (Muntz et al., 2017).

1.2. HISTORY OF ARTIFICIAL INTELLIGENCE

Artificial neural networks are at the beginning of the history of artificial intelligence. Artificial neural networks are computational models of nervous systems. Artificial neural networks are based on connected units called artificial neurons, which model neurons in a biological brain. The signal-receiving artificial neuron processes information and points to the neurons attached to it. It tries to solve problems that are proven impossible by human or statistical standards (Frankenfield, 2020).

The concept of artificial intelligence is based on a foundation by Turing. Turing stated that there is a possibility that the thinking system will turn into digital (Berber, 2019). In 1950, when Alan Turing wrote “Can machines think?” he first realized the concept of questioning the programming of machines by asking (Haton, 2006 & Turing, 1950). Later, in addition to this article, he designed a test called the “Turing Test” to measure the minds of machines (Perez et al., 2017: 9). Artificial intelligence is generally related to a software system that can solve problems requiring human ability and an application that continually transcends human knowledge. Artificial intelligence always uses digital data and software (Haton, 2006).

Dartmouth math professor John McCarthy originally coined the term “artificial intelligence” in 1955. The Dartmouth Conference of 1956 was edited by Marvin Minsky, John McCarthy, Claude Shannon, and Nathan Rochester. McCarthy and Rochester convinced Shannon and Minsky to prepare a workshop proposal to be held at Dartmouth. McCarthy was a crucial figure in the writing of this proposal and the “Artificial Intelligence Summer Research Project” event. McCarthy’s idea was to create

“an artificial language that the computer could be programmed to use in problems that require conjecture and self-reference” (Mandal, 2019). Following this development, in 1969, the first international conference on Computer Science was organized in Washington State, and the term “artificial intelligence” officially joined the system (Perez et al., 2017: 9).

One of the first applications of AI is ELIZA which was developed in 1966. Pioneering chatbot developed by Joseph Weizenbaum at MIT holds conversations with humans. Open-ended questions can be asked to ELIZA and it is designed to mimic a therapist and respond to these questions. ELIZA works by identifying keywords or phrases to generate responses using keywords from pre-programmed responses (Salecha, 2016).

The first expert systems were proliferated in the 1980s. Expert System is a reliable, computer-based decision-making system that uses heuristics to solve complex decision-making problems. For that period, it was considered the highest level of human intelligence (Brown,1995).

Deep Blue, designed by IBM in 1997, was an improved chess playing computer program. It is known as the first computer chess game system that could win against the world champion Garry Kasparov. Although DeepBlue was created with an algorithm provided by deep learning, developers of the program have even denied that it was based on artificial intelligence (Campbell et al.,1995).

In the 2000s, AI started to be used in home appliances. For example, Roomba is a series of autonomous robotic vacuum cleaners sold by iRobot. Roomba has many sensors to facilitate the cleaning process of the house. Roomba's sensors can detect obstacles and dirty stains (Vincent, 2020).

Artificial intelligence applications have taken steps that make our lives easier (Berber, 2019). For example, Google Now does voice recognition, schedule management, directions and more. Google Now provides convenience by playing the role of a digital assistant (Rougeau, 2012). Google’s artificial intelligence AlphaGo beat world champion Ke Jie in the complex board game of Go, notable for its number of possible positions. Thus, artificial intelligence defeated human intelligence, which was not thought to be its rival in the complex game of Go (Mozur, 2017). Artificial intelligence has shown that it can rise above human knowledge in the following years.

According to Herbert Simon (Ridder, 2018) artificial intelligence is expected to take time to adapt to our daily life. An example is Simon's assumption that artificial intelligence can beat a person in a chess game within ten years from 1957. Considering that Simon's estimate came true after 40 years, it can be said that the possibilities that could not have happened with the advancement of technology are now highly likely to happen. Artificial intelligence, combined with emerging technology, has brought innovation and reduced costs for computing technologies. It has attracted interest among investors and companies with the ability to access to more data (Cannella, 2018: 9).

Artificial intelligence has become an important concept for today and for years to come. The variety of uses of artificial intelligence is increasing every day. Critical interpretations are made for artificial intelligence. One of them belongs to Elon Musk.

In August 2014, Elon Musk expressed his misgivings:

"Worth reading Superintelligence by Bostrom. We need to be super careful with AI. Potentially more dangerous than nukes"(Sterne, 2017: 16).

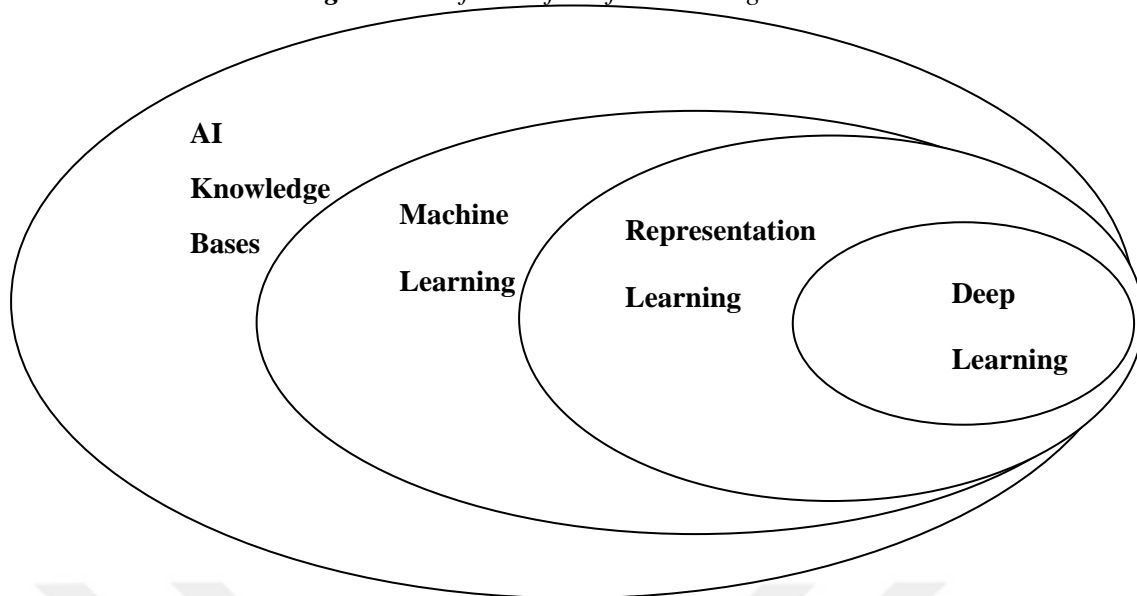
In 2014, Professor Stephen Hawking mentioned that the development of artificial intelligence could be dangerous to humanity. According to Rollo Carpenter, it is not clear whether machines will have a positive or negative impact on humans even if they pass human intelligence in the future (Cellan, 2014).

Charlie Ortiz, head of artificial intelligence at Massachusetts-based software company Nuance Communications, stated that there is no reason to believe that machines would be smarter than humans. He doesn't think robots will harm or destroy people. He said that there is too much to be done for artificial intelligence to reach this level. Andrew Ng, who researches on artificial intelligence at Stanford University, also thinks that it's too early for artificial intelligence to reach human intelligence (Adali, 2017).

1.3. OPERATION OF ARTIFICIAL INTELLIGENCE

AI works by combining large amounts of data with fast, iterative processing and intelligent algorithms; allowing the software to learn automatically from patterns or features in the data. AI is a broad field of study that includes many theories, methods and technologies, as well as the following significant subfields that are shown in Figure 1 (Sas, 2018).

Figure 1. Subfields of Artificial Intelligence

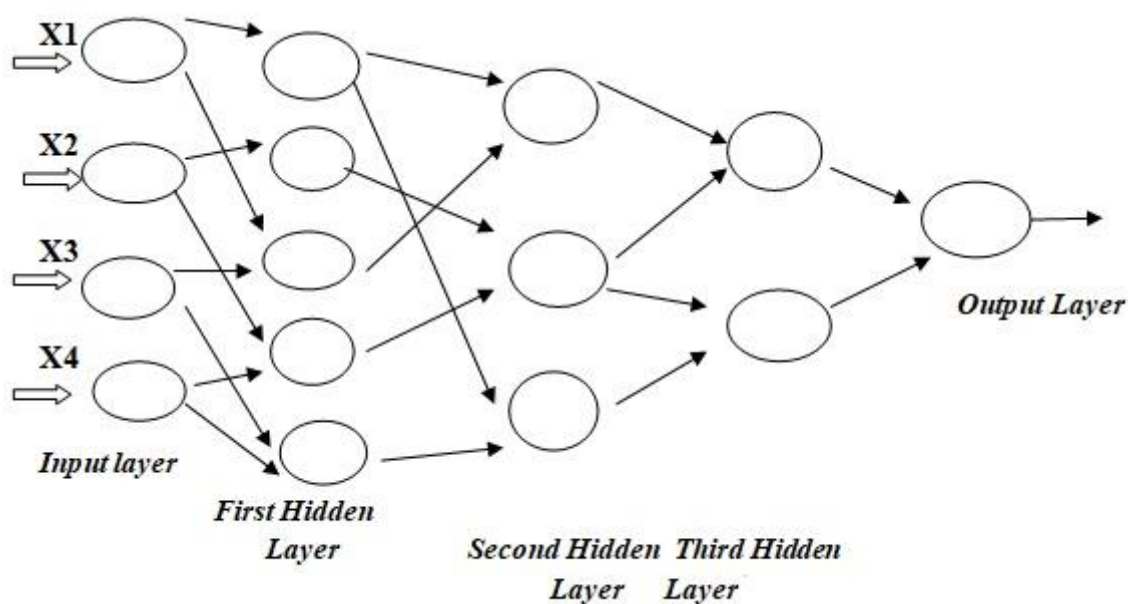


Source: Sas, (2018).

Deep Learning (DL): Deep learning is part of machine learning. It is also known as deep neural learning or deep neural network. It estimates the output with the available data and enables the development of artificial intelligence. Machine learning is approximate while deep learning algorithms scale with data. “Neurons” are used to analyze neural networks. Deep learning runs inputs through the structuring of neural networks. It allows for the best results. Current manual processes help speed up operations (Cannella, 2018: 15). Neural networks are built on a specific connection area to mimic the way the nervous system uses information (Perez et al., 2017: 18).

As it appears from Figure 2, the first general learning algorithm for supervised Deep-Fed multilayer perceptrons was published by Ivakhnenko and Lapa in 1965 (Şeker et al., 2017: 48). A perceptron is a single layer neural network model. It consists of artificial nerve cells that can train (Işıkhan, 2019). According to Ivakhnenko and Lapa (1965), the best features in each layer are selected using the statistical method and transmitted to the next layer. Later, technology companies such as Google and Facebook realized its trendiness and began to invest in the field of deep learning. Consequently, developments in the field of deep learning have accelerated (Şeker, 2017: 48-49).

Figure 2. First Known Deep Network



Source: Dettmers, (2015).

Representation Learning (RL): It is a learning method with multiple levels of representation, making the image a higher and more abstract representation, as opposed to the deep learning method, which allows the machine to feed on raw data and to discover the process of detection or classification automatically (LeCun et al., 2015: 436). In this learning, manual intervention is more. The manual feature allows the machine to both learn its features and use it to perform tasks (Bengio et al., 2013).

Machine Learning (ML): It is a subset of artificial intelligence that makes the results of large amounts of data as accurate as possible. Machine learning supports computer data. Statistical methods are used in machine learning. It aims to provide information to computers through data interaction (Cannella, 2018: 13). The model was created in 1949 by Donald Hebb in a book titled the Organization of Behavior. The book presents Hebb's theories on neuron excitement and communication between neurons. Machine learning is a fundamental concept for all developments in technological fields. Now, most systems use machine learning or robotic structures instead of low computing. It is used effectively in personalized marketing (Foote, 2019).

AI Knowledge Bases: It is a computer program that is used to solve complex problems. The concept of this term is quite broad. It is a system that provides an attempt to obtain information and represent it openly. It has two essential characteristics. These are the knowledge base and inference engine. Artificial intelligence researchers first developed knowledge-based systems (Smith, 1985: 5). Knowledge base is the

technology used to store structured and unstructured information created by the computer system. Inference engine is part of the system that applies rules to the knowledge base to create new information. All these systems are developed by expert systems that are a knowledge-independent framework. Thus, there is no need to program every new system from the beginning (Bullinaria, 2005). Expert systems are built individually and cannot be developed fast. It might take some years to build an expert system to solve a moderately difficult problem. In a rule-based expert system, the inference engine links the rules covered in the knowledge base with data given in the database (Negnevitsky, 2002: 260).

Cognitive computing is another important concept in AI. It is a subfield of AI that strives for natural, human-like interaction with machines. Using AI and cognitive computing, the ultimate goal for a machine is to simulate human processes through the ability to interpret images and speech; and then speak coherently in response. It is a term for hardware and software that mimics the way the human brain functions. Cognitive computing systems make context computable (Reynolds & Feldman, 2014).

1.4. BENEFITS AND DRAWBACKS OF ARTIFICIAL INTELLIGENCE

There are ideas that artificial intelligence will be either too good or too bad for humanity. In retrospect, it has not been thought that the application areas provided by artificial intelligence would expand to this extent. While countries have focused their investments on artificial intelligence recently, some famous names such as E.Musk and B.Gates have negative thoughts about artificial intelligence. The ambiguous aspect of artificial intelligence is whether it will be in a “positive” or “negative” direction. Famous names consider that the most critical issue for artificial intelligence is “control” (Bakırcı, 2017: 54).

Some benefits of artificial intelligence can be listed as the following (Tahir, 2017):

- Saves time for people and companies. It provides a focal point for companies with a personalized database.
- Greater efficiency.
- Less errors.
- Faster decisions.

- No breaks.
- Taking risks on behalf of humans: In various situations, robots can be used instead of humans to avoid the risks.

It is possible to use artificial intelligence in a beneficial way by ensuring that our goals are learned, embraced and protected. The necessary infrastructure and systems must be available for the artificial intelligence process to proceed in a healthy way. The most important thing for artificial intelligence is data. The more meaningful the data is, the healthier the process and decision phase for companies (Manhas & Hussain, 2016).

Max Tegmark expressed the potential of AI as follows (Tegmark, 2017):

“Everything we love about civilization is a product of intelligence, so amplifying our human intelligence with artificial intelligence has the potential of helping civilization flourish like never before – as long as we manage to keep the technology beneficial”.

According to Tegmark, it is uncertain how the process will emerge when we keep the technology at a beneficial level, because artificial intelligence has access to the human level of knowledge. In this process, the most important feature of artificial intelligence is to provide “control”. It is important that artificial intelligence makes critical decisions to ensure control. There should be a standard procedure against artificial intelligence (Sariel, 2017: 20).

Despite its many benefits, artificial intelligence also has some drawbacks which are stated as follows (Perez et al., 2017: 39):

- High costs required for software and hardware.
- Privacy issues.
- High dependence on machines: In today’s generation, most of the people are highly dependent on applications like Siri. By getting a lot of help from the applications, people's need for thinking skills will decrease. In future with the heavy use of application of artificial intelligence, humans may become entirely dependent on machines, losing their mental capacities (Machine Ethics).
- The possibility of using artificial intelligence in the military (National Security). Some negative situations may occur in this area. A global

armament situation may arise as a result of malware. The danger of using artificial intelligence in the military may be a loss of control over artificial intelligence.

- Use of personal data in marketing (Trust Issue).

General Data Protection Regulation of the European Union has taken some precautions such as (GDPR, 2018):

- *“the pseudonymization and encryption of personal data;*
- *the ability to ensure the ongoing confidentiality, integrity, availability and resilience of processing systems and services;*
- *the ability to restore the availability and access to personal data in a timely manner in the event of a physical or technical incident;*
- *a process for regularly testing, assessing and evaluating the effectiveness of technical and organizational measures for ensuring the security of the processing”.*

In all these processes, the risks arising from unauthorized disclosure or access to personal data stored or otherwise processed will be taken into account when evaluating the appropriate level of security (GDPR, 2018).

Artificial intelligence analyzes specific data quickly, but this is a limited capacity. Issues of diminishing people’s physical duties and income inequality are a few of the problems that may arise. After all these explanations, a machine’s ability to make mistakes in decision or application is all about bad data or software. Companies should, therefore, share data collection details with customers. Controlling a super-smart future is still a complicated situation. The answer is not yet known for sure. Some think everything is more authoritarian, while others believe individual power-gaining situations arise. Artificial intelligence will make the breakthrough either way. People and companies need to pay attention to these breakthroughs and design their positives to create a better world (Yereli & Şahin, 2019).

1.5. USES OF ARTIFICIAL INTELLIGENCE

The change in many industries and business models around the subjects of data science and machine learning has resulted in increased interest in artificial intelligence. While artificial intelligence is firstly used for testing purposes in the laboratory environment, today it is used in health, automotive, game sectors, etc. It started to be used in many areas in our daily lives and usage areas are increasing every day (Kelnar & Kostadinov, 2019: 7). Some of the sectors and areas that artificial intelligence is used are shown in Table 1.

Table 1. Contribution of Artificial Intelligence to Some Sectors and Usage Areas

SECTORS	USAGE AREAS
Asset Management	Investment strategy Portfolio Construction Risk Management Client Service
Healthcare	Diagnostics Drug Discovery Monitoring
Insurance	Risk Assessment Claims Processing Fraud Detection Customer Service
Programmatic Advertising	Personalization Digital Platform Customer Service Data Usage
Manufacturing	Predictive Maintenance Asset Performance
Retail	Price Optimization Customer Segmentation Content Personalization
Transport	Control Applications Autonomous Vehicles Fleet Management
Utilities	Supply Management Demand Optimization Security Customer Experience

Source: Kelnar & Kostadinov, (2019).

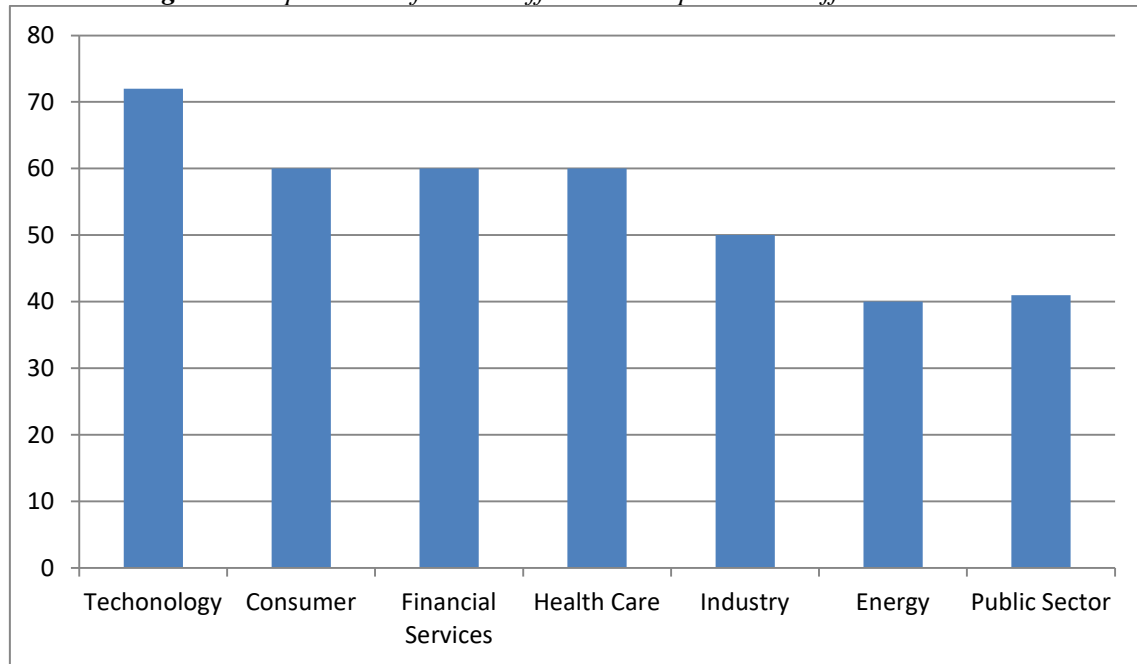
In addition to the applications in Table 1, artificial intelligence has several other uses. It is used in autonomic cyber security systems to prevent cyber-attacks and to analyze data flow. Vehicle detection solutions are used with the help of artificial intelligence to get the experience of advanced driving. In the field of audio and video, artificial intelligence provides chat interfaces, voice analysis, and data analysis; providing many tools that can be used to help. Artificial intelligence can improve our health problems and solutions can be found along with our daily exercises in health. In the field of education, it provides students with learning from the most basic level with difficulty degrees appropriate to their level. In the human resources area, it increases the productivity of human resources employees by finding qualified candidates with data processing capability and analyzing their results by evaluating them. In the law sector, it is used as a decision support system designed to make decisions for a specific purpose (Bsa, 2018).

Recently, digital marketing has become more important than traditional marketing methods. Artificial intelligence technology has enough consumer data in digital marketing applications (Cannella, 2018: 7). In the marketing and finance sector, AI provides pricing optimization, enabling companies to optimize discounts. In the sales area, artificial intelligence provides automatic and accurate sales forecasting based on previous sales of consumers/customers. Artificial intelligence also offers virtual shopping opportunities (Kızrak, 2019).

The worldwide share of artificial intelligence is also growing. As the importance of artificial intelligence grows, governments and public sectors are also increasing their investments. Some industries that invest in AI can be listed as healthcare, banking, energy, marketing, financial services, management consulting, manufacturing, advertising, and government administration (Bughin et al., 2017).

Figure 3 shows expectations for AI's effect on companies in different sectors. The figure shows the sectors on the horizontal axis and the percentage of respondents on the vertical axis. According to the research by Gerbert et al. (2017), 72% of the respondents in the technology industry expect major impacts from artificial intelligence. However, even in the public sector-the industry with the lowest overall expectations for AI's effect-41% of respondents expect large effects of AI within the following years.

Figure 3. Expectations for AI's Effect on Companies in Different Sectors

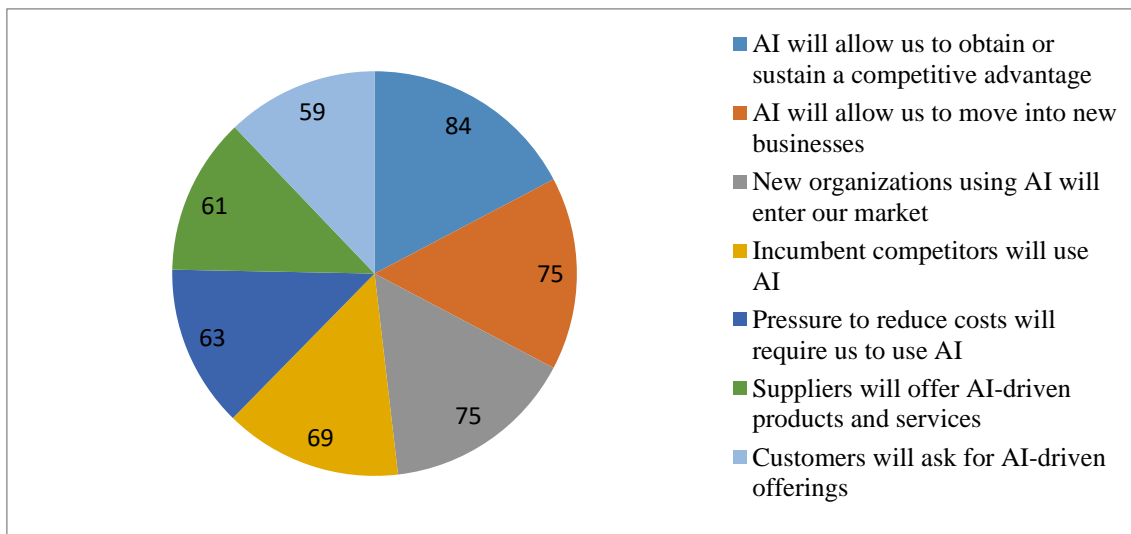


Source: Gerbert et al., (2017).

In many different industries where artificial intelligence is used, the goal is to use the potential offered by machines. It increases the investment rate in the sector by analyzing large amounts of data correctly. The common purpose of artificial intelligence in different industries is to automate processes and accelerate decision making (Decide, 2018).

According to another result of Gerbert's et al. (2017) research, Figure 4 shows the percentage of respondents who somewhat or strongly agree with each statement. As shown in Figure 4, 84% of respondents believe AI will provide a competitive advantage in organizations. Three out of four executives (%75) predict artificial intelligence will allow them to move into new businesses. Three-quarters of the respondents estimate that new businesses that use artificial intelligence will enter the market, while 69% expect their current competitors to adopt artificial intelligence (Gebert et al., 2017: 5).

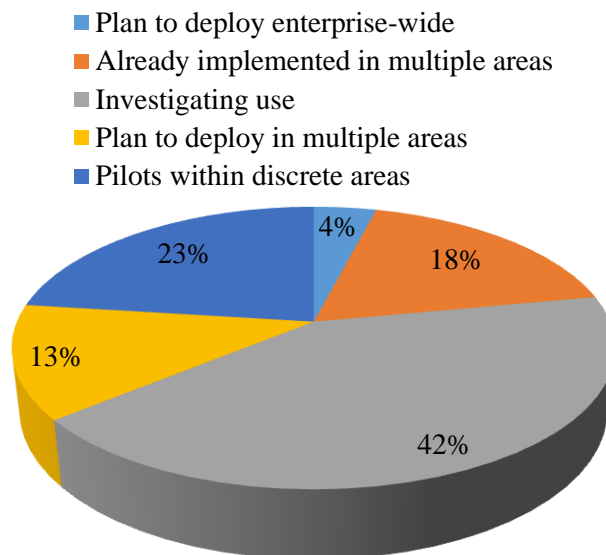
Figure 4. Reasons for Adopting for AI



Source: Gerbert et al., (2017).

PwC’s third annual AI Predictions report shows that only 4% of executives surveyed plan to deploy AI enterprise-wide in 2020 (Figure 5). According to the same report, 42% of executives are investigating the use of AI and 18% of executives have already implemented AI in multiple areas (PwC, 2020).

Figure 5. The Level of AI Implementation in Organizations



Source: PwC, (2020).

Artificial intelligence is crucial because it is above human abilities. It provides functions such as comprehension, reasoning and communication by using software to obtain more efficiency at lower cost. It saves cost and time in many sectors (OECD, 2020).

Artificial intelligence technology is authorized to assist in various marketing activities. Social media and marketing research are among the most known. It best matches product-related information and effectively provides feedback. It has recently known to be beneficial to marketing managers through personalized advertising and individual interpretation of consumer experiences (Sterne, 2017: 10-11). Artificial intelligence is also used to assist marketers in tasks such as programmatic buying, website operation and optimization and search engine optimization. It helps to use data most efficiently (Davenport, 2017). The current usage areas in marketing are explained in detail in the next section.

1.6. THE USE OF ARTIFICIAL INTELLIGENCE IN MARKETING

The application and use of artificial intelligence in marketing has begun to emerge in the last few years. The number of marketers who adopt artificial intelligence and start implementing it in their companies is increasing over time. Artificial intelligence is a very good option for developing and upgrading old marketing practices. It helps in developing new strategies in the field of sales and marketing. Study of Shahid and Li. (2019) contains the answers of 10 different marketing professionals. Rija Bakhtiar, who took part in the survey, is a marketing director with 7 years of experience in Pakistan. According to Bakhtiar artificial intelligence is used in all activities, including pricing, promotion, distribution and product development. Artificial intelligence can be used mainly in digital platforms, advertising function and Customer Relationship Management. Apps such as Chatbots and digital advertising are profitable for both customers and executives. Artificial intelligence applications are successful in creating personalized marketing campaigns by analyzing the data of companies. AI also helps to improve efficiency management by improving customer management with its dynamic pricing feature (Shahid & Li, 2019).

Practical and fast solutions to the growing consumer demands in the world are tried to be produced using technological developments. In line with these demands, applications such as “Siri” were developed. These apps communicate with the customer by using “voice recognition” feature. Voice recognition allows computers to decode the contents of the human voice input. The goal here is to help the customer’s problems at a basic level, practically and efficiently. On the other hand, applications like Facebook and Twitter are continually monitoring our activities. This is because of the desire to keep consumer/customer attention alive. These applications connect the customer to the

brand and provide satisfaction. That's why big companies and brands want to apply artificial intelligence to the marketing sector (Cannella, 2018: 17).

According to a Forbes research, 84% of marketing organizations benefited from artificial intelligence technologies in 2018 and provided better solutions to their customers. Thus, organizations obtained profitable results from their investments (Pehlivan, 2019).

Artificial intelligence saves time for companies and consumers in marketing applications. For example, Chatbots show specific content to users and help in customer service. Retailers are using AI to help save consumers time by eliminating the need to manually navigate product pages. Artificial intelligence helps companies with feedback and better analysis and interpretation of customer information. One of the features that artificial intelligence brings to the marketing industry is to give customers more value by keeping customer satisfaction at the top. Marketers are increasingly using "personalized" advertising applications. Personalization is useful for brands. For example, more personalized ads and products are now displayed in e-mail applications sent to consumers thanks to artificial intelligence. These customized advertisements attract the customer's attention and are being preferred by customers (Cannella, 2018: 28).

Thanks to artificial intelligence applications, operations in marketing and advertising are optimized. Through artificial intelligence, the collected data is better analyzed. It is presented to the service of the consumer in a personalized way (Oypan, 2019). According to Kibo (2017) unlike other advertising applications, customers are converted more than 42% to personalized advertising applications. Brands using these apps have an average order value higher than 40%. For example, people even order for food through apps now available on their phones (Kibo, 2017).

Customers interact more with the brand, resulting in a relationship that over time generates revenue for the brand and provides value to customers. As a result of the personalized advertising and increased marketing rate, people are willing to give their personal information (e.g. address, e-mail) to benefit from these types of applications (Cannella, 2018: 29).

The introduction of artificial intelligence in society and business could revolutionize the existing social structure. Possible risks should be guessed while

designing a technology which affects the security and prosperity of people (Alexandre, 2017). The most critical factor of artificial intelligence in marketing is that it creates a highly competitive environment. Most of the companies now know that it is necessary to adopt artificial intelligence. According to Gerbert, the most critical problem is “trust” in the adoption process. For all these reasons, companies must have the necessary infrastructure for artificial intelligence and reassure the customer (Gerbert et al., 2017: 12).

The founder of Marketing Artificial Intelligence Institute, Paul Roetzer, has developed a framework for artificial intelligence in marketing which is called as the 5Ps of Marketing Artificial Intelligence that is shown in Table 2 (Mölsä, 2017: 7).

Table 2. 5 Ps of Marketing AI by Paul Roetzer

PLANNING	Analyzing consumer behavior, strategizing, determining how to use marketing resources appropriately
PRODUCTION	Creating and continually optimizing content for e-mails, landing pages and blog posts
PERSONALIZATION	Showing consumer-specific content by customizing e-mail content, product suggestions, and consumer experiences by automating consumers’ web experiences
PROMOTION	Managing promotions using audience targeting and digital media management to improve channels and cross-device transactions
PERFORMANCE	Using this intelligence to optimize performance by converting data into information with automated predictions

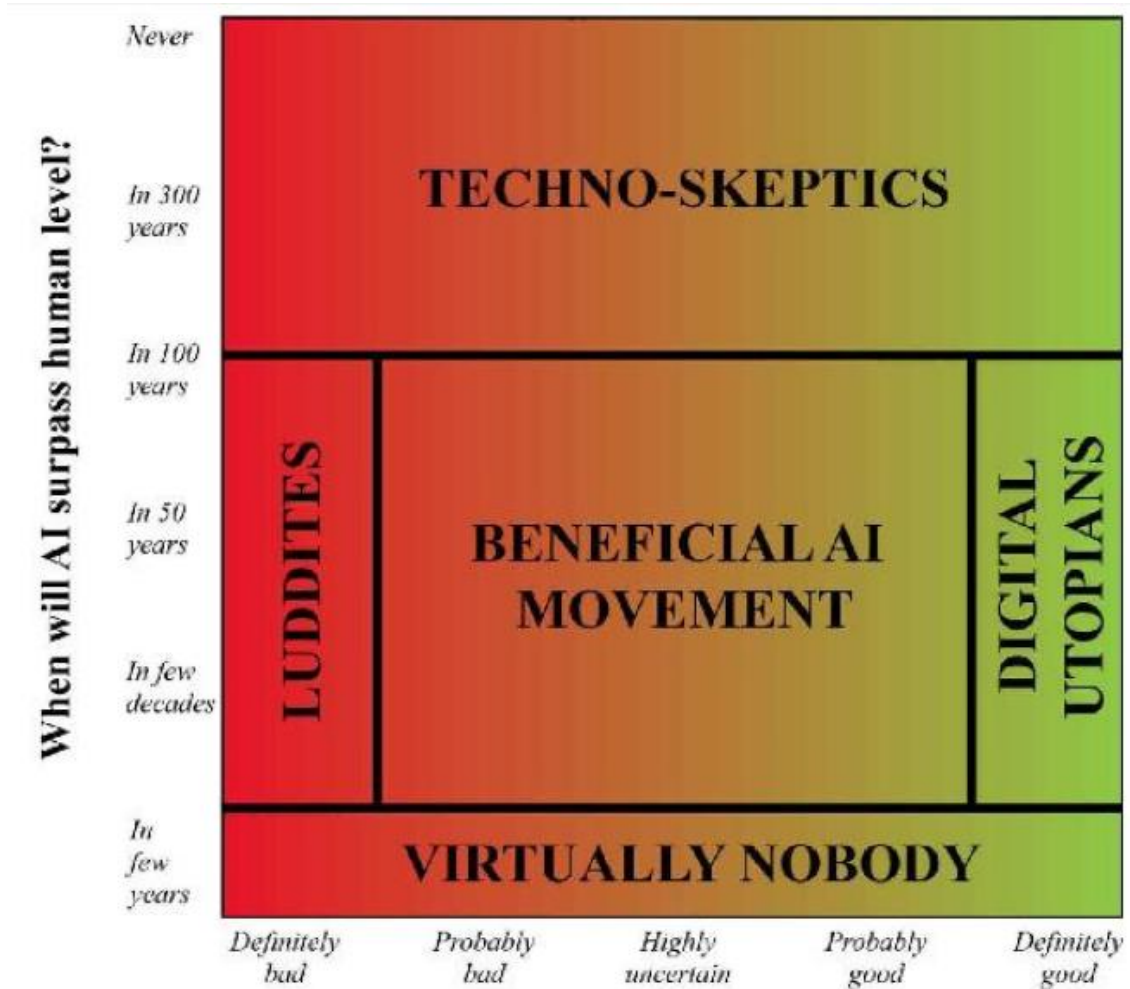
Source: Mölsä, (2017).

1.7. CONSUMERS’ PERCEPTION OF ARTIFICIAL INTELLIGENCE

In general, consumers do not have sufficient knowledge in artificial intelligence applications, leading to differences in the interpretation and perspective of artificial intelligence (Sterne, 2017: 14). Max Tegmark (2017) studied people's views of artificial intelligence and categorized them in five groups which are seen in Figure 6. In the

figure, people are grouped based on their perception of AI ranging from definitely bad to definitely good and on their answer to the question “When will AI surpass human knowledge?”.

Figure 6. Individuals’ Thoughts on Artificial Intelligence



Source: Tegmark, (2017).

Tegmark (2017) describes these groups as follows:

- **Digital Utopians:** According to this group, the result would be better if we freed digital life rather than let digital life try to enslave us.
- **Techno-Skeptics:** According to people in this group, there is no need to worry about artificial intelligence. Because it will take a lot of time to build a superhuman artificial intelligence.
- **The Beneficial-AI Movement:** The idea of people with this view is that artificial intelligence could be as useful as possible in future centuries.

- **Luddites:** This group consists of those who believe that an adverse outcome will occur and those who oppose artificial intelligence.

HubSpot has conducted a survey of over 1,400 consumers globally in the field of artificial intelligence and the results show that (An, 2016):

- 63% of people do not realize that they are using artificial intelligence technologies.
- Use of voice search has seriously increased.
- Consumers are making more convenient purchases thanks to customized service-providing applications.
- Consumers are open to using artificial intelligence-enabled customer service for their simple demands and problems.

Access to the source of information became easier thanks to the use of the Internet. The “trust” factor is important for consumers. Because consumers evaluate the product or brand with trust in terms of quality. Today, there is an intense competitive environment. Therefore, marketers should give a sense of trust in order to develop reputation and image. A factor of trust would convince the consumer (Acar, 2012). Firms should pay attention to whether artificial intelligence is used efficiently for consumers and whether artificial intelligence applications have “properly” adhered to privacy policies in terms of security and ethics. While there was less reliance on artificial intelligence in the past, this is changing today. The reason for this is the “persuasion” factor. Artificial intelligence has enabled the marketing industry to achieve diversity. This diversity has persuaded businesses and made it imperative to adapt to artificial intelligence (Müller, 2016: 88).

Artificial intelligence is today used to assist marketers in tasks such as digital advertising buying (programmatic buying), website operation and optimization (Mölsä, 2017: 7). Being one of the AI marketing applications, programmatic advertising interests consumers in terms of providing personalized offers. Therefore, programmatic advertising will be discussed in more detail in the next section.

2. PROGRAMMATIC ADVERTISING

The internet, with all its dimensions, has significantly changed our way of life. As a result of the level it has reached, it leaves a significant mark on all aspects of life.

With ever-evolving technology infrastructure, applications such as websites, social media and search engine have become a part of our lives. Digital platforms have become one of the primary building blocks in the world economy (IAB Turkey, 2017). Data is used to automate and personalize the marketing industry. With all this evolving technology, an advertising type has emerged that analyzes users' data accurately and gets efficient results. This method has created the concept of programmatic advertising, unlike the old ways in the digital field (IAB, 2015). Programmatic advertising provides high targeting and efficiency. Marketers interact with consumers through digital platforms and programmatic purchasing provides the consumer with a holistic view through various channels. Programmatic purchasing provides strategic and campaign performance efficiency to marketers (Janzen, 2014).

Although little was known in the programmatic start-up phase, it has managed to make its name known along with developing technology. Programmatic is the method of making media buying fast and efficient using technology that analyzes a lot of data in simple terms. The main goal is to manage digital advertising practices efficiently. This system works according to the users and their behavior. By analyzing users' data, it improves advertising efficiency by enabling the brand to reach the right audience by accurately analyzing the target audience. It does all this in real-time in a short period (Açar et al., 2017: 1).

Busch (2016: 7) defines programmatic advertising as: “*the automated serving of digital ads in real time based on individual ad impression opportunities*”. Advertisers and agencies that want to achieve ambitious business development goals see programmatic advertising as an opportunity (Rogers, 2017).

There are some differences between traditional advertising and programmatic advertising practices. The main difference in traditional buying is that the advertising is managed manually by buyers and publishers. Programmatic buying automates this process by bidding in real-time. Other differences between traditional advertising and programmatic advertising can be stated as the following (Sahistrom, 2019):

- In the process of buying, traditional media refers to buying from the salesperson by trying to compromise with the marketer on the price. This is a high-cost, complicated and time-consuming period for advertisers. Programmatic advertising, on the other hand, is appropriately evaluated by

collecting data through algorithms. It decides who looks at the advertising, where/which users have the potential to become customers.

- Differences in reporting are that in traditional media purchases, the marketer or agency collects data scattered across various sources and translates them into an understandable report. The most critical difference in programmatic buying is that this process is transparent. Programmatic helps you see how your campaign is performing in real-time, making specific changes more useful.
- In the case of campaign optimization, in traditional methods, evaluation is done after the campaign finishes. In programmatic purchases, changes can be made during the campaign with the targeting setting in the ongoing processes.
- The main difference in productivity is that the traditional method remains inadequate and slow compared to today. The margin of error is high and expensive because human labor is more. Programmatic advertising, on the other hand, automates the process of increasing return on investment by reducing costs.

When the above factors are evaluated, it can be said that programmatic advertising is more advantageous than traditional advertising in many aspects. There are benefits such as providing control power and optimizing. The goals of traditional advertising and programmatic advertising are the same. These are communicating advertising messages to customers, informing them about the product and creating a positive perception at the end of these processes. These transactions encourage purchasing in the long term. The difference here is the concept of participation in programmatic advertising and the way it is published (Sherman, 2019).

There are several uses and types of programmatic advertising. One of the uses of programmatic advertising is search engine advertising. When such advertisements are used, advertisers always try to control keywords and optimize campaigns in this way. This complicated process, of course, demands a strict follow-up. As a result of the developing technology and the opportunities it brings, automatic tools have started to take this process. Accurate data makes it easier to manage campaigns. As a result, operationally, advertisers and agencies have managed to achieve profitable results (Açar et al., 2017: 3). Private market place (PMP) is another use of programmatic advertising,

which makes presentations to advertisers only by invitation. Publishers generally reserve premium advertising inventory for specific advertisers. The private market place is used by websites and publications with mass reach. Advertisers using the PMP know on which websites the ads are being shown. Another area of use is “programmatic guaranteed” which is an agreement between the advertiser and the publisher. The difference from other usage areas is that it does not follow the programmatic direct bidding process. Once negotiated, the inventory sold directly to an advertiser. Programmatic guaranteed provides audience targeting for advertisers and advertisers know exactly where ads are placed. In “preferred deals”, the advertisement inventory can be selected at a fixed price, in auctions that can be attended by everyone, before being offered to private markets. The advertiser can browse the publisher's ad inventory. As a result, the advertiser does not have to make a purchase. In preferred deals, both parties agree on pricing and targeting in advance (Davis, 2019).

2.1. PROGRAMMATIC ADVERTISING ECOSYSTEM AND PROCESS

Programmatic advertising works with an automated bidding system. Programmatic advertising enables brands and agencies to purchase ad impressions through the developed ecosystem (Deshpande, 2019). Smart bidding adapts to changes with reduced budgets, which is better than interrupt campaigns (Vallaey, 2020).

Main characteristics of programmatic advertising can be stated as follows (Busch, 2016: 8):

- **Granularity:** Includes specific ads for specific buyers. Granularity allows advertisers to optimize budget efficiency as they can select, evaluate and price individual ad impression opportunities through scientific forecasting methods.
- **Real-time bidding (RTB):** It is the technology that enables advertising to be shown at the right place and right time according to users' interests.
- **Real-time information:** Evaluates the available opportunity based on the data collected.
- **Real-time creation:** It is for advertisers to deliver dynamic and data-driven advertising.
- **Automation:** Enables automatic booking operations. Automation will enable people to monitor a comprehensive decision-making process throughout the

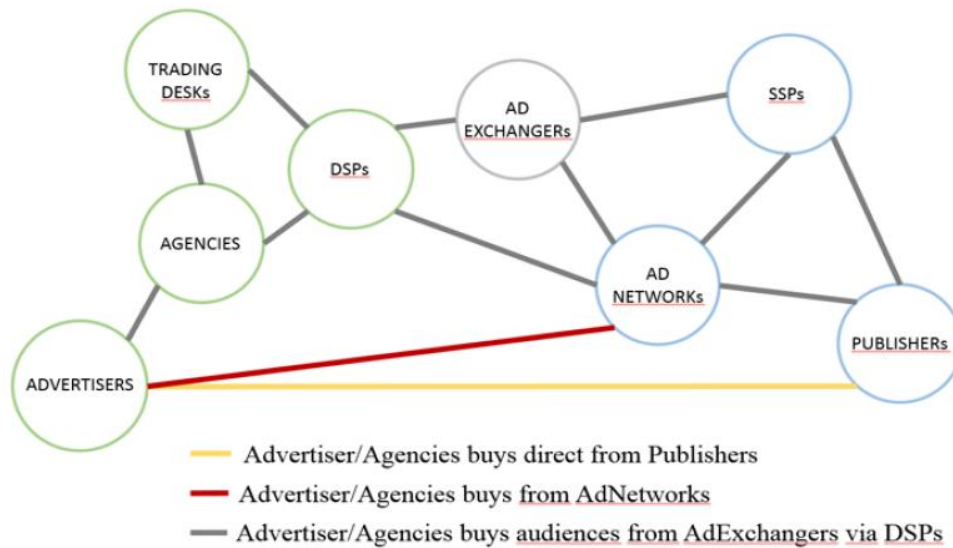
entire campaign period. This opens the way to look at individual advertising opportunities. Unlike previous ad practices, the goal here is to create long-term value instead of focusing on low prices with the way advertisers bid in real-time if they see value. Unlike complex manual applications, programmatic advertising applications are more advantageous in terms of cost because the focus here is clear.

It is essential to examine the concept of “cookies”, which is also the basis of programmatic advertising. Cookies are small files that are stored by users in browsers when a web page is visited. It keeps the records of people browsing websites in their browser history. Cookies started to be used by Netscape in 1994. The first purpose of the use is to control whether the person who enters the site has joined the site again (Örnek, 2016).

Although cookies are still used for this purpose today, they are now used to access more information. Cookies are text files that allow the systems to remember. Since our data is in this file, the system recognizes us again when we log in to the same site and ensures that we do not have to write our information again. The number of people shopping online is increasing in daily life. Users are members of various sites for this purpose and enter their user name and password. Consumers click on the “Remember Me” icon to avoid wasting time. After clicking on this icon, cookies are activated. The information contained in our private text files are saved and the data read in the cookies will reach the site and recognize us from the moment we access the site. “Cookies” are used on websites that require membership, e-commerce sites and programmatic advertising applications. For programmatic advertising, “cookies” are tools that enable displaying ads based on our interests. Which sites we visit during the day, where we click the most, which products we review on e-commerce sites are all saved as cookies. These saved cookies provide advertising based on our interests (Örnek, 2016).

Figure 7 shows the ecosystem of programmatic advertising. The following model shows how advertisers and publishers can now choose between buying and selling through advertising networks. With the development and expansion of Internet access, both the number of publishers and the volume of content produced by publishers have increased (González & Mochón, 2016: 6).

Figure 7. Programmatic Advertising Ecosystem



Source: González & Mochón, (2016).

Below are a few key factors that should be known about the programmatic advertising ecosystem (Açar et al., 2017: 2):

Data Management Platform (DMP): The data management platform enables the creation of advertising strategies or proper management of sites using user data. DMP provides extensive insight for users. Women who fill most of the forms on the Internet or those who prefer online games are specific audiences for DMPs. For example, a business can use DMP to collect and organize data, then use that data to direct specific advertisement to mothers between the age of 30 and 45.

Supply Side Platform (SSP): This technology is used to sell publisher inventories programmatically. Demand Side Platform determines the request for products. SSPs provide the ability to set base prices against multiple purchase situations and perform optimization of selling ad spaces in the most valuable way. DoubleClick Ad Exchange by Google, Adform, AppNexus, PubMatic, Yieldlab and Rubicon Project are examples of SSPs.

Demand Side Platform (DSP): Many advertising requests are made to be accepted, evaluated and processed by a DSP in just milliseconds. It provides the opportunity to reach the right people one-to-one instead of bulk sales. When the situation meets the targeting criteria, the system decides how much to bid according to

its algorithm. DoubleClick Bid Manager by Google, MediaMath, AppNexus, Adform and The Trading Desk are examples of DSPs.

Trading Desk: Trading desk is the technology that manages DSP on behalf of advertisers. It provides the ability to work with more than one DSP and allows to improve ad performance. WPP's (advertising and public relations company) trading desk Xaxis is one of the fastest-growing parts of GroupM and has continued to grow in 2019. Trading desks like Xaxis are capitalizing on the fast-growing programmatic markets that are often less mature (Joseph, 2019).

Data Aggregators: Data aggregators are to compile information from databases to prepare existing datasets for data processing. Data aggregation is essential to achieve the necessary reach and to deliver campaigns to large-scale audiences (IAB Europe, 2019). Examples of aggregate data include voter turnout by state or county, average age of customer by product, number of customers by country (Rouse, 2020).

Ad-Exchange: An ad exchange is a digital marketplace that allows advertisers and publishers to sell and buy ad space through real-time auctions. Generally, it is preferred to sell video and display advertising inventory. It is where the buyer and seller intersect.

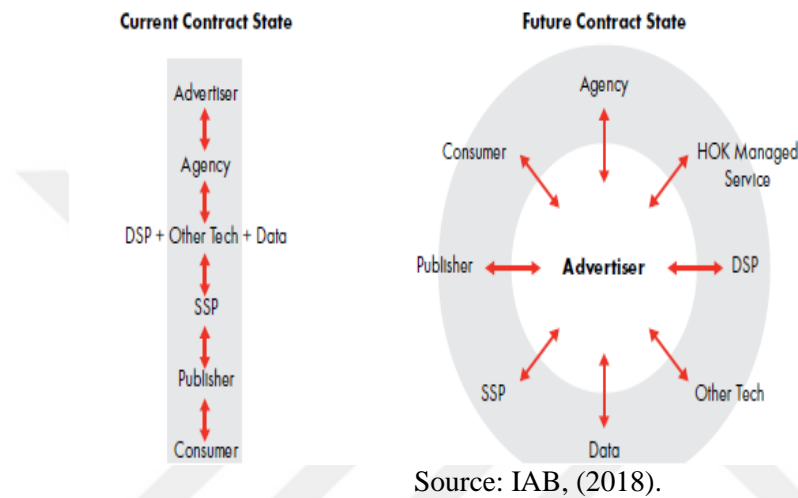
The programmatic advertising process consists of several stages. When a user enters the site, they encounter an advertising. This process happens in seconds and proceeds as follows (Martínez et al., 2017):

- The visitor/user logs in to the page.
- There is an exchange of information about the user profile and the ad space availability between the servers. The SSP auctions the ad display by adding information such as location, time, publisher, etc. and asks advertisers for their bids to show the ad.
- Ad server connects to SSP.
- Advertisers see that SSP is auctioning through DSPs and evaluate by bidding. DSP works as a meeting point for platforms such as digital advertising networks.

- The winning DSP sends their information to the SSP. Thus, the ad places it in the right place to reach the user's eyes. This whole process is carried out in a short time around 100ms.

Figure 8 shows the current programmatic ecosystem layout and the ecosystem that will occur in the future with the “advertiser” factor at its main center (IAB, 2018: 13).

Figure 8. Future Programmatic Ecosystem



In the future, artificial intelligence technology will continue to make significant strides in programmatic advertising. Programmatic purchases will be more valuable in personified ad spaces by better observing the user's movements. Communication between the advertiser and the user will become more attractive. In this new model, the advertiser is more centralized and manages all contracts in the programmatic ecosystem. This new management will show more resources on behalf of the advertiser and ensure that the brand is primarily engaged in specific contract coordination with DSPs (IAB, 2018: 13).

2.2. IMPORTANCE OF PROGRAMMATIC ADVERTISING

With the development of technology, users have started to spend more time in digital environments. This has become an opportunity for advertisers and agencies. Advertisers act according to the wishes and desires of the consumer. At this point, programmatic purchases come to the fore. Today investment in programmatic acquisitions is increasing (Jensen & Sund, 2018).

New models are used in digital advertising, while traditional advertising areas are negotiated and traded through representatives or publishers. Programmatic advertising has ushered in a new era in digital marketing. Programmatic technology helps brands deliver their messages effectively with real-time signals while enabling advertisers to deliver the right content to the right buyers at the right time. This technology allows advertisers and agencies to achieve more fruitful results. It increases productivity by reducing operational workload and cost by making bidding/receiving work in online ad buying through software (IAB, 2019: 3).

IAB Turkey (2018) has examined the aims of using programmatic advertising from the perspectives of advertisers, agencies and publishers in 2016 and 2017. Table 3 shows the percentage of responses and N/A means no response for that aim and year.

Table 3. Aims of Using Programmatic Advertising

	Advertiser		Agency		Publisher	
	2016	2017	2016	2017	2016	2017
Lower cost of media	%53	%22	%41	%28	N/A	N/A
Targeting efficiencies	%76	%71	%78	%75	N/A	N/A
Change in data strategy to increase data quality	%30	%43	%52	%46	%37	%55
Maximizing media value	N/A	N/A	N/A	N/A	%55	%37
Trading/operational efficiencies	%29	%29	%55	%60	%49	%34
Gain competitive advantage	%26	%29	%45	%38	%44	%48
Making premium inventory available at scale	N/A	N/A	N/A	N/A	%44	%37
Delivery of brand advertising campaigns at scale to target audience	%49	%40	%45	%44	N/A	N/A
Gaining access to premium inventory at scale	%21	%23	%30	%28	N/A	N/A
Delivering audiences via programmatic mobile	N/A	N/A	N/A	N/A	%30	%25
Reaching audiences via programmatic mobile	%30	%26	%41	%35	N/A	N/A
Increased engagement via programmatic video	%19	%49	%23	%21	%15	%21
Agency recommendation	N/A	%17	N/A	N/A	N/A	N/A
Client demand	N/A	N/A	%29	%29	%60	%71
Increased granular control of media/inventory	%23	%48	%37	%41	%27	%29

Source: IAB Turkey, (2018).

The importance of programmatic advertising for advertisers, agencies and publishers can be explained as follows:

Advertisers: The benefits of programmatic ads for advertisers are to ensure transparency, accessibility, cost, efficiency, reliability and consistency (Busch, 2016: 60). In programmatic advertising, advertisers have the opportunity to access detailed and transparent information about the campaign they are buying while analyzing the data that is specific to manual advertising purchases. Instant tracking of consumer preferences has made it easy to track how advertisers spend their budgets. Advertisers

run an effective advertising campaign with less budget (Stevens et al., 2016). Accessibility means an increase in the number of publishers that are involved in the programmatic ecosystem, and the reach of advertisers is also increasing. As an example, the brand that wants to deliver its ads anywhere in the world can reach accurate data and make an effective investment decision. Reliability and consistency are issues that advertisers pay attention to. One problem that advertisers complain about is that the purchased ad spaces do not have a certain standard. This sometimes creates a negative brand image when advertising spaces are not in a specific order. Google and IAB Tech have taken significant steps towards a solution through their work together (Zeren & Keşlikli, 2019).

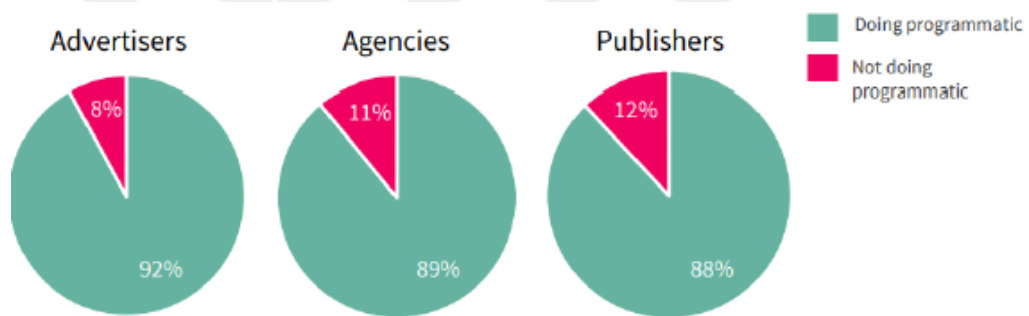
Agencies: Media agencies are institutions where Internet advertising purchases are made for advertisers. After receiving the relevant authorization certificate from the advertiser, the media agency starts to apply prediction systems used in Internet advertising with the programmatic ecosystem. The site determines the target audience by predicting specific viewers. Then the purchase is made. With the increase in purchasing power through programmatic practices, agencies have made progress in terms of performance. Programmatic advertising gives agencies the chance to buy from the entire Internet universe in line with their target audience. Agencies can enter auctions and make purchases in inventories filed by publishers. Technological investment agencies can use a trading desk. The trading desk is the platform used by agencies that purchase programmatic media which allows improving ad performance (IAB, 2019).

Publishers: Websites are physical environments for publishers that enable advertisers to reach the consumers in a quality environment by using programmatic advertising practices to increase their earnings in the programmatic ecosystem. Examples include in-text ads and video ads. In-text ads are ads that link using keywords. In-text ads are primarily used on e-commerce sites. Video ads are ad content that can be skipped and not skipped, especially before, during and after watching a content that is constantly seen on YouTube. These advertisements are used as an advertising tool because they are rich in visual and auditory aspects (Erdem, 2017). Publishers have a specific audience and generate revenue using programmatic advertising types. The important thing here is to generate income, in the long run, using the efficient way of existing follower traffic (IAB, 2019: 11).

Due to high access, high usage and new formats, Facebook has managed to create a well-positioned programmatic advertising environment. Facebook, which plays a vital role in social media advertising, bears a similar resemblance to Google during social media searches. Facebook has taken an essential role in building its ecosystem through the integration of advertising platforms. The high use of mobile Facebook and efficient forms of local ad integration, puts the company in a strong position in programmatic advertising (Busch, 2016: 43).

In a research conducted for the “IAB Europe” market, including Turkey, there are 92 advertisers, 332 agencies, 243 publishers. Figure 9 shows the proportion of programmatic users for display campaigns as a result of this research. As the following figure shows, most of the advertisers (92%) use programmatic for display campaigns. Then come the agencies (89%) and publishers (88%) respectively.

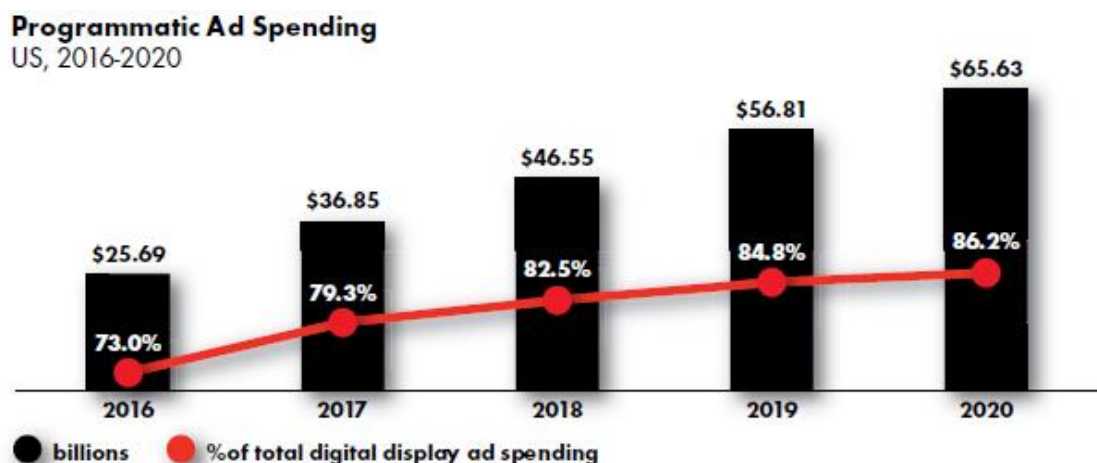
Figure 9. Proportion of Programmatic Users for Display Campaigns



Source: IAB Turkey, (2018).

According to eMarketer (IAB, 2018), 73% of total digital display ad spending was used for programmatic ad spending in 2016, which raised to 86,2% in 2020 (Figure 10).

Figure 10. Programmatic Ad Spending



Source: IAB, (2018).

Programmatic advertising applications are more used on mobile platforms (such as phones, tablets). It has also started to appear in TV advertising, but this process is very new. Soon, scheduled TV operations are expected to increase (IAB, 2018: 6).

2.3. ADVANTAGES AND DISADVANTAGES OF PROGRAMMATIC ADVERTISING

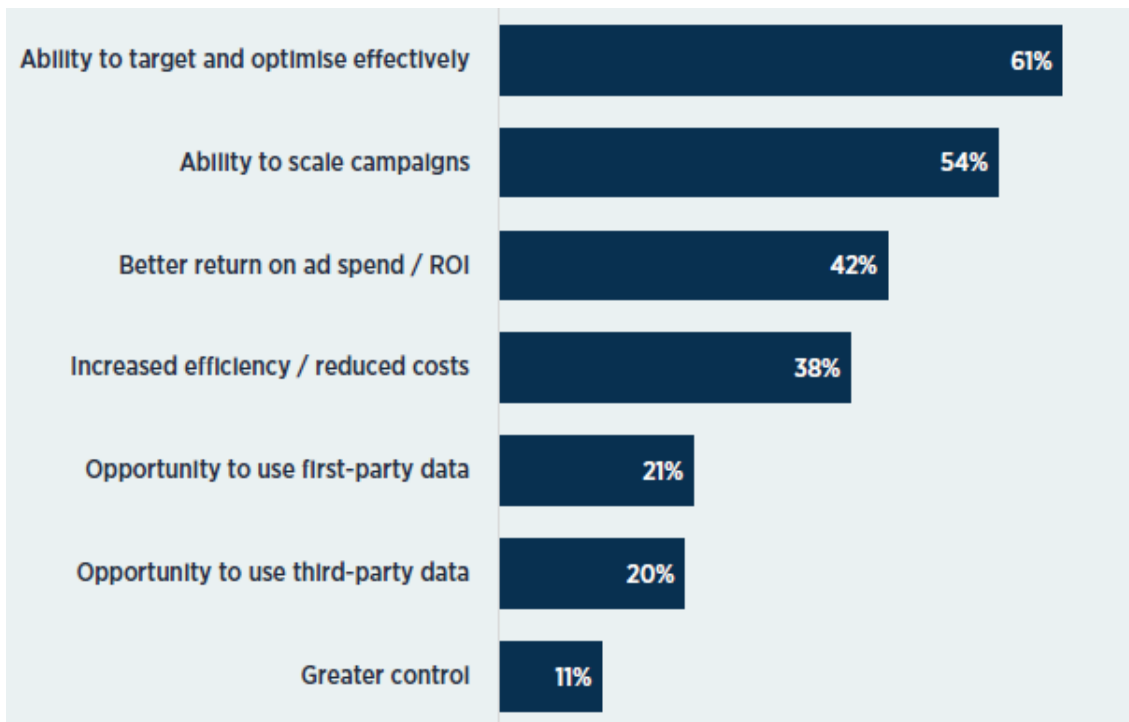
Programmatic advertising has many advantages as well as some disadvantages. These are detailed in the following subheadings.

2.3.1. Advantages of Programmatic Advertising

Programmatic advertising has several advantages for advertisers and marketers. Advantages of programmatic advertising applications include user targeting, offering real-time bids, and customizing ad visibility according to the consumer. It also provides the opportunity to work between platforms (Cross Device). It is possible to combine user data of both search engine, display and mobile campaigns using DMP. Thus, advertisers optimize their communication on all channels (Örmeci, 2016).

According to the results of a study by Gregoriadis & Nutley (2018: 7), the benefits of programmatic advertising practices are listed in Figure 11. Most of the senior executives surveyed (61%) have stated that programmatic advertising is advantageous in targeting and optimization. In addition, 54% of senior executives surveyed think that programmatic ads have the advantage of scaling their campaigns. 42% of senior executives expect a return on investment for advertisers and 38% of senior executives expect cost savings.

Figure 11. Benefits of Programmatic Advertising



Source: Gregoriadis & Nutley, (2018).

Some other benefits of programmatic buying can be listed as follows (Busch, 2016: 64):

- Managing a specific audience.
- Offering consumer-specific advertising.
- Efficient advertising.
- Effective advertising campaigns.
- Efficient feedback from the consumer.

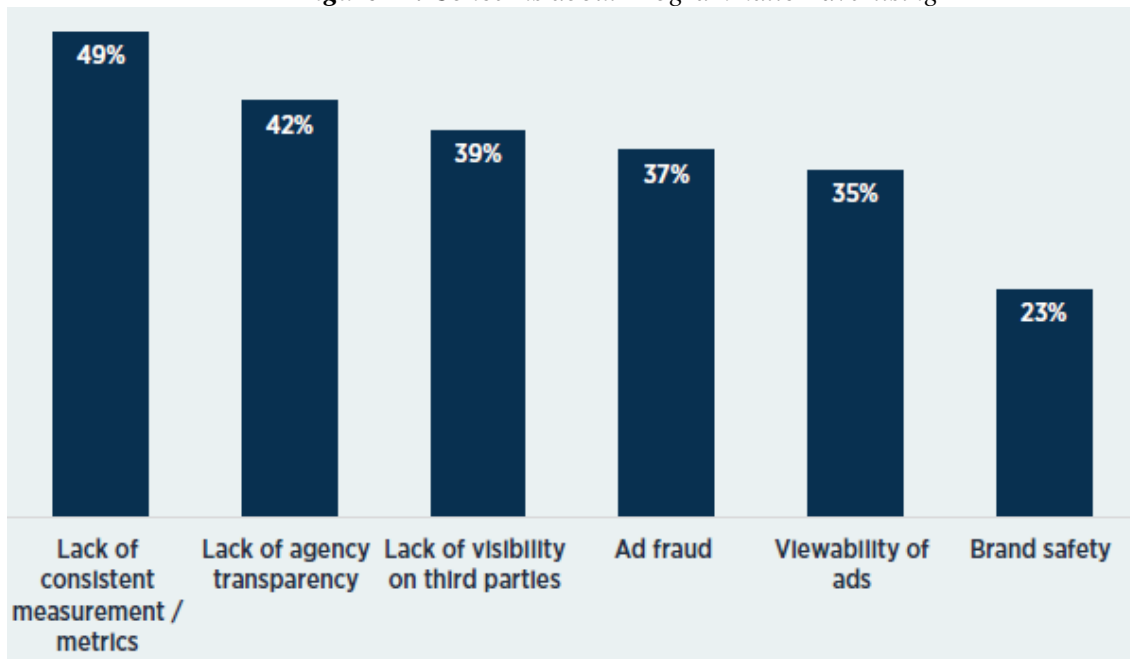
2.3.2. Disadvantages of Programmatic Advertising

Programmatic advertising practices provide a significant benefit to brands by increasing advertising performance, investment opportunities and cost savings. But they may also cause organizational disruption. Failure to apply a standard procedure when using the data, and inconsistency and inaccuracy of the data can be causes of organizational failure. On the Internet, users may have doubts about the privacy of their data. Users may think that the usage limits of their data are exceeded. Even so, users/consumers accept legal problems (Ammerman, 2015).

A study by Gregoriadis & Nutley (2018: 7) indicates that senior executives working for specific brands are concerned about several issues related to programmatic

advertising (Figure 12). According to the results of the study, almost half of the respondents (49%) lack a sufficient measure to evaluate the performance of programmatic advertising practices. Many client-side executives also raise concerns over poor visibility of the activities (42%) and value added (or indeed not added) by agencies and third parties (39%). They have significant fears over ad fraud (37%), viewability of ads (35%), and brand safety (23%) (Gregoriadis & Nutley, 2018: 7).

Figure 12. Concerns about Programmatic Advertising



Source: Gregoriadis & Nutley, (2018).

According to Saman (2020), programmatic Internet advertising has the following disadvantages:

- Extra taxes issued.
- Mismanagement of technology integrated products.
- Products cannot harmonize with each other.
- Difficulties in reaching technology.
- Ordinary due to standards.
- Service and technology expenses.

There is a lack of coordination in programmatic advertising applications. The execution of programmatic advertising practices involves a brand that coordinates the process in a potential series of multiple media agencies and DSP. This contract coordination will require more internal advertiser resources to manage the process, so brands primarily undertake specific contract coordination with DSPs (IAB, 2018: 12).

Programmatic advertising also raises ethical issues. Cookies and geolocation usage on the Internet can be considered offensive (Palos et al., 2019). It offers products that people like at relevant times or in past uses when they visit websites, thanks to algorithms that analyze areas that users follow. Identifying processes with positive and negative outcomes is important in terms of protecting the interests of consumers and creating sustainable value for businesses. Gómez and Feijóo (2013) expressed their contradictions in programmatic advertising in terms of the privacy of consumers' personal data.

The privacy of personal data is a major problem in programmatic advertising. Businesses have access to a lot of consumers' data from digital media and social accounts. This reveals privacy violations. Accessing this personal information can lead to fraud and privacy violations. Moreover, establishing marketing communications and over-communicating with consumers may cause negative situations. Data are collected for the demands and needs of the consumer. However, consumer data can be stolen by malicious individuals or software (Zeren & Keşlikli, 2019). In order to avoid such situations, businesses want to protect users in various ways. One of these ways is permission marketing. Permission marketing refers to marketing offers and announcements selected by consumers (Carmicheal, 2019). Google advertisers support the execution of programmatic advertising practices within the framework of certain standards and guidelines to protect the brand image and provide a more efficient experience for users (Zeren & Keşlikli, 2019).

2.4. CONSUMERS' PERCEPTION OF PROGRAMMATIC ADVERTISING

The most crucial target for agencies and advertisers in the investment part of programmatic advertising applications is the consumer. Delivering campaigns to specific audiences is vital for advertisers. Programmatic advertising consists of the collection of data related to consumers' online behavior (IAB, 2019).

The demands and needs of the consumers are the building blocks of marketing. The needs of consumers are also changing rapidly, with the effect of continuous developments. For consumers, speed and the ability to meet lifestyle-appropriate messages at the right time and in the right place are among the superior aspects of programmatic advertising compared to traditional advertising. Mobile devices have become an indispensable part of consumers. When using location-based services, past

shopping data is automatically displayed. Thus, the right product is delivered to the potential customer in the most personalized way. Meeting consumers with customized offers shown explicitly to them in the areas they are interested in is the most advanced point in the field of marketing in terms of satisfaction and relationship building (Zeren & Keşlikli, 2019).

The data management platform (DMP) supports the formation of a consistent set of metrics to identify, target, and track the consumer audience across channels and devices. The data management platform works with DSP to deliver ads to the right consumer, at the right time and in the proper context. In this process, data performs three functions; identity, target, and deliver. Identity data tries to find out which consumer belongs to which impression, regardless of the consumer. Targeting data is used to decide in determining the price by analyzing whether the consumer is worthy of bidding. Delivery data is used to serve appropriate creative content once the user is identified. Some of the data in the programmatic advertising process are social media data, e-mail data, and online shopping data (Watts, 2016: 8).

The advancement of data collection is an essential goal for marketers. It has contributions such as higher productivity, improved targeting and optimized campaigns. Marketers think that this is a paradox among consumers. It is referred to by some as the “privacy paradox”. Research shows that consumers have a positive attitude to increasing online personalization but believe the data will still be misused (Watts, 2016: 9). It is observed that people have inconsistent and contradictory impulses when it comes to protecting their data (Turow et al., 2015: 5). According to a YahooAdvertising report (2014), “*roughly two-thirds of consumers find it acceptable or are neutral to marketers using online behavior or information to craft better ads*”. The programmatic advertising industry continuously seeks transparency in its processes. Marketers should analyze thoroughly where and how they spend their investments. As a result of this paradox, there needs to be more transparency in the collection and use of personal data. Users have fundamental rights to data privacy. Users need to know how the data is used and on which platforms it is shared. They have the right to determine whether the data will be used for advertising purposes (Gregoriadis & Nutley, 2018: 6).

According to Watts (2016), programmatic advertising has greatly influenced the purchasing intentions of online shoppers compared to other forms of online advertising, providing evidence of more positive attitudes towards brands. As a result of his

research, Watts (2016) revealed that consumers react positively to programmatic advertising. By the end of the study, more than half of the respondents (56%) announced that they believe websites use their personal data (to sell and make a profit from it). More than 20% of respondents believe websites use their data to “enhance their online experience”. Also, at the end of the study, it was mentioned that the ads served with programmatic advertising had a more positive effect than other types of online advertising and that consumers had a more positive attitude towards brands. The result of his work supports the “privacy paradox”(Watts, 2016: 15).

Today, about 65% of all digital advertising is bought and sold by machines, while the expectation of programmatic advertising to leave a positive perception of consumer behavior is quite limited (Watts, 2016: 5). The main reason for this is that consumers do not have sufficient knowledge of programmatic advertising. In the IAB (2015) survey, 47% of respondents stated their level of knowledge about the subject by saying “I don't know what programmatic advertising is or I'm not quite sure what it is”.

SECOND PART

TRUST, PERSONALIZATION AND PURCHASE INTENTION

1. TRUST

Trust is the fulfillment of the promises reliably made by individuals or companies (Schurr & Ozanne, 1985). Trust determines the balance of social and commercial order and the quality of business relations (Kumar et al., 1995). People can avoid any activity if they do not feel a sense of trust (Blau, 1964 & Luhmann, 1979). Trust is also an important factor in marketing. Without the trust factor, the development of marketing cannot be expected. Security and privacy factors are some of the factors that affect this development (Cheskin Research & Sapient, 1999). As with traditional marketing methods, trust is important for consumers in digital marketing. There are positive developments in online marketing levels for consumers with positive security experience (Krishnamurthy, 2001). In the privacy factor, if consumers have doubts about privacy, they are more likely to give incomplete information to websites (Franzak et al., 2001; Kim & Hoy, 1999). Providing effective information in digital marketing is another factor that affects the trust factor. Effective information creates awareness for the product or service. Irrelevant information reduces consumers' belief in the product or service (Meyvis & Janiszewski, 2002).

1.1. CONSUMERS' PERCEPTION OF ONLINE TRUST

Trust is a factor intended to attract and protect consumers' interest. It effects the behaviors of consumers significantly; and research on trust in marketing has focused on the buyer-seller relationship in the industrial and consumer markets (Morgan & Hunt, 1994; Anderson & Narus, 1990).

Trust is recognized as a key factor in establishing and maintaining long-term relationships with consumers (Sharma et al., 2000: 471). Trust has an economic value between buyer and seller in the long run. According to this value, consumers show an attitude towards the perception of trust. The risk perception level of the buyer in any product / service purchase process forms the basis of the concept of trust (McCole, 2002: 82). The factor of trust in marketing research is to create long-term value for consumers, to exchange services, and to ensure consumer loyalty (Sirdeshmukh et al., 2002).

When consumers want to buy products or services in the online marketplace, trust becomes an essential factor because the online consumer cannot directly examine the product or service and their behavior during the shopping process is not clear (Grabner, 2004: 2). In the online market, consumers can solve the uncertainty of transactions with the trust factor (Luhmann, 1989). When consumers evaluate a web store online, the trust factor positively affects consumers' attitudes towards shopping (Wang, 2003).

Consumers may not always have access to the online trust factor. Nohria and Eccles (1992) explain online trust threats as follows:

- Non-concurrence of the concepts of time and space.
- Lack of auditory, visual, touch emotions.
- Lack of feedback.

These factors can build insecurity and privacy issues. That is why Internet marketers must create a much more reliable and long-term trust than offline marketers (Keen, 1997: 80). Hoffman et al. (1999) argue that lack of trust prevents consumers from engaging in online transactions and the consumers are unlikely to trade with a web retailer that cannot convey the sense of reliability.

In the sector of increasing e-commerce, information technology researchers have focused their attention on information security and privacy issues that affect trust (Shankar et al., 2002). The trust factor reduces the perceived risk (Fukuyama, 1995 & Morgan & Hunt, 1994).

Trust creates behavioral control in online transactions and provides expectations for satisfactory purchase (Pavlou, 2003). The trust factor is considered as a determining factor in online shopping (Gefen et al., 2003). The reason why this factor is important is that in the absence of any warranty, the consumer cannot be sure that he/she will not resort to unwanted behavior, such as the seller's privacy violation, unauthorized use of credit card information, access to illegal transactions (Reichheld & Scheffer, 2000). Therefore, the consumer may be concerned about the privacy and control of personal information. The trust factor can address privacy and security concerns for companies in e-commerce (Rifon et al., 2005). Thus, it may be possible to increase sales (Stewart, 2003).

The security of the systems used is one of the factors that prevent consumers from making online purchases (Choi et al., 2004). Internet security is becoming a focus point as most people use the Internet these days (Nikhashemi et al., 2013). Yoon (2002) classified online trust into three categories:

- Technical base.
- Process and security uncertainty.
- Reputation.

In the context of online shopping, the trust factor points out that the consumers' purchasing intentions, satisfaction and loyalty are related to the formation of consumer trust (Ba & Pavlou, 2002). Brynjolfsson & Smith (2000) stated that there are uncertainties and risks in online environments between online consumers and web retailers. First, there are risks associated with monetary loss, as online consumers need to rely on electronic information. Consumers may be exposed to missing or corrupt product information. Second, there are risks associated with disclosure of personal information to online shopping sites and third parties. To eliminate the risks, consumers who have a high level of trust in specific shopping sites are willing to pay price premiums for the purchase of certain products.

According to Bélanger et al. (2002), online security is valued more than the privacy factor by consumers. Based on the large-scale survey conducted by Fogg et al. (2001), they concluded that the ease of use of a website is among the factors that create online trust. According to Holliman and Rowley's (2014) findings, long-term content can create trust. Marketers can increase online trust by publishing more step-by-step educational content.

1.2. CONSUMERS' TRUST IN PROGRAMMATIC ADVERTISING

Programmatic advertising applications are one of the online advertising applications. Programmatic advertising applications provide benefits for both consumers and marketers. Consumers see more personally specific advertisements, while marketers save time and money (Faulkner, 2014). Ads shown in programmatic advertising applications should be economical for consumers. In other words, the consumer should be reached with the price and target determined as a result of proper data analysis of the consumers. Marketers who provide control can hold the consumer in the long term with transparent management and economic controls (Algo, 2019).

When any advertisement is programmatically purchased, marketers should trust technology. Marketers don't have enough ability to validate millions of ads. There is concern among marketers on how to evaluate programmatic advertisements through consumers' eyes due to software errors and technology limitations (Siebelink & Belani, 2013).

Despite the compatibility of programmatic advertising with digital data sources, there are some problems in terms of budget issue and technology trust. Consumers now expect more transparent practices in ads display, as they have greater knowledge. Another problem of consumers is the protection of their personal data. Programmatic advertising requires control, transparency and training for the security of personal data (Orange, 2014).

A survey by GfK (2014) reported consumers' concerns about personal data in terms of use. The respondents of the survey were skeptical of how marketers and advertisers use their personal data. Respondents were asked: "*How much do you trust marketers and advertisers with regard to how your personal data is handled?*" The results revealed that 64% of Americans do not trust marketers, and only 25% of them trust marketers. The remaining 11% responded "don't know". In 2016, the annual TRUSTe US Consumer Privacy Index indicated that 92% of US Internet users were skeptical of their online privacy. 31% of US Internet users know how their personal information is shared with other organizations. 56% of US Internet users trust that companies use consumers' personal information appropriately (Stevenson, 2016: 30-32).

There are studies in literature that have investigated programmatic ads and the trust factor, and that have discussed the issues of privacy, transparency and security in general (Palos et al., 2018; Algo, 2019; González & Mochón, 2016). In this study, consumers' perception of trust in programmatic advertising applications and the effect of trust on their purchase intention are investigated. The study conducted by Leiva et al. (2016) examined mobile banking applications by integrating user perceived risk and trust; and the results showed how mobile apps determine their intended use and ignore risk. In the study conducted by Gefen (2000), searching for books on the internet and purchasing books were examined within the scope of e-commerce; and results stated that participants' trust in internet sellers affect the purchase intentions of them.

2. PERSONALIZATION

The concept of personalization emerged as early as late nineteenth century (Ross, 1992). It is commonly referred to as targeting and profiling (Petrisson et al., 1997). As stated by George (2017), personalization is “*a process that creates a relevant, individualized interaction between two parties designed to enhance the experience of the recipient*”. Personalization is a special form of differentiation that changes product design from an inherent compromise to a process of deciding what features would benefit an individual (Hanson, 2000). Personalization is a customer-oriented marketing strategy which includes sending private and convincing messages to individuals (Maslowska et al., 2011). Personalization is about selecting or filtering products using information about the individual. Personalization can be tailored to a group of people or a specific individual (Schubert & Koch, 2002). Personalization is to customize the consumer’s experience according to individual needs based on the information provided by the consumer (Goward, 2019).

In face-to-face communication, companies want their employees to adjust the service according to the customer. This is a time consuming and costly application (Aguirre et al., 2015).

Personalization is also used in online environments and it is integrated to support the interfaces of websites. It is used to collect data and then make the website more personalized (Pierrakos et al., 2003). Marketers often implement this personalization strategy in online communication messages (Aguirre et al., 2015). Consumers should have a freer impression of online advertising applications. Contents that is under the control of the consumer should be allowed. More personalized contents should be served online without the need for ad blocking (Han, 2019). Many companies prefer to create personalized online advertising, for example Facebook. Because it is less expensive than the face- to- face communication (Tran, 2017).

2.1. PERSONALIZATION TYPES

Personalized service is an interactive process in which a vendor provides relevant customized content based on clients’ preferences (Miceli et al., 2007).

Table 4 shows the types of personalization. The table also shows the basic idea of the types of personalization, when it is used, customer information and basic

examples. Table 4 also has information about learning opportunity, customer interaction, change in presentation, and variation of product.

Table 4. Types of Personalization

Type of Personalization	Segment Marketing	Adaptive Personalization	Cosmetic Personalization	Transparent Personalization	Collaborative Personalization
Typical Actor	Reader's digest	Yahoo.com	Google.com	Amazon.com	Hairdresser
Basic Idea	To match customer preferences better than with mass-marketing	To let customers choose from different options	The organization changes the package of standard good	The organization changes the content of a good with a standard look	The organization and customer are together building the product
When to use	Little customer knowledge, cheap	A lot of choices to choose from	Customer sacrifice is due to presentation	Customer contents are repetitive	Determining either-or choices
Customer Information	Purchase/Demographic information	Direct choice by customer	Purchase /Demographic /Behavioral information	Purchase /Demographic /Behavioral information	Direct interaction
Learning Opportunity	Low	Medium	Medium	Medium	High
Customer Interaction	None	High	Low	Low	High
Change in Presentation	Possibly	No	Yes	No	Likely
Variation of Product	Possibly	No	No	Yes	Likely

Source: Michelsson, (2005) partly adapted from Joseph and James, (1999).

The main personalization types which are summarized in Table 4 can be explained as follows:

The key to segment marketing is to define the market, to set policies for existing brands and products, and to capture new product opportunities in the market (Drayton & Tynan, 2010). Segmentation increases the quality level of websites and email content. It is a strategic plan as it addresses a specific target. Thus, the general level of participation also increases. The downside is that the level of personalization is limited as it appeals to all people (Onespot, 2018). As can be seen from the Table 4, there is no customer interaction in segment marketing.

Adaptive strategy is used to present customer information in real time. For example, Groupon.com offers daily deals for products and services from local or national retailers. Customer interaction is high as this strategy includes adaptive personalized messages (Tam et al., 2010).

Cosmetic personalization is also known as the most innovative way of personalization. It is technology-based. Each time the users visits the page, they get different experiences. It is like a machine that can show personalized messages on own devices. This strategy is based on a comprehensive customer analysis. Provided by existing technology, customer profiles are constantly updated with new data. Every browsing click, adding to the cart, etc. affect the recommendation improving their relevance to the buyer (Radu, 2015).

In the transparent personalization, Amazon.com shows users why a product is recommended to them and explains the source of this information, and they have a transparent attitude. “Recommended for You” option by Amazon.com states that it does not offer random suggestions to the user. There is a “Recommended because ..” description under each product. The Amazon user has the right to turn off browsing history. If the user does not want to receive personalized messages, he/she can define it. Amazon’s Recommended for You page features product recommendations based on items one has ordered. The user can customize the suggestions by controlling which products he/she is interested in according to the needs. With this user-specified feature, Amazon.com helps better adapt its recommendations to users. Amazon.com is an example of making the customization easier for users (Baker, 2014).

Collaborative personalization tries to match users. It can also provide the customization feature of the profiles of consumers without having a specific transaction history. Matching takes place based on the information of the liked people. The basic idea is to support the principle of the “word of mouth electronically”. Collaborative personalization is about using data obtained by other customers to improve a client's offers (Schubert & Koch, 2002). Companies like P&G communicate effectively with consumers. It does this thanks to smart products and solutions. For example, Oral-B's web-enabled toothbrush offers customers a personalized service. Even while the consumer is watching Oral-B advertisements, he/she has an application that he/she can use on his/her phone in his/her desired setting. Oral-B provides a more personalized service every time based on the data of the consumers. This feature attracts the attention of the consumer (WARC, 2019).

2.2. CONSUMERS' PERCEPTION OF ONLINE PERSONALIZATION

In web-based communications, companies use personal data to show ads according to the previous behavior by personalizing search results in search engines. Thus, by analyzing the prior behavior of consumers in online communication, marketers can personalize the messages more accurately.

Personalization is one of the structures that helps to define the effectiveness of the consumer on the website (Chakraborty et al., 2002). In online transactions, personalized content is prepared individually for each consumer. It is a way to help the consumers discover what they do not know (Belkin, 2000). It is used for personalization, pricing and product distribution on online sites. The feature that distinguishes online personalization from other applications is that consumer can track everything with a click. Thus, there is a close communication between companies and consumers. Personalization in online transactions enable sending personal emails to potential consumers. Online personalization helps customers spend quality time and it may increase sales (Ramnarayan, 2005). Personalization creates a service that better meets the wishes of the consumer (Vesanen, 2005).

Marketers provide more individualized service to their customers' needs (Aguirre et al., 2015). E-mail messages are at the beginning of effective methods as an individual service. According to the study conducted by Ansari and Mela (2003), consumers are more concerned with personalized email messages. Marketers can increase response rates by 62% by personalizing the content of e-mails to consumers' attention. According to study of the Howard and Kerin (2004), personalization causes a significant (6,2% personalized vs. 2,8% not personalized) increase in e-mail response rates. Internet retailers use online recommendation systems to strategically analyze and use personalized product information; and such systems are more effective for consumers than traditional sources of advice (Senecal & Nantel, 2004).

2.3. PERSONALIZATION IN PROGRAMMATIC ADVERTISING

Programmatic advertising allows marketers to segment consumers by acquiring information from them. It is used in marketing by combining programming with personalization in many brands and websites. With the personalization feature in programmatic advertising applications, the targeted consumer is focused. Thus, special

content is offered to the consumer. Programmatic advertising applications are easier to manage with creative personalization (Adadyn, 2019).

Consumers see personalized ads a lot throughout the day. Programmatic advertising applications have a lot of personalized contents. For example; Netflix shows certain content to people based on the movies they have watched before. Thus, people are more willing to use the application (Türkyılmaz, 2019).

Hawkins et al. (2008) explain the distinction between the three personalization tactics with the following examples. In the identification tactic, the personal information of the recipient such as his/her birthday and name is included in the message content. For example: “Dear Edward, today you get a special 10% discount for your birthday”. In contextualization tactic, the key is to create the message in a meaningful context for the recipient. For example, to present the recipient's hometown in the message content such as “People from Spain get a 10% discount today”. Customization tactic is a service designed specifically for a specific audience. Customization tactic is a marketing strategy that aims to offer customized products or services (Murat, 2013). “The following message was created for you” is an example in the customization tactic. But this message does not include the recognizable aspect of the individual. Each recipient gets the same message, but it is customized for recipients by design (Dijkstra, 2008).

Personalization uses information about consumers. The general term for stored consumer information is “user profile” or in the context of electronic shopping “customer profile” (Schubert & Koch, 2002). Since online personalized messages consist of consumers’ previously collected data, marketers must first collect consumers’ data (Aguirre et al., 2015). One of the data collection methods is to ask website users to create online profiles by registering (Kazienko & Adamski, 2007). During registration, personal data such as name and e-mail are requested. Also, interests, hobbies, social activities can be required. There is often a requirement to create profiles for users to participate in social networking sites. Thus, social networking sites are considered as proper personal information gathering tools. For example, Facebook users reveal their interests by liking a particular brand (Walrave et al., 2016). Although the interests, likes and personal information are entered, the accuracy of the data is not clear for marketers.

Another data collection method is to collect from web server logs. Web server logs are computer activity logs that store the content of websites. The advantage of this

method is that users do not need to register to use their website. The script reads the cookies on the users' computer and then perform operations based on this data. Browser data, previous online behavior, age and geographical location are examples of data that can be collected by cookies (Kazienko & Adamski, 2007).

Personalization is frequently used in programmatic advertising applications. This is because programmatic advertising applications are used according to users' data. Personalized ads are a way to propose accurate offers to consumers (Jung, 2017). If a consumer is shown a personalized advertisement different from regular advertising practices, this will be more valuable for the consumer (Simonson, 2005).

Companies devote part of their budgets to personalized message promotions in programmatic advertising practices (Cruz et al., 2017). However, according to Treiblmaier and Pollach (2007), if companies send personalized messages to the consumers in this way, consumers may ignore these offers after a certain period.

Sending personalized messages to consumers in programmatic advertising applications sometimes causes privacy problems. Information privacy is explained as controlling and owning individuals' information (Bélanger & Crossler, 2011; Pierce et al., 2001). Consumers have concerns about how personal data are used and collected. According to the results of a US national survey, privacy concerns of consumers are observed to affect purchasing intentions negatively (Phelps et al., 2001). Doorn and Hoekstra (2013) state that consumers with a high level of privacy concern perceive personalized advertisements as intrusive, thus they are less likely to purchase. The privacy paradox theory shows that users are concerned about their privacy on social platforms, but they do not take these concerns into account according to their behavior. Debatin et al. (2009) claim that consumers still upload large amounts of personal information to social platforms, although they know that they have privacy problems. This confirms the existence of the privacy paradox. 92% of American Internet users are concerned about their online privacy on social platforms (Karwatzki et al., 2017). Pagani & Malacarne (2017) argue that when privacy problems arise, some consumers use the location settings by disabling them to change the behavior.

A consumer who previously had a privacy violation problem is less likely to trust social media (Culnan & Armstrong, 1999). Xu et al. (2010) argue that consumers who are open to innovations and adopt innovations early have a higher perception of

personalized ads. Mosteller & Poddar (2017) explain that companies' regular control of customer information creates a sense of trust in the consumer. As mentioned before, "Permission marketing" can be considered to solve the privacy problem. Reimers et al. (2016) state that companies should send only accepted messages. They also state that messages should be suitable for customer needs that are conveyed to create value; otherwise the customer is likely to unsubscribe from the mailing list. Jung (2017) states that negative attitudes might arise if customers are exposed to personalized advertisements.

There are studies in literature that have investigated programmatic ads and the personalization factor, and that have discussed the issues of personalization levels and privacy in general (Bleier & Eisenbeiss, 2015; Palos et al., 2018). Xu (2006) stated that the high penetration rate of mobile phones became a marketing channel tool for mobile advertising and investigated the factors that affect consumer attitude towards mobile personalization. The results of the study showed that there is a direct relationship between the consumers' attitude towards and mobile personalization. In the current study, consumers' perception of personalization in programmatic advertising applications and the effect of personalization on their purchase intention are investigated.

3. PURCHASE INTENTION

The intention to purchase represents the possibility or willingness of consumers to purchase a particular product or service in the future. If the intention to purchase increases, this means that the probability of buying increases (Dodds et al., 1991; Schiffman & Kanuk, 2007).

Purchase intention is used as an indicator to predict consumer behavior. If the consumer has a positive purchase intention, this creates a positive brand commitment that drives consumers to make real purchases (Fishbein & Ajzen, 1975; Schiffman & Kanuk, 2007). The intention to purchase is the form of planning that is consciously made to purchase a product (Spears & Singh, 2004). The purchase intention is the determinant of the purchase decision process and indicates the probability of an individual purchasing a product (Isaksson & Xavier, 2009). Purchase intention is the intention that consumers plan to purchase a brand or product (Lin et al., 2013).

3.1. ONLINE PURCHASE INTENTION

Internet environments are where e-commerce transactions are made and where consumers make purchases. Consumers use websites for both getting information and making purchases. The purpose of the purchase is to obtain the product or service that the consumer requests in online transactions (Pavlou, 2003).

First-time visitors to a website may be concerned about information security and the technology involved in online transactions. Consumers want an atmosphere of trust between the user and the seller on a website or service. This situation is essential for the control of personal information. Also, consumers want to see apps that provide online security. For example, symbols such as Visa provide an increase in trust. If consumers have a sense of trust, they can make purchases in the long run. As trust increases, consumers pay more attention to brand and technology in online transactions. Transaction security also positively affects the intention to purchase on web visitors (Yoon, 2002: 51).

Moreover, consumers' beliefs influence their purchase intentions. The online trust factor positively affects purchase intention (Yoon, 2002; Grabner-Krauter & Kaluscha, 2003; Pavlou, 2003; Gefen & Straub, 2004). One of the indicators of the success of online advertising is the intention to purchase (Brown & Stayman, 1992; Moe & Fader, 2004; Raney et al., 2003). According to the Online Publishers Association (2008), 66% of online consumers remember content messages posted on their websites and this can improve their purchase intention with brand advantage (Wei, 2010). Also, the design of websites is an essential factor in creating a good advertising perception by promoting e-customers' purchase intention (Ranganathan & Ganapathy, 2002).

Online consumers with strong purchase intention in e-commerce often have prior online purchasing experiences thanks to personalization (Enginkaya, 2016: 12). Previous buying habits are positively associated with e-commerce purchasing intentions (Shim et al., 2001; So et al., 2005).

The intention to purchase is the potential to buy a product of a specific brand. Purchase intention consists of various factors such as motivation and perception. Consumer motivation can have a positive or negative impact when purchasing a product

or service. The perception of the consumer can always vary in the product or service. (Belch, 2015).

Gazley et al. (2015) noted that consumers may be exposed to SMS (Short Messaging Service) advertisements before and after the purchase phase. When customers receive such messages, they think that someone is watching them. SMS messages delivered at the right time affect consumers' intentions at the purchase stage. (Sunaga & Ishii, 2014).

Yoon (2002) distinguishes purchase intention as buying online and buying offline. Those who are satisfied with the website or trust the site are likely to buy online. Those who are dissatisfied and who trust less tend to buy offline.

Transaction security is the institutional indicator of the online company's payment system, as well as the measurement of the risk level of the consumer. Thus, the security and privacy of payment systems in online purchases directly affect consumers' purchase decisions (Çadircı & Güngör, 2018).

3.2. PURCHASE INTENTION IN PROGRAMMATIC ADVERTISING

According to Watts (2016), programmatic advertising has greatly influenced the purchase intentions of online shoppers compared to other forms of online advertising; providing evidence of more positive attitudes towards brands.

Zarouali et al. (2017) states that the effect of targeted advertisements on purchase intention is higher than that of non-targeted advertisement. Bleier & Eisenbeiss (2015) observe that targeted ads containing the products that consumers previously placed in the shopping cart attract the attention of consumers more than other advertising applications. It is understood that programmatic advertising offers that are related to consumer preferences have a positive effect on purchase intentions (Doorn & Hoestra, 2013).

According to Saman (2020) programmatic purchases are more effective than traditional purchases. Also, publishers and large agencies are more interested in programmatic advertising practices. However, small and medium-sized businesses are not highly involved in programmatic purchases because service and technology expenses are higher in programmatic purchases.

Since programmatic advertising practices are shown to affect consumers' purchase decisions in literature, the third part of this study is devoted on a research that investigates the effect of programmatic advertising on purchase intention as well as the effects of trust and personalization.



THIRD PART

THE EFFECT OF TRUST AND PERSONALIZATION IN PROGRAMMATIC ADVERTISING ON CONSUMERS' PURCHASE INTENTION

1. THE PURPOSE AND IMPORTANCE OF THE RESEARCH

The primary purpose of this study is to investigate the effect of consumers' perception of trust and personalization in programmatic advertising on their purchase intention. Programmatic advertising is one of the artificial intelligence applications that is actively used by marketers. The topic of programmatic advertising is of high importance to researchers, organizations and policy makers. This is one of the instances where consumers' online behavior is measured as an effect of programmatic advertising (Keane, 2018).

Programmatic advertising has brought many developments. Some of them are; fast data connections, science in marketing, personalization and inexpensive data storage. These developments have provided new opportunities for the marketing industry (Busch, 2016: 6). Programmatic advertising practices are a way to optimize all inventory. Consumers gain more confidence in programmatic advertising practices with data-based strategies (Cerezo, 2004).

In the previous literature, programmatic advertising was discussed in terms of concept and functioning (Zeren & Keşlikli, 2019). González & Mochón (2016) described the basic functioning of programmatic advertising. On the other hand, Watts (2016) mentioned that programmatic advertising violates consumer privacy.

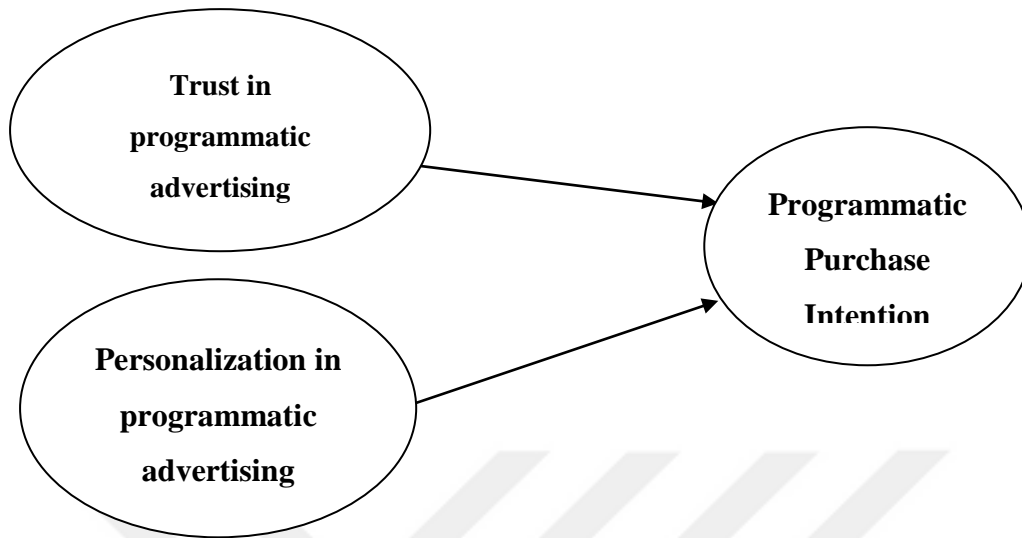
“Trust” and “personalization” are two factors which are investigated in other research areas, but there is a lack of research especially in the field of programmatic advertising, which makes this study important. This research is also important as it examines the effect of programmatic advertising practices on consumers' purchase intention. The results are expected to contribute to theoretical literature and to give insight to marketers in planning programmatic advertising strategies.

2. RESEARCH HYPOTHESES AND RESEARCH MODEL

In this study, consumers' perceptions of trust and personalization towards programmatic advertisements and the effect of these two factors on purchase intention are examined using a cause and effect research model. Research model of this study is

shown in Figure 13 and the variables of the model are explained below, along with the hypotheses.

Figure 13. Research Model



Some studies in the literature investigated trust and personalization factors in online transactions on social platforms (Yang et al., 2015; Yoon, 2002). Yoon (2002) concluded that when consumers visit a website for the first time in online transactions, consumers are skeptical about the trust and protection of their data. Consumers want to feel safe during the purchase process. Various applications can be used to ensure the trust of consumers. For example, in Internet banking, personal questions are asked to customers for security. These types of applications provide trust and positively affect the purchase intention.

The concept of trust is an essential key for programmatic advertising practices. It is effective in creating a safe market place. Environments that provide trust on behalf of all parties should be encouraged to avoid problems such as Uniform Resource Loader (URL) theft. Advertisers and publishers should attempt to build an environment of trust. Trust and a more transparent environment is needed in digital media for the advancement of programmatic advertising practices. Marketers and publishers must give attention to fake applications (Cerezo, 2004).

Companies use digital channels to create a sense of trust with customers and to protect their image. Firms thus enable the purchasing process to be realized by winning potential customers (Mills, 2012: 165).

Consumers cannot fully create a sense of trust in purchases made on digital channels and consumers are anxious at the point of digital money transfer. In this case, the purchasing intention of the consumer may be negatively affected (Wind & Mahajan, 2002). According to the studies in the literature, the first hypothesis of this study has been established as the following:

H₁: Trust in programmatic advertising positively affects purchase intention.

Personalization features are used to generate value for the customers of many types of e-service websites. Companies prepare offers according to the needs of the customers (Vassiliou et al., 2003). As mentioned before, marketers need to collect personal data in order to personalize the advertisements (Kazienko & Adamski, 2007). Personalized messages are messages that incorporate recognizable aspects of a person in the content information (Dijkstra, 2008). A personalized message refers to the individual and therefore triggers self-reference (Dijkstra & Ballast, 2011). These personalized messages in programmatic advertising are expected to affect purchase decisions.

In some researches, it was found that personalization had a positive effect on purchase intention (Arora et al., 2008; Postma & Brokke, 2002; Tam et al., 2010) while in some researches it had no effect (Wessel & Thies, 2015). Moreover, Wanger & Balke (2003) stated in their study that personalized offers may result in purchasing more products than the purpose of the consumer. An example is the display of headphone products to someone who bought a mobile phone.

The personalization of a website has positive effects on the attitude towards the advertisements on that website (Kim & Sundar, 2012). Personalization on social networking sites positively affects advertisements through the intention of clicking (Keyzer, Dens & Pelsmacker, 2015). Yang et al. (2015) stated that personalized advertisements are shaped according to online users' previous shopping behavior. These data of consumers are collected through "cookies". For example, after a user likes a brand on Facebook, he/she receives personalized messages in different social media posts. Personalized mobile advertisements positively affect the consumer behavior of users (Xu et al., 2008). Therefore, it is proposed:

H₂: Personalization in programmatic advertising positively affects purchase intention.

3. SCOPE AND LIMITATIONS OF THE RESEARCH

The scope of this research covers everyone who uses the Internet and data was collected using an online questionnaire using a convenience sampling procedure.

Despite its strengths, this study also has some limitations. One of the limitations of the study is that only two factors –trust and personalization- are included as factors that can affect purchase intention of consumers. But, there may be other factors in programmatic advertising that can affect purchase intention of consumers as well. Another limitation may be the choice of the sampling method in data collection. The data was collected using convenience sampling; therefore, the generalization of the results to the whole population may be limited.

4. RESEARCH METHOD

The main research question of this thesis is “How do the factors of trust and personalization affect consumers’ purchase intention in programmatic advertising applications?” To find an answer to the question, a structural equation model in the explanatory research type was established and the cause and effect relationships between the factors were examined. Accordingly, one of the most critical factors that make up the purchasing behavior, “purchase intention”, was investigated and determined as a dependent variable. The variables of “trust” and “personalization” compiled from the studies in the literature were included in the model as factors affecting purchase intention.

In addition to the structural equation model, the effect of other variables on purchase intention were also examined in this study. According to demographic characteristics such as gender, age, income, occupation, education, and marital status, the differences in purchase intention between groups were analyzed. Lastly, the effect of consumers’ online shopping status and frequency on purchase intention was examined and findings are interpreted.

4.1. DATA COLLECTION METHOD

The questionnaire was applied to the participants by the online survey method via Google Forms between 01.04.2020 and 31.05.2020. The questionnaire included four main parts. In the first part, there were questions about demographic characteristics, Internet usage and programmatic advertising. In the second part of this study, there were questions about measuring the perception of trust in programmatic advertising

applications. In the third part, there were questions about measuring the perception of personalization in programmatic advertising applications. The questions in the fourth part were about purchase intention.

The research model was investigated with the structural equation modeling, which was used to investigate the effects of trust and personalization on purchase intention. 5-point Likert scale was used for the variables in the structural equation model. Questions were prepared according to the Likert scale as 1-Strongly Disagree, 2-Disagree, 3- Undecided, 4- Agree, 5-Strongly Agree.

The scales from Leiva et al. (2016) and Gefen (2000) were used for the trust variable. The questions for the purchase intention variable were adapted from the scales of Pavlou (2003) and Hong & Cho (2011). The questions for the personalization variable were adapted from the scale of Xu (2006).

In addition to the questions related to the structural model variables, the participants were asked about their demographic characteristics such as gender, age, income, marital status, and educational status. Also, questions were directed to participants to understand their Internet usage and their approach to programmatic advertising.

English and Turkish versions of the applied questionnaire can be seen in Appendix 1 and 2 respectively. The Ethics Committee Approval required for the questionnaire's implementation can be seen in Appendix 3.

4.2. POPULATION AND SAMPLE

The population of this study consists of consumers who use the Internet for several purposes. These people may encounter programmatic advertising applications while they are using the Internet and their perceptions about programmatic advertising form the basis of this study.

In this study, the convenience sampling method was used considering the answers of those who want to join the survey. The research model was measured using an online questionnaire and 400 people were reached. However, 12 participants (because they were under age 18) were excluded from this sample. Analysis was conducted with the remaining 388 participants.

4.3. DATA ANALYSIS

After collecting the data via Google Forms, SPSS program is used to analyze the descriptive statistics about participants' demographic characteristics, Internet usage and approach to programmatic advertising.

After the descriptive statistics are made, exploratory factor analysis (EFA) is performed to see if the items of the variables are collected under the relevant factors as planned. Then, the validity and reliability analyses of EFA are performed. After the EFA, confirmatory factor analysis (CFA) is performed in AMOS and the reliability and validity of the factors are checked again.

The proposed model and the hypotheses are tested using the structural equation modeling (SEM) in AMOS. In addition to the structural equation model, the differences in purchase intention according to the participants' demographic characteristics, Internet usage and approach to programmatic advertising are analyzed using One-Way ANOVA and T-Test in SPSS due to the normal distribution of the data. AMOS 24.0 program is used for CFA and SEM, and SPSS 25.0 program is used for other analysis.

5. RESEARCH FINDINGS

Results of descriptive statistics, EFA, CFA, analysis of SEM, and analyses of differences in purchase intention according to participants' demographic characteristics, Internet usage, and approach to programmatic advertising are included in the following sections.

5.1. DESCRIPTIVE STATISTICS

According to 388 questionnaires that are suitable for analyses, the majority of the participants are women (57,5%), and more than half of the participants are married (54,6%). Regarding the education levels, majority of the participants have at least a bachelor's degree (88,6%). Considering the monthly income distribution of the participants, it can be concluded that there is no significant concentration in a certain category and the monthly income levels of the participants are distributed among the categories. According to the data, most of the participants are aged between 18 and 35 (67%) which means the sample mainly consists of young people. Nearly half of the participants are occupied in public sector (43,0%). The distributions of these demographic data are given in Tables 5, 6, 7, 8, 9 and 10.

Table 5. Distribution of Gender

Gender	Frequency	Percentage
Female	223	57,5
Male	165	42,5
Total	388	100,0

Table 6. Distribution of Marital Status

Marital Status	Frequency	Percentage
Single	176	45,4
Married	212	54,6
Total	388	100

Table 7. Distribution of Educational Level

Educational Level	Frequency	Percentage
Secondary School	5	1,3
High School	39	10,1
Bachelor's Degree	274	70,6
Master's Degree and up	70	18,0
Total	388	100

Table 8. Distribution of Monthly Income

Income Status	Frequency	Percentage
Under 1.000 TL	72	18,6
1.000 – 1.999 TL	39	10,1
2.000- 2.999 TL	59	15,2
3.000- 3.999 TL	75	19,3
4.000- 4.999 TL	59	15,2
5.000 TL and up	84	21,6
Total	388	100

Table 9. Distribution of Age Groups

Age Groups	Frequency	Percentage
18-25	84	21,6
26-30	95	24,5
31-35	81	20,9
36-40	43	11,0
41-45	19	4,9
46-50	13	3,4
51 and up	53	13,7
Total	388	100

Table 10. Distribution of Occupation

Occupation	Frequency	Percentage
Not working	75	19,3
Student	61	15,7
Self-Employment	25	6,5
Public Sector	167	43,0
Private Sector	60	15,5
Total	388	100

The distributions of the status of online shopping, frequency of online shopping, ownership status of digital tools of participants are given in Table 11, 12, and 13. Most of the participants stated that they shop online (92,5%). 29 participants who participated in the survey stated that they do not shop online, as seen in Table 11. Table 12 shows the percentage of participants' frequency of online shopping who have stated that they shop online in the previous question. Results show that most of the participants do online shopping at least once a month (62,2%). Table 13 shows the percentage of participants' ownership of digital tools. According to data, almost all the participants own a smartphone (99,5%) and most of them also own a computer (79,6%).

Table 11. Online Shopping Status

Do you shop online?		
	Frequency	Percentage
Yes	359	92,5
No	29	7,5
Total	388	100

Table 12. Distribution of Frequency of Online Shopping

	Frequency	Percentage
Several times a week	13	3,6
Once a week	22	6,1
Several times a month	127	35,3
Once a month	61	17,2
Less than once a month	136	37,8
Total	359	100

Table 13. The State of Ownership of Digital Tools by Participants

	Frequency	Percentage
Smartphone	386	99,5
Computer	309	79,6
Tablet	109	28,1
Smart TV	159	41,0

Participants' approach to programmatic advertising was also questioned in the survey and they were able to select more than one answer. The distribution of responses is given in Table 14. According to the results, nearly half of the participants (46,6%) are uncomfortable with advertisers following their transactions on digital media. However, (32,2%) of the participants stated that these ads get their attention since they are related to the products they are interested in. An interesting result for advertisers is that (17,5%) of the participants stated that these ads create a purchase intention.

Table 14. Participants' Approach to Programmatic Advertising

	Responses	
	Frequency	Percentage
These ads do not get my attention at all.	87	22,4
I'm not comfortable with these advertisers tracking my transactions on digital media.	181	46,6
These ads get my attention because they are related to the products I am interested in, but I do not shop according to these ads.	125	32,2
Since these ads are intended for my needs, they create purchase intention for me.	68	17,5
Other (please specify).	4	1,0

Another question was “Have you ever purchased a product recommended to you with a programmatic advertisement based on your digital transactions?” and the majority of the participants answered as no (62,6%) as shown in Table 15.

Table 15. Buying Products with Programmatic Advertising

Have you ever purchased a product recommended to you with a programmatic advertisement based on your digital transactions?		
	Frequency	Percentage
Yes	145	37,4
No	243	62,6
Total	388	100

5.2. EXPLORATORY FACTOR ANALYSIS

The purpose of factor analysis is to group those that are correlated with each other (Hair et al., 2010). Rennie (1997) defines factor analysis as an analytical technique that aims to reach a few explanatory factors and calculates the relationships between variables. Exploratory factor analysis (EFA) was performed in SPSS with the valid 388 questionnaires. Kaiser- Meyer-Olkin (KMO) test and Bartlett's test of sphericity were used to test the adequacy of data for factor analysis. Direct-Oblimin factor rotation method was used to distribute factor loadings. The item PI5 (fifth item of the purchase intention variable) was excluded from the analysis since its factor loading was low (<0,4). The analyses were conducted with the remaining items.

After the necessary arrangements were made, KMO and Bartlett's tests were applied and according to the results in Table 16, it can be said that the data is suitable for analyses since the result of KMO test is over 0,7 and Bartlett's test result is significant (Table 16).

Table 16. Data Suitability Test for Exploratory Factor Analysis

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0,859
Barlett's Test of Sphericity	Chi-Square	2.838,976
	df	55
	p	0,000

As a result of exploratory factor analysis, the items were grouped under three factors as theoretically assumed. These three factors account for approximately 77% of the total variance.

Cronbach's alpha coefficient is used to measure the reliability of the scales. Nunnally and Bernstein (1994) suggested that Cronbach's alpha coefficient should be higher than 0,7 for all factors. Cronbach's alpha coefficients for all the factors in the model were found to be above 0,7 (Table 17). Therefore, it can be said that reliability of the scale is provided. The mean and standard deviation values of the items are also shown in Table 17.

Table 17. Exploratory Factor Analysis Statistics

Factors	Items	Factor Load	Mean	Standard Deviation	Cronbach's Alpha
TRUST (TR)	T1	0,865	2,530	1,025	0,837
	T2	0,926	2,559	1,028	
	T3	0,654	2,574	0,957	
	T4	0,690	2,482	1,035	
PERSONALIZATION (PERS)	PERS1	0,904	3,435	1,404	0,936
	PERS2	0,962	3,448	1,329	
	PERS3	0,937	3,451	1,288	
PURCHASE INTENTION (PI)	PI1	0,735	2,564	1,149	0,884
	PI2	0,890	2,430	1,040	
	PI3	0,887	2,420	1,047	
	PI4	0,862	2,494	1,079	

All the constructs in this study were examined for convergent validity and discriminant validity (Chin et al., 1997). Convergent validity is tested by analyzing whether factor loadings are greater than 0,6 thus the criteria for convergent validity was satisfied (Table 17). For discriminant validity to be accepted, the factors must be separate from each other and there is no correlation between them. According to Gaskin (2016), in EFA, correlations between factors should be less than 0,7. According to EFA, all items were loaded under one factor with the highest load, and as seen in Table 18, the correlations between factors were less than 0,7. Therefore, it can be said that discriminant validity is provided.

Table 18. EFA Factor Correlation Matrix

Factor	TR	PERS	PI
TR	1,000	0,325	0,483
PERS	0,325	1,000	0,417
PI	0,483	0,417	1,000

Since the reliability and validity of the scales of the factors are ensured, the next step is the confirmatory factor analysis and the analysis of the structural equation model.

5.3. CONFIRMATORY FACTOR ANALYSIS

The purpose of Confirmatory Factor Analysis (CFA) is to determine how well the measurement model fits the data and to evaluate the factor scales (Bollen, 1989). Acceptable and good fit values for some of the goodness of fit statistics that can be used to evaluate the model are shown in Table 19 (Meydan & Şeşen, 2015).

Table 19. The Goodness of Fit Values for Confirmatory Factor Analysis

Goodness of Fit Statistics	X²/df	RMSEA	RMR	CFI	NFI	GFI	AGFI
Acceptable	≤ 5	≤ 0,08	≤0,08	≥ 0,95	≥ 0,90	≥ 0,85	≥ 0,85
Good fit	≤ 3	≤ 0,05	≤0,05	≥0,97	≥ 0,95	≥0,90	≥0,90

The confirmatory factor analysis of the measurement model, which was performed in the AMOS program, correlations between latent variables and standardized factor loadings of the items are shown in Figure 14. According to the CFA results of the model, in order to achieve a better fit in general terms, modification indexes were looked at (Table 20). For achieving a better fit of the model, as suggested by Meydan and Şeşen (2015), covariances were applied between error terms by considering the modification indices; and then the model was tested again. The modified model is given in Figure 15. The goodness of fit statistics for the modified model are shown in Table 21. All of the goodness of fit statistics were at least at an acceptable level for the modified model.

Figure 14. CFA, Standardized Factor Loadings and Correlations of Measurement Model

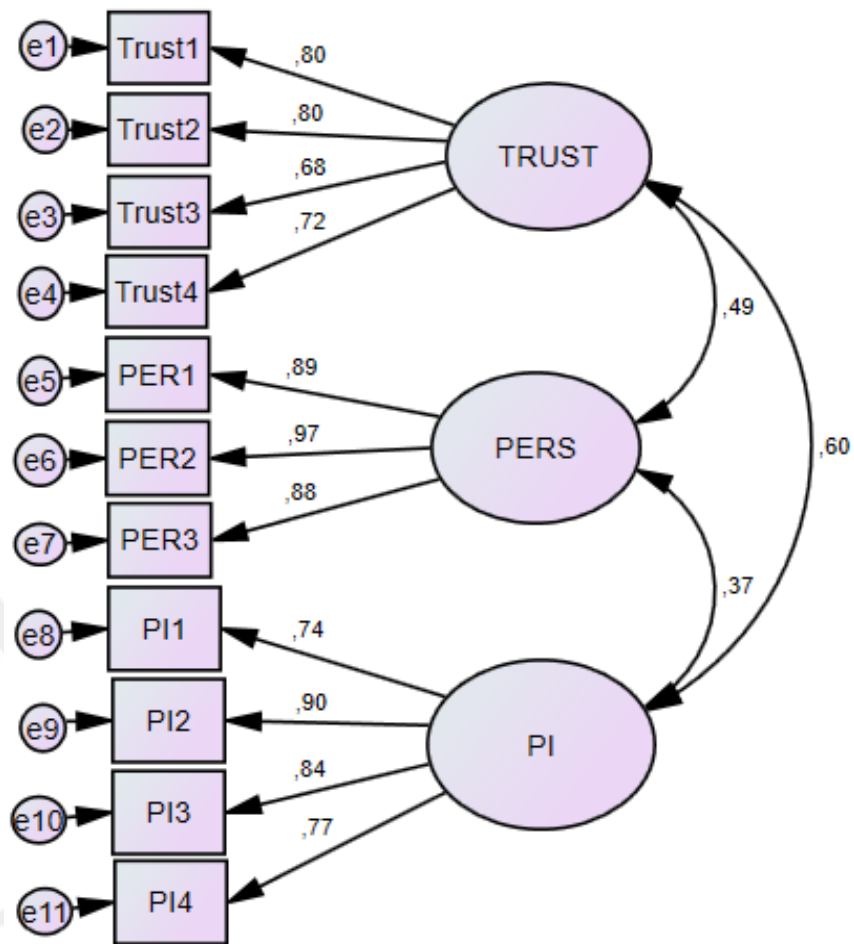


Table 20. Goodness of Fit Statistics for the First Model

Goodness of Fit Statistics	X^2/df	RMSEA	RMR	CFI	NFI	GFI	AGFI
First Model	3,764	0,085	0,067	0,960	0,946	0,931	0,889

Figure 15. CFA, Standardized Factor Loadings and Correlations of the Modified Model

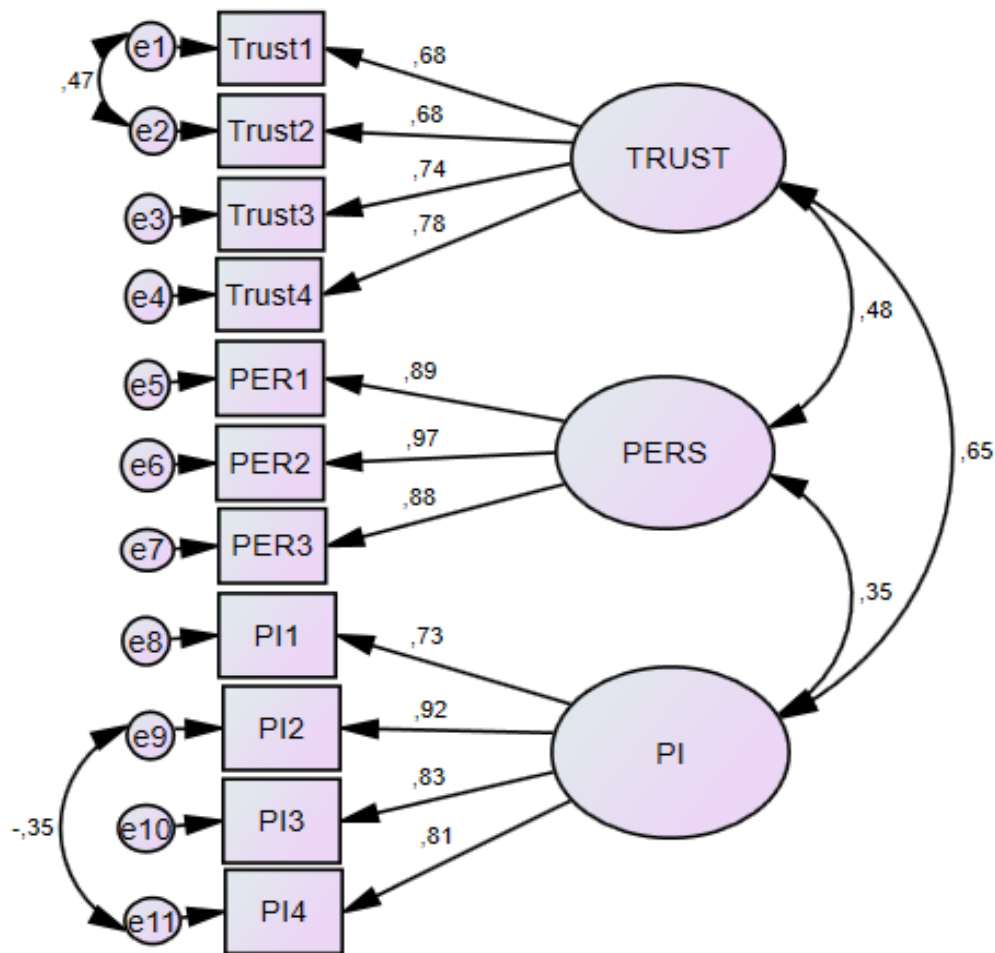


Table 21. The Goodness of Fit Statistics of Confirmatory Factor Analysis for the Modified Model

Goodness of Fit Statistics	χ^2 / df	RMSEA	RMR	CFI	NFI	GFI	AGFI
Modified Model	2,323	0,058	0,061	0,982	0,968	0,962	0,935

Before performing the structural equation model (SEM) analysis, the CFA model's reliability and validity were checked. For reliability, Composite Reliability (CR) values should be controlled (Gaskin, 2016) and it is suggested that CR values should be above 0,7 (Hair et al., 2010). CR values for each factor were found to be greater than 0,7 so it can be said that the reliability of the modified measurement model is provided (Table 22).

Table 22. CR, AVE and Factor Correlation Values of Modified Model

	CR	AVE	TRUST	PERS	PI
TR	0,868	0,627	0,79		
PERS	0,953	0,873	0,48	0,69	
PI	0,909	0,715	0,65	0,35	0,84

The square root of the AVE value for each factor is shown in bold face in the table.

To ensure convergent validity, Average Variance Extracted (AVE) values must be greater than 0,5 for each factor (Hair et al., 2010). As seen in Table 22, the AVE values are higher than 0,5. Therefore, convergent validity is ensured. To provide discriminant validity, the square root of AVE values should be higher than the correlations between the factors (Hair et al., 2010). As seen in Table 22, the square roots of AVE (showed with bold font in the Table 22) values for all factors are higher than the correlations between factors, and it can be said that discriminant validity is provided.

5.4. ANALYSIS OF STRUCTURAL EQUATION MODEL AND HYPOTHESIS TESTING

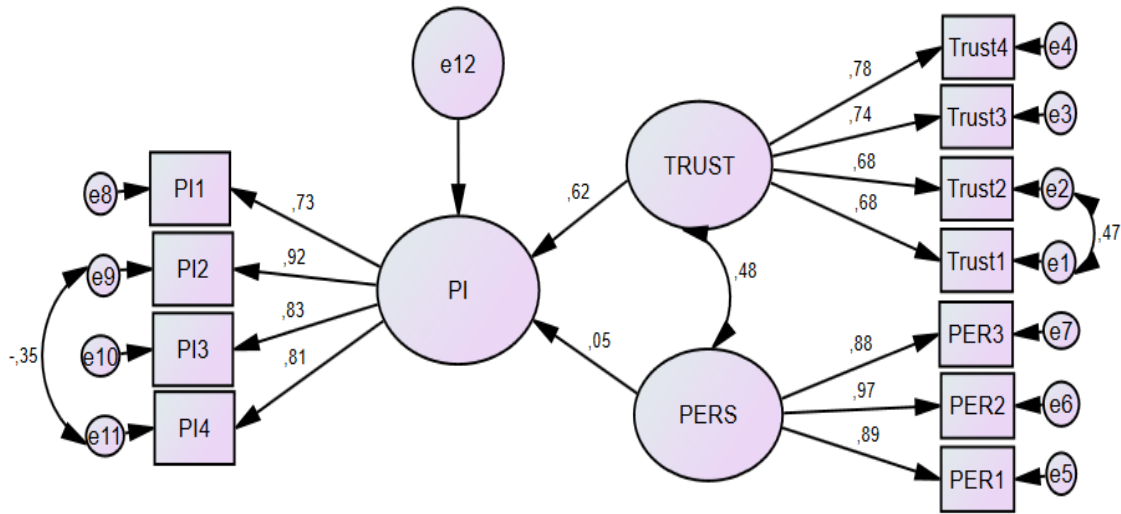
Structural Equation Model (SEM) analysis was performed since the measurement model provided an acceptable fit in CFA. The analysis of the structural equation model shown in Figure 16 was done using the AMOS program. The goodness of fit statistics of this structural model is given in Table 23.

Table 23. The Goodness of Fit Statistics for Structural Equation Model

Goodness of Fit Statistics	X ² /df	RMSEA	RMR	CFI	NFI	GFI	AGFI
Structural Model	2,323	0,058	0,061	0,982	0,968	0,962	0,935

Standardized regression coefficients of the structural model are shown in Figure 16. It was seen that the path from trust the purchase intention in the model was statistically significant ($p < 0,001$).

Figure 16. Standardized Regression Coefficients of the Structural Model



Basically, two hypotheses were examined in the structural model. **H₁**: Trust in programmatic advertising positively affects purchase intention, **H₂**: Personalization in programmatic advertising positively affects purchase intention.

According to the results obtained in the structural model, it was observed that the model was compatible and the model fit index values were obtained within the desired limits. In SEM, the path coefficient between trust and purchase intention was found to be statistically significant ($\beta_1 = 0,62$). Hence, the H₁ hypothesis is supported. The path coefficient between personalization and purchase intention was not statistically significant ($\beta_2 = 0,05$). This shows that H₂ hypothesis is not supported.

5.5. ANALYSES OF DIFFERENCES IN PURCHASE INTENTION ACCORDING TO DEMOGRAPHIC AND OTHER VARIABLES

In the previous section, the relationships between variables were examined using the structural equality model (SEM). In this section, it is examined whether there is a difference in purchase intention according to demographic variables and according to perceptions of participants on programmatic advertising.

The entire data set was taken into consideration (388 data) and analyses were carried out using the SPSS program. The average score of the items regarding purchase intention (PI_{avg}) was calculated for each participant. Firstly, it was checked whether PI_{avg} data is normally distributed. According to the results of the Kolmogorov-Smirnov normality test (Table 24), the data is not normally distributed. But, according to George & Mallery (2010), if skewness and kurtosis values are between -2 and +2, the data can

be considered as normally distributed. When the descriptive statistics of the PI_{avg} variable are examined (Table 25), it can be assumed that the data is normally distributed.

T-test was performed to test the differences between the two groups. A one-way ANOVA test was performed for differences between more than two groups. In cases where there was a significant difference in the result of a one-way ANOVA test, all groups were examined using Post Hoc analysis with LSD method. The results of the analyses are given in the relevant sections separately for each variable.

Table 24. Normality Test for PI_{avg} Variable

Kolmogorov-Smirnov Test

	Statistic	df	Sig.
PI_{avg}	0,155	388	0,00

Table 25. Descriptive Statistics of PI_{avg} Variable

	Statistic	Std. Error
Mean	2,4774	0,04724
95% Confidence Interval for Mean	Lower Bound Upper Bound	2,3846 2,5703
Median	2,2500	
Variance	0,866	
Std. Deviation	0,93055	
Skewness	0,508	0,124
Kurtosis	-0,069	0,247

5.5.1. Purchase Intention Based on Gender

T-test was applied to test whether there is a difference in purchase intention between male and female participants. According to the results of this test, no significant difference is found between the two groups as seen in Table 26 ($p > 0,05$).

Table 26. Results of the T-Test for Gender Groups

Gender	n	Mean	Std. Deviation	t	df	p
Female	223	2,4529	0,88406	-0,603	386	0,547
Male	165	2,5106	0,99172			

5.5.2. Purchase Intention Based on Age Groups

One-Way ANOVA test was applied to examine the differences between seven groups that are separated depending on the age groups stated in Table 9. As shown in

Table 27, there is no significant difference in terms of purchase intention between groups at different age groups ($p>0,05$).

Table 27. Result of the One-Way ANOVA Test for Age Groups

Age Groups	Sum of Squares	df	Mean Square	f	p
Between Groups	6,891	6	1,149	1,333	0,241
Within Groups	328,224	381	0,861		
Total	335,115	387			

5.5.3. Purchase Intention Based on Education Level

One-Way ANOVA test was applied to examine the differences between four groups that are separated depending on the education level stated in Table 7. As shown in Table 28, there is no significant difference in terms of purchase intention between groups at different education levels ($p>0,05$).

Table 28. Result of the One-Way ANOVA Test for Education Levels

Education Levels	Sum of Squares	df	Mean Square	f	p
Between Groups	1,492	3	0,497	0,572	0,633
Within Groups	333,623	384	0,869		
Total	335,115	387			

5.5.4. Purchase Intention Based on Monthly Income

One-Way ANOVA test was applied to examine the differences between six groups that are separated depending on the income level stated in Table 8. As shown in Table 29, there are significant differences in terms of purchase intention between groups at different income levels ($p<0,05$).

Table 29. Result of the One-Way ANOVA Test for Monthly Income Groups

Income Levels	Sum of Squares	df	Mean Square	f	p
Between Groups	11,196	5	2,239	2,641	0,023*
Within Groups	323,920	382	0,848		
Total	335,115	387			

Post Hoc test (LSD) was performed to find the source of the differences (Table 30). According to results, the purchase intention of the participants whose income level is 3.000-3.999 TL and 4.000-4.999 TL are significantly higher than those whose purchase intention level are under 1.000, between 1.000 and 1.999, and between 2.000 and 2.999TL.

Table 30. Result of the Post Hoc Test for Monthly Income Groups

(I) Income Levels	(J) Income Levels	Mean Difference (I-J)	p
Under 1.000 TL	1.000-1.999 TL	0,11138	0,543
	2.000-2.999 TL	-0,01183	0,942
	3.000-3.999 TL	-0,33708*	0,027
	4.000-4.999 TL	-0,37624*	0,021
	5.000 TL and over	-0,19196	0,195
1.000-1.999 TL	Under 1.000 TL	-0,11138	0,543
	2.000-2.999 TL	-0,12321	0,517
	3.000-3.999 TL	-0,44846*	0,014
	4.000-4.999 TL	-0,48761*	0,011
	5.000 TL and over	-0,30334	0,090
2.000-2.999 TL	Under 1.000 TL	0,01183	0,942
	1.000-1.999 TL	0,12321	0,517
	3.000-3.999 TL	-0,32525*	0,043
	4.000-4.999 TL	-0,36441*	0,032
	5.000 TL and over	-0,18014	0,250
3.000-3.999 TL	Under 1.000 TL	0,33708	0,027
	1.000-1.999 TL	0,44846*	0,014
	2.000-2.999 TL	0,32525*	0,043
	4.000-4.999 TL	-0,03915	0,807
	5.000 TL and over	0,14512	0,322
4.000-4.999 TL	Under 1.000 TL	0,37624*	0,021
	1.000-1.999 TL	0,48761*	0,011
	2.000-2.999 TL	0,36441*	0,032
	3.000-3.999 TL	0,03915	0,807
	5.000 TL and over	0,18427	0,240
5.000 TL and over	Under 1.000 TL	0,19196	0,195
	1.000-1.999 TL	0,30334	0,090
	2.000-2.999 TL	0,18014	0,250
	3.000-3.999 TL	-0,14512	0,322
	4.000-4.999 TL	-0,18427	0,240

5.5.5. Purchase Intention Based on Marital Status

The marital status distribution of the participants was previously divided into two groups (Table 6). T-test was applied to test whether there is a difference in purchase intention between single and married participants. According to the results of this test, there is no significant difference between the two groups as seen in Table 31 ($p > 0,05$).

Table 31. Results of the T-Test for Marital Status Groups

Marital Status	n	Mean	Std. Deviation	t	df	p
Married	176	2,4247	0,90693	-1,017	386	0,310
Single	212	2,5212	0,94963			

5.5.6. Purchase Intention Based on Occupation

One-Way ANOVA test was applied to examine the differences between five groups that are separated depending on the occupations stated in Table 10. As shown in Table 32, there is no significant differences in terms of purchase intention among occupation groups ($p>0,05$).

Table 32. Result of the One-Way ANOVA Test for Occupation Groups

Occupation	Sum of Squares	df	Mean Square	f	p
Between Groups	1,895	4	0,474	0,545	0,703
Within Groups	333,220	383	0,870		
Total	335,115	387			

5.5.7. Purchase Intention Based on Online Shopping Status

The online shopping distribution of the participants was previously divided into two groups (Table 11). Whether there is a difference in purchase intention based on online shopping status of participants was examined by the t-test. According to the results of this test, there is no significant difference between the two groups as seen in Table 33 ($p>0,05$).

Table 33. Results of the T-Test for Online Shopping Status

Do you shop online?	n	Mean	Std. Deviation	t	df	p
Yes	359	2,4903	0,92711	0,953	386	0,341
No	29	2,3190	0,97490			

5.5.8. Purchase Intention Based on Frequency of Online Shopping

One-Way ANOVA test was applied to examine the differences between five groups that are separated depending on the frequency of online shopping stated in Table 12. As shown in Table 34, there are no significant differences in terms of purchase intention between groups ($p>0,05$).

Table 34. Result of the One-Way ANOVA Test for Frequency Online Shopping

Frequency Online Shopping	Sum of Squares	df	Mean Square	f	p
Between Groups	3,725	4	0,931	1,085	0,364
Within Groups	303,991	354	0,859		
Total	307,716	358			



DISCUSSION, CONCLUSION AND SUGGESTIONS

In today's competitive market environment, businesses try to develop offers in accordance with the wishes of consumers and it is not enough for businesses to send the right message to their target audiences. With the ever-evolving technology, many businesses are in touch with consumers through websites and mobile apps. Programmatic advertising is one of applications that allow businesses to transmit the right message to the right consumer at the right time (Zeren & Keşlikli, 2019).

Today's technology allows advertisers to target consumers according to their values. But in addition to their current values, consumers' future values should also be considered. For this reason, regulations in internet environments should be continuous and constructive (Tahal, 2014).

This study focused on the effects of trust and personalization in programmatic advertising on consumers' purchase intention. There is limited research in the literature analyzing these variables in the context of programmatic advertising practices (Bleier & Eisenbeiss, 2015; Wessel & Thies 2015). Therefore, it is believed that results of this study will contribute to theoretical literature on programmatic advertising and give insight to marketers that apply programmatic advertising practices.

One of the findings of the structural equation model is that trust in programmatic advertising positively affects purchase intention. The results of this study support similar findings in the literature. According to Busch (2016), it was observed that personalized programmatic advertisements sent to consumers positively affect the trust factor. Orange (2014) found that in digital environments, consumers expect more transparent practices in protecting their personal data. Data-driven advertising models are widely used by marketers lately. Internet Advertising Bureau UK (2011) recommends that companies use certain icons, such as 3D Security and Visa to ensure security of data. Such symbols affect the perception of trust. Programmatic advertising applications use a lot of data to use advertising campaigns effectively. For this system to make a fair analysis, it is necessary to rely on programmatic advertising applications (DoubleClick, 2014). On the other hand, entrusting programmatic advertising campaigns to an automated process is not easy. From the point of view of marketers, it is difficult to understand the whole process. It is not easy to combat the perception of mistrust, especially created by little transparency (Waddell, 2017).

Looking at these studies in literature, it can be said that the positive effect of security and transparency is important for building trust in programmatic advertising applications. Marketers should inform consumers about when and how their data is used. Marketers should also inform about how consumers' data is stored and how it can be used in other transactions. Thus, by creating an atmosphere of trust for consumers, purchase intention can be positively affected.

It is determined in this research that personalization in programmatic advertising has no significant effect on consumers' purchase intentions. As mentioned before, Doorn & Hoekstra (2013) state that consumers with a high level of privacy concern perceive personalized advertisements as intrusive, so consumers are less likely to purchase. Wessel & Thies (2015) categorized levels of personalization (no personalization; in-advance; in-advance and continuous; in-advance, continuous and design) and concluded that, different levels of personalization create different purchase intentions. The result of Wessel & Thies's (2015) study showed that user-oriented personalization has a marked impact on purchase intention. On the other hand, Goldfarb & Tucker (2011) found that limited behavioral advertising (classification of individuals according to their characteristics) regulations reduce users' purchase intention of the advertised product by approximately 65%. Consumers are often unaware of the use of their data for digital advertising purposes (Boerman et al., 2017) which can cause concerns. In fact, the study of Strycharz et al. (2019) showed that if detailed information about the personalization processes are provided to the consumers, they are better aware of the risks they face and this may reduce their desire to give up using the services to protect their data. Looking at the literature, it can be inferred that further research may be necessary to explore the relationship between personalization and purchase intention especially in the programmatic advertising environment. Marketers need to inform consumers on how they use personal data and ensure consumers that personalization will be beneficial for them.

In addition to the structural equation modeling, the effects of demographic characteristics of the participants such as gender, age, education, marital status, monthly income and occupation on purchase intention were also investigated in this study. In addition, the effect of online shopping status and frequency of online shopping on purchase intention were analyzed.

No significant differences in purchase intention of the participants were found according to their marital status, gender, age, education levels, occupation; and status and frequency of online shopping. In the data of the research conducted by Wekeza & Sibanda (2019), it was examined whether there was a difference in terms of consumer intentions according to their marital status and gender, and no significant differences were observed. In the data of the research conducted by Bermudez et al. (2019: 10), it was examined whether there was a difference in terms of consumer intentions according to their education levels and significant differences were observed. In this study, there was no significant difference between education level and consumer purchase intention. Ariffin et al. (2018) found a relationship between online shopping frequency and purchasing intentions of consumers. In the same study, a significant relationship was found between occupational levels and purchase intention. In this study, occupational groups and the online shopping frequency were not significant with the purchase intention of consumers.

In this study, groups with monthly incomes of 4.000 –4.999 TL and 3.000 – 3.999 TL were found to have significantly higher purchase intentions than lower income groups. But for the group having income level above 5.000 TL, the same proposition does not apply. In particular, it can be said that those with a monthly income of between 3.000 TL and 5.000 TL are more affected by programmatic advertising. Wekeza & Sibanda (2019) also stated, that there is a statistically significant association between monthly income and consumer purchase intention.

In this study, the majority (99%) of respondents stated that they own a smartphone. According to Doğaner & Kuyucular (2017), there is a significant relationship between consumers' attitudes towards mobile advertising and their purchase intention and in their study 69,7% of respondents found it amusing to receive advertising messages on a mobile phone. Since the advertisements on mobile phones attract consumers, showing programmatic advertisements more frequently in mobile applications may be beneficial for marketers and it may increase purchase intention.

46,6% of the respondents stated that they are uncomfortable with the monitoring of their transactions in digital environments. This finding implies the importance of regulations in data use of companies. For example, Facebook misused consumers' data and received heavy fines (Snider & Baig, 2019). Such events show that data laws must exist and be controlled in the Internet environment.

According to the research (Hawkins et al., 2008), personalized programmatic advertisements are sent to consumers in various ways and these personalized content gets the attention of consumers. In the current study, 37,4% of consumers stated that they purchased the product proposed by programmatic advertising, and this promises potential for marketers. However, the fact that 62,6% of consumers did not buy the products offered by programmatic advertising shows that there is much more to do in this area and there are issues to be dealt with. Content in programmatic advertising applications on Internet websites should be clear, understandable and short. As well as easily getting permission from consumers on the Internet, consumers should be able to give up these ad impressions or message content at any time (Lomas, 2020).

Evaluating all the results of this study, it can be concluded that programmatic advertising applications are important for marketers in increasing purchase intention of consumers. But the factors that can affect purchase intention should be analyzed carefully while applying programmatic advertising practices. This study is one of the few studies that investigate the effect of trust and personalization in programmatic advertising on consumers' purchase intention. Therefore, it is believed that this study will contribute to theoretical literature. On other hand, from the point of view of marketers, it is necessary to ensure consumer trust in programmatic advertising applications in the long term. A transparent environment must be created where consumers can legally apply for this process and receive its results immediately. Such practices are expected to benefit both marketers and consumers (Lomas, 2020).

There are some limitations to the study. One of the limitations of the study is that only two factors –trust and personalization- are included as factors that can affect purchase intention of consumers. But, there may be other factors in programmatic advertising that can affect purchase intention of consumers as well. Future research may expand the literature by examining other factors in addition to these factors.

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APPENDICES

Appendix 1: Questionnaire in English

Dear participant,

This questionnaire is designed to collect data for the thesis titled **“The Effect of Trust and Personalization in Programmatic Advertising on Consumers’ Purchase Intention”**. The results of this study will only be used for scientific purposes and individual data will be kept confidential and they will not be shared with third parties. For the study to be successful, it is important to answer the questionnaire sincerely and not to omit questions. Thank you in advance for your interest.

Please read the definition of the concept of “Programmatic Advertising” below before starting the survey.

Programmatic advertising is one of the digital advertising technologies; which is an advertising technology that allows to analyze the behavior of users and to show advertisements that are personalized for users based on these analyzes. For example, you can see an advertisement related to the product you have previously viewed on any website again on a different website at a different time due to programmatic advertising applications.

QUESTIONNAIRE

Please select the answer that suits you.

1.Your gender

Female Male

2.Your Age

Under 18 18-25 26-30 31-35
 36-40 41-45 46-50 51 and above

3.Your level of education

Secondary education High School Undergraduate
 Graduate (Master’s Degree or Higher)

4.Your monthly income

- less than 1.000 TL 1.000-1.999TL 2.000-2.999 TL
 3.000-3.999 TL 4.000-4.999 TL 5.000 TL and above

5.Your marital status

- Single Married

6.Your occupation

- Unemployed Student Self-Employment Public Sector Private Sector

7.Which digital tool/tools do you have?

- Smartphone Computer Tablet Smart TV

8.Do you shop online?

- Yes No

9.How often do you shop online? (Please answer if you have marked the previous question as “Yes”)

- Everyday Several times a week Once a week
 Several times a month Once a month Less than once a month

10.How is your approach to the programmatic advertisements shown to you as a result of your transactions in the digital environment (pages you visit / products you view / videos you watch, etc.)?

- These ads do not get my attention at all.
 I'm not comfortable with these advertisers tracking my transactions on digital media.
 These ads get my attention because they are related to the products I am interested in, but I do not shop according to these ads.
 Since these ads are intended for my needs, they create purchase intention onme.
 Other (please specify)

11.Have you ever purchased a product recommended to you with programmatic advertising based on your digital media operations?

- Yes No

Please choose the degree of your agreement to the following statements.

QUESTION NO		Strongly Disagree	Disagree	Undecided	Agree	Strongly Agree
Questions about measuring trust						
1	I generally trust programmatic advertising practices.	()	()	()	()	()
2	I think programmatic advertising practices are reliable.	()	()	()	()	()
3	I trust that programmatic advertisers are doing their job right, even if it is not followed.	()	()	()	()	()
4	I trust programmatic advertisements.	()	()	()	()	()
Questions about measuring personalization						
5	I feel that programmatic ads show me a personalized message.	()	()	()	()	()
6	I feel programmatic ads are personalized for my use.	()	()	()	()	()
7	The contents in programmatic ads are personalized.	()	()	()	()	()
Questions about measuring purchase intention						
8	I guess that if I have the opportunity, I will buy a product recommended with programmatic advertising in the future.	()	()	()	()	()
9	It is likely that I will soon purchase a product	()	()	()	()	()

	recommended by programmatic advertising.					
10	If I have the opportunity, I intend to purchase a proposed product with programmatic advertising.	()	()	()	()	()
11	I can consider purchasing a product recommended with programmatic advertising in the next three months.	()	()	()	()	()



Sayın Katılımcı,

Bu anket formu “**Programatik Reklamcılıkta Güven ve Kişiselleştirmenin Tüketicilerin Satın Alma Niyetine Etkisi**” konulu tez çalışması için bir veri toplama aracı olarak hazırlanmıştır. Araştırmanın sonuçları sadece bilimsel amaçlar için kullanılacak olup bireysel veriler gizli tutularak kesinlikle üçüncü kişilerle paylaşılmayacaktır. Çalışmanın başarılı olabilmesi için anket sorularına içtenlikle cevap verilmesi ve boş soru bırakılmaması önem arz etmektedir. Göstereceğiniz ilgi için şimdiden teşekkür ederim.

Ankete başlamadan önce sorularda yer alabilecek “Programatik Reklamcılık” kavramının tanımını lütfen okuyunuz.

Programatik reklamcılık, dijital reklamcılık teknolojilerinden biri olup; kullanıcıların davranışlarını analiz etmeye ve bu analizlerden hareketle kullanıcılar için kişiselleştirilmiş olan reklamları onlara göstermeye imkan veren bir reklamcılık teknolojisidir. Örnek olarak; programatik reklam uygulamaları sayesinde daha önce herhangi bir web sitesinde incelediğiniz ürünle ilişkili reklamı farklı zamanda farklı bir web sitesinde tekrar görebilirsiniz.

ANKET SORULARI

Lütfen size uygun cevabı işaretleyiniz.

1.Cinsiyetiniz

Kadın Erkek

2.Yaşınız

18 altı 18-25 26-30 31-35
 36-40 41-45 46-50 51 ve üzeri

3.Eğitim durumunuz

İlköğretim Lise Üniversite Yüksek lisans ve üzeri

4.Aylık Geliriniz

- 1.000 TL'nin altında 1.000-1.999 TL arası
 2.000-2.999 TL arası 3.000-3.999 TL arası
 4.000-4.999 TL arası 5.000 TL ve üzerinde

5. Medeni durumunuz

- Bekar Evli

6. Mesleğiniz

- Çalışmıyor Öğrenci Serbest Meslek Kamu Özel sektör

7. Hangi dijital araç/araçlara sahipsiniz?

- Akıllı telefon Bilgisayar Tablet Akıllı televizyon

8. İnternette alışveriş yapıyor musunuz ?

- Evet Hayır

9. İnternette alışveriş yapma sıklığınız ne kadardır? (Bir önceki soruyu "Evet" olarak işaretlediyseniz yanıtlayınız.)

- Her gün Haftada birkaç kere Haftada bir kere
 Ayda birkaç kere Ayda bir kere Ayda bir kereden daha seyrek

10. Dijital ortamdaki işlemlerinizi (gezdiğiniz sayfalar/incelediğiniz ürünler/izlediğiniz videolar vb.) neticesinde size gösterilen programatik reklamlara karşı yaklaşımınız nasıldır?

- Bu reklamlar hiç ilgimi çekmez.
 Bu reklam verenlerin benim dijital ortamdaki işlemlerimi takip etmesinden rahatsız olurum.
 Bu reklamlar dikkatimi çeker çünkü ilgilendiğim ürünlerle ilgilidirler, fakat bu reklamlara göre alışveriş yapmam.
 Bu reklamlar ihtiyaçlarıma yönelik olduğundan bende satın alma isteği oluşturur.
 Diğer (lütfen belirtiniz): _____

11. Dijital ortamdaki işlemlerinize istinaden programatik reklamlarla size önerilen bir ürünü hiç satın aldınız mı?

() Evet () Hayır

Lütfen aşağıdaki sorulara katılıp katılmama derecenizi belirtiniz.

SORU NO		Kesinlikle Katılmıyorum	Katılmıyorum	Kararsızım	Katılıyorum	Kesinlikle Katılıyorum
Güven algısını ölçmeye yönelik sorular						
1	Genel olarak programatik reklamlara güvenirim.	()	()	()	()	()
2	Programatik reklamların güvenilir olduğunu düşünüyorum.	()	()	()	()	()
3	İzlenmiyor olsa bile programatik reklamcılarının işini doğru yaptığına güvenirim.	()	()	()	()	()
4	Programatik reklamcılara güveniyorum.	()	()	()	()	()
Kişiselleştirme algısını ölçmeye yönelik sorular						
5	Programatik reklamların bana kişiselleştirilmiş mesaj gösterdiğini hissediyorum.	()	()	()	()	()
6	Programatik reklamların kullanımım için kişiselleştirildiğini hissediyorum.	()	()	()	()	()
7	Programatik reklamların içeriği kişiselleştirilmiştir.	()	()	()	()	()
Satın Alma Niyetini ölçmeye ilişkin sorular						
8	Fırsatım olursa, gelecekte programatik reklamla önerilen bir ürünü satın alacağımı tahmin ediyorum.	()	()	()	()	()
9	Programatik reklamla önerilen bir ürünü yakın zamanda satın almam olasıdır.	()	()	()	()	()
10	Fırsatım olursa, programatik reklamla önerilen bir ürünü satın alma niyetindeyim.	()	()	()	()	()
11	Gelecek üç ay içinde programatik reklamla önerilen bir ürünü satın almayı düşünebilirim.	()	()	()	()	()



CURRICULUM VITAE

Burçin SÜRÜCÜ was born in Ankara in 1994, completed her undergraduate education at Afyon Kocatepe University, Department of Business Administration in English in 2017, and completed her master's degree at Afyon Kocatepe University, Department of Business Administration in English in 2021.

