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Doctor of Philosophy (Ph.D.)

**DIGITALIZATION IN BUSINESS TO BUSINESS MARKETING:
DEVELOPMENT OF STRATEGIES AND TECHNOLOGIES FOR THE
TRANSFORMATION OF MARITIME TRANSPORTATION**

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İZMİR-2020

DOCTORAL THESIS
APPROVAL PAGE



DECLARATION

I hereby declare that this doctoral thesis titled as “**Digitalization in Business to Business Marketing: Development of Strategies and Technologies for the Transformation of Maritime Transportation**” has been written by myself in accordance with the 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 honour.

01/06/2020

Fevzi BİTİKTAŞ

ABSTRACT

Doctoral Thesis

Doctor of Philosophy (Ph.D.)

Digitalization in Business to Business Marketing: Development of Strategies and Technologies for the Transformation of Maritime Transportation

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Digitalization offers various opportunities such as access to new markets, cost reduction and competitive advantage, the ability to develop and control products more agile, by profoundly influencing the activities of almost all businesses. However, as in many B2B markets, it is observed that it is too late to adapt to this transformation in maritime transportation. In this context, it becomes crucial to emphasize the importance of digitalization to maritime businesses and to identify digital technologies that are appropriate for their purposes and nature and to propose strategies for these technologies.

This study addresses the issue of digitalization in maritime transportation in the marketing communication dimension. In this regard, firstly, a literature study was carried out with a deductive approach and digital marketing technologies were handled within the scope of maritime transportation market characteristics. Then, the focus was on social media, which is accepted as the most up-to-date technology of maritime transportation digital marketing communication, and research was carried out to develop strategies for container shipping companies to use social media more effectively. In this process, it has been determined that the engagement rate calculation formulas commonly used in the social media influence literature have expired as a result of the new algorithms used by the platforms and a new calculation method has been developed.

In the empirical part of the study, firstly, the current situation of container shipping companies on social media platforms has been revealed. Then a content analysis of 4076 publicly-shared posts for a year was carried out on the companies' LinkedIn pages. This process was developed based on the “Social Media Communication Model” and “Word-of-Mouth (WOM) Psychological Motivation Theory”. Accordingly, a theory-based approach consisting of brand strategy (company or product), message appeal (functional or emotional), selling strategy, and external information categories was preferred in coding the posts on the LinkedIn page of the companies. In addition, LinkedIn posts have been categorized in terms of media type, message richness, and level of interactivity.

In the research, the highly engaged LinkedIn messages were determined through the engagement calculation method developed as a result of qualitative and quantitative studies, and an answer was sought to the question of whether the engagement rate (target variable) could be predicted with the message characteristics (input variables). In the development of the prediction model, two different learning algorithms were applied by using IBM Watson machine learning services. According to the results of the training and test data, the accuracy rate of the Chi-square Automatic Interaction Detector algorithm was found to be higher. Accordingly, the features that affect the engagement rate of the companies' LinkedIn messages are the level of interactivity, resharing, word count, message purpose, media type, and link usage, respectively. Overall, the results of this study show that it is possible to predict the success of social media communication strategies in terms of engagement level in the container shipping markets with message-oriented features.

Keywords: Container shipping, business-to-business digital marketing, social media, machine learning, C&RT, CHAID, service marketing.

ÖZET

Doktora Tezi

İşletmeden İşletmeye Pazarlamada Dijitalleşme: Deniz Taşımacılığının

Dönüşümü için Strateji ve Teknolojilerin Geliştirilmesi

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Dijitalleşme günümüzde hemen hemen tüm işletmelerin faaliyetlerini derinden etkileyerek onlara yeni pazarlara erişim, maliyetlerin azaltılması ve rekabet avantajı, ürünleri daha çevik geliştirme ve kontrol etme yeteceği gibi çeşitli fırsatlar sunmaktadır. Ancak birçok B2B pazarında olduğu gibi deniz taşımacılığında da bu dönüşüme uyum sağlanması konusunda geç kaldığı gözlemlenmektedir. Bu bağlamda deniz taşımacılığı işletmelerine dijitalleşmenin önemini vurgulamak ve onların amaçlarına ve doğasına uygun dijital teknolojileri belirlemek ve bu teknolojilere yönelik stratejiler önermek önemli hale gelmektedir.

Bu çalışma deniz taşımacılığında dijitalleşme konusunu pazarlama iletişimi boyutunda ele almaktadır. Bu doğrultuda çalışmada öncelikle tündengelim bir yaklaşımla literatür çalışması yürütülmüş ve dijital pazarlama teknolojileri deniz taşımacılığı pazar özellikleri kapsamında ele alınmıştır. Daha sonra deniz taşımacılığı dijital pazarlama iletişiminin en güncel teknolojisi olarak kabul gören sosyal medya konusuna odaklanılmış ve konteyner deniz taşımacılığı işletmelerin sosyal medyayı daha etkili kullanabilmesi için stratejiler geliştirmeye yönelik bir araştırma yürütülmüştür. Bu süreçte sosyal medya etkileşim literatüründe yaygın olarak kullanılan etkileşim oranı hesaplama formüllerinin, platformların kullandığı yeni algoritmalar neticesinde geçerliliğini yitirdiği tespit edilmiş ve yeni bir hesaplama yöntemi geliştirilmiştir.

Çalışmanın ampirik kısmında, ilk olarak, konteyner taşımacılığı işletmelerinin sosyal medya platformlarındaki mevcut durumu ortaya çıkarılmıştır. Daha sonra, şirketlerin LinkedIn sayfalarında, bir yıl boyunca paylaşılan 4076 adet halka açık gönderi için bir içerik analizi yürütülmüştür. Bu süreçte “Sosyal Medya İletişim Modeli” ve “Ağızdan Ağıza (WOM) Psikolojik Motivation Teorisi” temel alınmıştır. Buna göre işletmelerin LinkedIn sayfasındaki gönderilerin kodlanmasında marka stratejisi (işletme ya da ürün), mesaj çağrısı (fonksiyonel ya da duygusal), satış stratejisi ve dış bilgi kategorilerinden oluşan teori temelli bir yaklaşım tercih edilmiştir. Ayrıca LinkedIn gönderileri medya türü, mesaj zenginliği ve interaktiflik seviyesi bakımından da kategorilendirilmesi söz konusu olmuştur.

Araştırmada kalitatif ve kantitatif çalışmalar neticesinde geliştirilen etkileşim hesaplama yöntemi aracılığıyla en yüksek etkileşimli LinkedIn mesajları tespit edilmiş ve bu mesajların özellikleri (girdi değişkenleri) bakımından etkileşim oranının (hedef değişken) önceden tahmin edilip edilemeyeceği sorusuna cevap aranmıştır. Tahmin modelinin geliştirilmesinde IBM Watson makine öğrenim hizmetlerinden faydalanılarak iki farklı öğrenme algoritması uygulanmıştır. Eğitim ve test verilerinin sonuçlarına göre Ki-kare Otomatik Etkileşim Dedektörü algoritmasının doğruluk oranının daha yüksek olduğu tespit edilmiştir. Buna göre işletmelerin LinkedIn mesajlarının etkileşim oranını etkileyen özellikler önem derecesine göre sırasıyla interaktiflik seviyesi, tekrar paylaşma, kelime sayısı, mesaj amacı, medya türü ve link kullanımı olmuştur. Genel olarak bu araştırmanın sonuçları konteyner taşımacılığı pazarlarında sosyal medya iletişim stratejilerinin etkileşim açısından başarısının mesaj yönlü özelliklerle tahmin edilebilmesinin mümkün olduğunu göstermektedir.

Anahtar Kelimeler: Konteyner deniz taşımacılığı, işletmeden işletmeye dijital pazarlama, sosyal medya, makine öğrenmesi, C&RT, CHAID, hizmet pazarlaması.

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CONTENTS

APPROVAL PAGE	ii
DECLARATION	iii
ABSTRACT	iv
ÖZET	vi
CONTENTS	viii
ABBREVIATIONS	xiii
LIST OF TABLES	xvi
LIST OF FIGURES	xviii
LIST OF APPENDICES	xx
INTRODUCTION	1

CHAPTER ONE

DIGITALIZATION IN BUSINESS-TO-BUSINESS MARKETS

1.1. B2B MARKETING	11
1.2. EVOLUTION OF DIGITAL MARKETING CONCEPT IN MARKETING LITERATURE	14
1.2.1. Digital Marketing: Definition, Types and Elements	14
1.2.2. Historical Review of Digital Marketing	18
1.2.2.1. The Technologies Behind the Digital Communication	18
1.2.2.2. Network, Internet and Browser Technologies	21
1.2.3. Digital Marketing Concept in Marketing Literature	23
1.2.3.1. Marketing Strategy	24
1.2.3.2. Marketing Mix Considerations	26
1.2.3.3. Marketing Communication	28

1.2.3.4. Direct marketing and its Relations with Digital Marketing	29
1.3. DIGITALIZATION IN B2B MARKETING	33
1.3.1. The Role of Digital Channels in B2B Marketing	36
1.3.2. Business Buyers with Digital Marketing	40
1.3.3. Advantages and Disadvantages of B2B Digital Marketing	44

CHAPTER TWO

TECHNOLOGIES AND STRATEGIES IN CONTAINER SHIPPING MARKETING IN TERMS OF DIGITALIZATION

2.1. DIGITAL TECHNOLOGIES IN CONTAINER SHIPPING MARKETING	50
2.1.1. Online Technologies	52
2.1.2. Mobile Technologies	70
2.1.3. Social Media	74
2.2. THEORETICAL BACKROUND OF SOCIAL MEDIA COMMUNICATION	81
2.2.1. Main Theories and Models in Social Media Communication	81
2.2.2. Social Media Communication Model	84
2.2.3. Word-of-Mouth (WOM) Psychological Motivation Theory	86
2.3. SOCIAL MEDIA MARKETING IN CONTAINER SHIPPING	87
2.3.1. Social Media Strategies in Container Shipping Markets	89
2.4. SOCIAL MEDIA ENGAGEMENT	91
2.4.1. Engagement Measures of Social Media Communication	92
2.4.2. Determinants of Engagement of Social Media Communication	93
2.4.2.1. Message Strategy	95
2.4.2.1.1. Brand Strategy	95
2.4.2.1.2. Message Appeal	96

2.4.2.1.3. Direct selling strategy	97
2.4.2.1.4. Information Strategy	98
2.4.2.2. Media Type	99
2.4.2.3. Message Richness	100
2.4.2.4. Interactivity	101

CHAPTER THREE

CLASSIFICATION AND REGRESSION MODELS IN MACHINE LEARNING

3.1. DATA MINING	103
3.1.1. Data Mining Methods	105
3.2. MACHINE LEARNING	107
3.2.1. Machine Learning Methods	109
3.2.1.1. Supervised Learning	110
3.2.1.2. Unsupervised Learning	110
3.2.1.3. Reinforcement Learning	111
3.2.2. Relationship Between Machine Learning and Data Mining	111
3.3. CLASSIFICATION AND REGRESSION MODELS	113
3.4. DECISION TREES AND LEARNING ALGORITHMS	114
3.4.1. Classification Trees	117
3.4.2. Regression Trees	119
3.4.3. Learning Algorithms in Classification and Regression Trees	121
3.4.3.1. The Classification and Regression Algorithm	123
3.4.3.2. Chi-square Automatic Interaction Detection Algorithm	124

CHAPTER FOUR

A MACHINE LEARNING APPLICATION FOR SOCIAL MEDIA COMMUNICATION IN CONTAINER SHIPPING

4.1. METHODOLOGY	127
4.1.1. Population and Sampling of the Study	127
4.1.2. LinkedIn Overview	132
4.1.2.1. LinkedIn Privacy Policy and Data Restriction	133
4.1.3. Data Collection	137
4.1.4. Content Analysis	139
4.1.5. Validity and Reliability	141
4.2. FINDINGS AND RESULTS OF THE STUDY	143
4.2.1. Descriptive Statistics	143
4.2.2. Engagement Rate	146
4.2.2.1. Current Engement Rate Formula	147
4.2.2.2. Development and Implementation of a New Calculation Method	149
4.2.2.2.1. Curve Estimation Analysis	150
4.2.2.2.2. Non-Linear Regression Analysis	151
4.2.3. Tools and Resources Used for Machine Learning Modeling	156
4.2.4. Development of Machine Learning Flow Models	157
4.2.4.1. Selection of Variables	158
4.2.4.2. Data Processing	159
4.2.4.3. Application of the Learning Algorithms	162
4.2.4.3.1. C&RT Algorithm	162
4.2.4.3.2. CHAID Algorithm	165
4.2.4.4. Assessment of Model Performance	166
4.2.4.4.1. C&RT Model Performance	166
4.2.4.4.2. CHAID Model Performance	169
4.2.4.5. Selection of Best Model	170
4.2.4.6. Interpretation of Rules	171
4.3. GENERAL DISCUSSION AND CONCLUSION	177

THEORETICAL IMPLICATIONS	181
MANAGERIAL IMPLICATIONS	183
LIMITATIONS AND FURTHER RESEARCH	188
REFERENCES	190
APPENDICES	



ABBREVIATIONS

AI	Artificial intelligence
AID	Automatic interaction detection
AMA	American Marketing Association
ANNs	Artificial neural networks
ANOVA	Analysis of variance
API	Application programming interface
ARPA	Advanced Research Project Agency
B2B	Business to business
B2C	Business to customer
BI	Business intelligence
C&RT	Classification and regression trees
C2B	Customer to business
C2C	Customer to customer
CART	Classification and regression trees
CHAID	Chi-square automatic interaction detector
CPM	Cost per mille
CRM	Customer relationship management
CTR	Click through rate
DARPA	Defense Advanced Research Projects Agency
DMA	Direct Marketing Association
DNS	Domain name system
DOI	Diffusion of innovation theory
DQN	Deep Q network
DSPs	Demand side platforms
E-mail	Electronic mail
GDN	Google display network
GDPR	General data protection regulation
HTML	Hypertext markup language
IAB	Interactive Advertising Bureau
IBM	International Business Machines

IoT	Internet of the things
IP	Internet protocol
k-NN	K-nearest neighbor
KPI	Key performance indicator
LSD	Least squared deviation
MIT	Massachusetts Institute of Technology
MMA	Mobile Marketing Association
MMS	Multimedia message service
PBC	Perceived behavioral control
PCA	Basic component analysis
PPC	Pay per click
PR	Public relations
QR	Quick response
REST	Representational state transfer
ROI	Return of investments
RTB	Real-time bidding
SARSA	State action reward state action
SEM	Search engine marketing
SEO	Search engine optimization
SERP	Search engine results page
SMS	Short message service
SVM	Support vector machine
TAM	Technology acceptance model
TCP	Transmission control protocol
TEU	Twenty-foot equivalent unit
THAID	THeta automatic interaction detection
TPB	Theory of planned behavior
TRA	Theory of reasoned action
TUİK	Turkey Statistical Institute
U&G Theory	Uses and gratifications theory
UGC	User-generated content
URL	Universal resource location

US	United States
WML	Watson machine learning
WOM	Word of mouth
WWW	World wide web
XLM	Extensible markup language



LIST OF TABLES

Table 1: Definition of Digital Marketing in the Literature	p.17
Table 2: The Most Popular and Effective B2B Marketing Channel	p.35
Table 3: Types of Content Produced by B2B Companies	p.37
Table 4: Characteristics of Business Buyers	p.41
Table 5: Types of Internal and External Information of Business Customers	p.44
Table 6: Advantages and Disadvantages of Digital Marketing in Terms of Customers and Companies	p.48
Table 7: Categorization of Social Media Channels	p.75
Table 8: Categorized Metrics of Social Media Engagement	p.93
Table 9: Summary of Different Discipline Perspectives in Relation to Data Mining	p.112
Table 10: Decision Tree Algorithms	p.122
Table 11: Social Media Accounts of the Top 30 Businesses Listed in Alphaliner (Nov, 2019)	p.129
Table 12: Selected Companies' Market Share and LinkedIn Status	p.131
Table 13: Social Media Channels and Their Relationship with APIs	p.136
Table 14: Public Data on the LinkedIn Platform	p.137
Table 15: Public Data on LinkedIn Pages of Companies	p.138
Table 16: LinkedIn Message Coding Examples	p.141
Table 17: Engagement Rates According to the Current Formulas in the Literature	p.149
Table 18: Model Summary and Parameter Estimates	p.150
Table 19: Model Summary	p.151
Table 20: ANOVA Results of Regression Model	p.152
Table 21: Coefficients Results of Regression Model	p.152
Table 22: Actual and Predicted Engagement of Companies	p.153
Table 23: Correlations between Actual Engagement and Predicted Engagement	p.154

Table 24: Optimized Actual and Predicted Engagement of Companies	p.154
Table 25: Optimized Correlations between Actual Engagement and Predicted Engagement	p.155
Table 26: Engagement Rates of Companies' LinkedIn Accounts	p.156
Table 27: Training and Test Data (C&RT)	p.163
Table 28: Training and Test Data (CHAID)	p.165
Table 29: Comparing \$R-Engagement with Engagement (C&RT)	p.167
Table 30: Comparing \$R-Engagement with Engagement (CHAID)	p.169
Table 31: Linear Correlations of C&RT and CHAID Algorithm Results	p.171
Table 32: Model Information (CHAID)	p.172
Table 33: Top Decision Rules of Learning Outputs	p.174

LIST OF FIGURES

Figure 1: Direct and Indirect Marketing Channels, for Both B2C and B2B	p.13
Figure 2: Comparison of the Concepts of Digital Marketing, Online Marketing, Web Marketing, and Internet Marketing	p.15
Figure 3: The 4Ps of the Marketing Mix	p.27
Figure 4: The Evolution of Direct Marketing and Media Terminology	p.32
Figure 5: Forms of Direct and Digital Marketing	p.33
Figure 6: The Importance of Content Marketing Objectives for Organizations	p.38
Figure 7: B2B Buying Process	p.43
Figure 8: Digital Marketing Technologies Around Digital Marketing Communication Strategy	p.50
Figure 9: The Three Foundations of Digital Marketing Delivery Mix/Channel and Integration With Digital Marketing Strategy	p.51
Figure 10: Search Engine Marketing Types	p.61
Figure 11: Google SERP for “Maersk” Search Term (29.04.2019)	p.62
Figure 12: Organic Click Through Rate (CRT) By Search Position	p.64
Figure 13: Main Factors for SERP Ranking in SEO	p.66
Figure 14: E-mail Marketing Process	p.69
Figure 15: Desktop and Mobile Market Share Worldwide from May 2009 to May 2019	p.71
Figure 16: The World's Most Popular Social Media Sites and Applications as of April 2019, Sorted by the Number of Active Users (Millions)	p.76
Figure 17: Schematic Diagram of General Communication Systems	p.84
Figure 18: Social Media Communication Model of Container Shipping Companies	p.85
Figure 19: Stages of Design and Development of Data Mining Processes	p.105
Figure 20: Descriptive and Predictive Technics is Data Mining	p.106
Figure 21: Classification of Machine Learning Methods	p.109
Figure 22: Disciplines Related to Data Mining	p.112
Figure 23: A Simple Decision to Buy a Car	p.116

Figure 24: Branching of CHAID and C&R Trees	p.125
Figure 25: Installation and Authorization Information of the API Created on LinkedIn	p.134
Figure 26: A Ahare of MSC Business on LinkedIn Page	p.139
Figure 27: Distribution of the Number of Messages by Companies	p.144
Figure 28: Distribution of Company Shares by Message Purpose Category	p.144
Figure 29: Distribution of Company Shares by Media Type Category	p.145
Figure 30: Link Usage Status in LinkedIn Messages	p.145
Figure 31: Reshare Status of LinkedIn Messages	p.145
Figure 32: Interactiviy Status of LinkedIn Messages	p.145
Figure 33: All Functions and Power Function Curves	p.151
Figure 34: Process of Machine Learning Flow Model	p.158
Figure 35: A Screenshot From the Dataset of the Initial Target and Input Variables	p.159
Figure 36: Initial and Final Input Variables	p.160
Figure 37: Descriptive Information of the Target and Input Variables	p.161
Figure 38: C&RT and CHAID Flow Model	p.164
Figure 39: Predictor Importance of Engagement (C&RT)	p.163
Figure 40: Predictor Importance of Engagement (CHAID)	p.165
Figure 41: Evaluation Chart of Training and Testing Records (C&RT)	p.168
Figure 42: Evaluation Chart of Training and Testing Records	p.170
Figure 43: Nodes in Tree Data Structure	p.172
Figure 44: Tree Diagram of CHAID Algorithm	p.173
Figure 45: A Blueprint for Publishing on LinkedIn Business Page for Container Shipping Marketers.	p.187

LIST OF APPENDICES

Appendix 1: Message Strategy Coding Scheme app.p.1

Appendix 2: Content Coding Scheme app.p.2



INTRODUCTION

Background and Importance of the Study

Digitalization is profoundly influencing the activities of almost all businesses today, but business to business (B2B) companies such as shipping companies are late to adapt to this transformation. Late adaptation to digitalization leads to uncertainties and weaknesses of competitiveness for B2B companies. Digitalization offers business opportunities such as access to digital markets, increased productivity, significant cost reduction and competitive advantages, and the ability to improve and control their products (Riedl et al., 2018). Therefore, digitalization has gained great research interest both in scientific studies (Fruth and Teuteberg, 2017; Reis et al., 2018: 414) and in practice (Morakanyane et al., 2017: 427).

On the other hand, digitalization can be subject to different strategies and technologies according to the purposes of users. For example, it is inevitable to examine the digitalization of marketing communication within the scope of mobile, online and social media technologies (Zahay, 2015; Johnson and Kotler, 2017; Kotler and Keller, 2016; Armstrong et al., 2015). In this study, the digitalization of marketing communications (Rizomyliotis et al., 2017a; Patrutiu-Baltes, 2016) is discussed in terms of technology of social media and strategies for the maritime transport companies.

In communication, various methods have emerged throughout history and social media has become the newest communication technology of the 21st century. As one of the most important digital transformation indicators in marketing practices, social media enabled by Web 2.0 brought a two-way interaction feature with one-way online communication with customers (Lacka and Chong, 2016). Social media technologies are increasingly used and studied in many markets (Salo, 2017) and this trend is expected to continue. As of 2019, the number of social media users worldwide rose 9% year on year to 3,484 billion or 79% of all Internet audiences (Chaffey, 2019). As one of the biggest marketplaces for digital advertising, social media has a huge increase in advertising expenditures. Social media spending, which was 76.2 billion

U.S. dollars worldwide in 2018, is expected to rise to 125.5 billion U.S. dollars by 2023 (Statistica, 2019a).

The rapid growth of social media has affected the traditional B2B market buying process. Typical B2B content marketing or a sales representation is no longer the only way to build trust with customers. The Danish shipping company Maersk says, in today's digital world, there are multiple ways to build trust with the audience (Chan, 2018). The Danish shipping company, Maersk, has worked hard to promote brand awareness and humanize the brand through social media. Maersk company, whose original mission was to get closer to its customers, started to implement its social media strategy in 2011 and reached more than 400,000 people on Facebook in less than one year (Katona and Sarvary, 2014). Another important player of maritime transportation, MSC, which had previously been away from social media other than LinkedIn, started making a radical decision on August, 2018 and started sharing it on their official social media accounts (MSC, 2018). These examples actually reflect the breakdown of social media communication in the maritime transport sector.

Most B2B companies, however, have questions about how social media can help their business and how it should be used because this usage is not as clear as in business-to-customer (B2C) markets (Wichmann, 2018). Alphaliner's maritime research concludes that the container shipping industry, like other industrial sectors, has a long way to go to reach its customers (shippers) through digital tools (Johnson, 2018). Some reasons for this include late adoption of technological innovation, limited customers in the market, long sales cycles, and multiple decision-makers (Holliman and Rowley, 2014; Leake et al., 2012; Ramos and Young, 2009; Siguaw et al., 2003; Zeng et al., 2003).

The buying process in B2B markets involves multiple decision-makers (Holliman and Rowley, 2014: 274). This means that there are more people to be convinced than the number of companies. And these people on average complete 60% of their purchasing decisions before negotiating with a supplier (Adamson et al., 2012: 60). Container shipping companies should, therefore, focus on all decision-makers involved in the buying process of the businesses they serve with a strategic approach. As stated in McMaster (2010), B2B buyers are affected by information from many sources in their purchasing decisions, and the Internet is often one of the leading

sources of this data (Holliman and Rowley, 2014: 274). At this point, it is clear that social media has a significant impact on B2B buyers' decision-making processes.

In the past, some even claimed that because B2B means “Boring-to-Boring”, social media is unnecessary for B2B companies and that they have no place on social media (Agerdal-Hjerminde, 2014). However, as the case of Maersk proves, social media offers many opportunities to B2B companies, such as strong brand reputation, competitiveness, increased market share and strong relationships between suppliers and customers (Nunan et al., 2018). Social media can also be used as a communication technology to support sales, recruitment, job seeking, and provide product information (Andersson and Wikström, 2017). Given these features, social media is a critical technology that supports traditional B2B marketing (Rosenbloom, 2007; Järvinen et al., 2012). It is therefore critical for companies to determine the most appropriate social media platform for their target audiences and decide what kind of communication techniques they will engage in.

Another value proposition of social media is that it gives companies a rich data environment that can contribute to business goals, such as customer satisfaction. This is directly related to the Business Intelligence (BI) strategy (Dinter and Lorenz, 2012: 12, 13). The integration of the new-age range of BI and social media analytics tools such as Application Programming Interface (API) has significantly improved business efficiency and decision support mechanisms (Krishnan and Rogers, 2014: 23). Today, the effect of social analytics on BI has reached a certain level. Therefore, the concept of “*social business intelligence*” has emerged in the literature (Dinter and Lorenz, 2012). Today, social media is seen as one of the four components of BI analysis, others are marketing activities, customer relationship management (CRM), and internal process (Krishnan and Rogers, 2014: 24).

On the other hand, social media, seen as “user-generated communication”, offers a variety of new information sources (Blackshaw and Nazzaro, 2006). It consists of a wide range of online channels, such as social networking sites (Facebook), business networking sites (LinkedIn), video sharing sites (YouTube), photo sharing sites (Instagram), user or company blogging sites (blogger, medium), microblogging sites (Twitter), collaborative websites (Wikipedia), and commerce communities (Letgo). These platforms provide companies to talk to their customers and

stakeholders interactively as they usually include scope for making suggestions, requests, or complaints. In some cases, these conversations can go viral to reach hundreds of thousands of people outside the control of companies (Mangold and Faulds, 2009). This proves that social media is actually an extension of Word-of-Mouth (WOM) marketing (Kozinets et al., 2010).

Strategically designed messages can motivate network members to share the message and can promote WOM communication about the brands (Swani et al., 2017). Yet, despite its growing importance, increasing relevance, and perceived value for B2B companies, the role of social media in business markets has not been sufficiently addressed and research on its usage is still embryonic (Juntunen et al., 2019; Ancillai et al., 2019; Dwivedi et al., 2019; Weerakkody, 2019; Lashgari et al., 2018; Lacka and Chong, 2016; Siamagka et al., 2015; Karjaluo et al., 2015b; Michaelidou et al., 2011). This study contributes to scientific literature regarding the role of social media in B2B markets, specifically for container shipping companies.

Research problem, aim and scope of the study

As mentioned earlier, only social media from digital marketing channels was focused in this study. To be more specific, the subject of the influence of social media communication has been examined within the scope of technology and strategy. Moreover, in social media influence, the focus is on message-oriented engagement.

It is challenging to gather social media studies within a single framework due to its multidisciplinary nature. However, there have been attempts to create this framework. Salo (2017) has suggested an integrative framework for social media research topics and their linkages. This framework categorizes social media studies under the following six research headings: “social media influence”, “suppliers”, “customer acquisition”, “customers”, “business outcomes”, and “business/channel relationships”. This study focuses on “social media influence”. The most important metric that shows social media influence is the engagement rate (Jayasingh et al., 2018; Jaakonmäki, 2017).

On the other hand, engagement is a contested concept that has been defined from diverse perspectives. The literature includes different kinds of engagement, such

as political, civic, community, employee, stakeholder, and public (Taylor and Kent, 2014). This study focuses on public engagement as it explicitly uses indicators of public participation (reaction and comments) on social media. In other words, the subject of engagement is approached within the framework of the interaction of individuals with social media content.

The main question of this study can be expressed as “How can the digital transformation of maritime transportation be achieved in terms of strategies and technologies?”. In the study, looking for the answer to this question in the dimension of marketing communication. On the other hand, since B2B companies have more specific targets (Hellman, 2005) than many B2C companies, they are known to prefer relational communication forms mostly (Caliskan and Esmer, 2019), and social media offers attractive opportunities to keep such customer-supplier relations strong (Karjaluoto et al., 2015b). Therefore, we need to explore how this can be applied to container shipping companies' social media communication. To be more specific, considering the nature of the markets in which container shipping companies operate (Balci et al., 2018), it is necessary to determine the right channels and message strategies that are appropriate for the communication purposes of the companies. In order to measure the success of these goals, the engagement rate, which is the most important metric of social media (Pick, 2016; King, ____ a), is generally used. In this context, this study can help to find answers to the following sub-questions; Are there any message-oriented features that distinguish high engaging social media posts from less engaging ones? If so, what are the most prominent features of social media messages that get more engagement? Are there any features specific to container shipping companies among the significant characteristics of engaging in social media messages? Are there similarities between different platforms, such as LinkedIn and Facebook, for prominent features that affect the engagement of social media messages? Finally, can the level of engagement of social media posts of container shipping companies' be predicted?

In the light of research questions, scope, and theoretical background, the purpose of this study is to reveal the social media usage status of container shipping companies, to examine message strategies, to reveal the features of highly engaged contents and to develop a prediction model to the level of engagement of messages by

taking into account their existing posts. In order to accomplish the main aim of the study, the following objectives are generated;

- To understand the current social media usage status of container shipping companies and determine which channels they most prefer
- To identify what kind of messages container shipping companies post on social media.
- To evaluate the engagement level of the posted social media messages of container shipping companies and identify those with the highest engagement
- To propose an effective posting strategy for social media communication of container shipping companies
- To develop a prediction model that explains the characteristics of social media messages that receive high engagement.

In the study, a new categorization framework is presented for social media messages of businesses, adapted from Swani (2014) and North (2015) and by considering the social media strategies of maritime transport companies. Thus, future research will be able to use a more theoretical categorization for social media work in the shipping industry.

According to the researcher's knowledge, although there are various studies in the literature to understand the engagement of social media messages (Denktaş-Şakar and Sürücü, 2018; Khan, 2017; Swani et al., 2014; Swani et al., 2013), there is no comprehensive study to determine the social media message strategies appropriate for the nature of the container shipping companies which are B2B characteristics and to predict the engagement of these messages. In addition, this study presents the first machine learning modeling developed to predict the social media engagement of shipping companies, moreover B2B markets.

One of the most important contributions of this study to the literature is the proposition of a new method for calculating social media engagement. As previously determined by Bitiktas and Tuna (2020) as a preliminary study of this research, the engagement calculation formulas used in the literature have made erroneous calculations due to the constantly changing algorithms of the platforms. In this study, a novel approach is proposed for this calculation problem.

Another differentiating feature of this study is that it is one of the rare studies that used the LinkedIn platform. Although it is known that B2B decision-makers use the LinkedIn platform more intensively, in the literature, Facebook and Twitter messages are used which are relatively easy to collect data. Finally, the study contributes to the gap in the literature on the determination of social media communication strategies based on B2B advertising and WOM theory.

Research design of the study

This study consists of four chapter. Chapter one provides introduction of digital marketing within the scope of B2B. The purpose of this chapter is to understand the technologies that cause the transformation of marketing communication. For this, the first developments that digital technologies meet with marketing have been handled through the historical process. This section focuses on important communication technologies and their impact on marketing theory. The effects of digital marketing technologies on B2B markets and their current status in the academic literature are presented. This process based on deductive understanding has enabled the researcher to identify gaps in the digital marketing literature and to understand the current trends with the perspective of 360-degree digital marketing.

In the second part, an introduction is made on digital marketing technologies and their classification. In this section, a distinction has been made for digital marketing technologies that will affect the continuation of the study; online, mobile, and social media technologies. After making this distinction in digital marketing technologies, the focus of the study continued with social media technology and strategies. For this purpose, firstly, the theoretical background of social media communication has been put forward. In this section, important theories and models used in social media literature are listed. In this study, the social media communication model based on classical communication theory has been redesigned in the dimension of shipping companies. Furthermore, Word-of-Mouth (WOM) Psychological Motivation Theory, which forms the basis of the research, is discussed in detail. The most important subject of this section is the engagement theory, which is at the center of the study. The factors determining engagement in social media communication have

been handled with previous studies. The current social media strategies of container shipping companies, which form the sample of the study, are also discussed in this section.

Chapter three provides a summary of data mining literature and machine learning technology used in the analysis part of the study. This section first presents the relationship between machine learning and data mining subjects. Machine learning and data mining methods are discussed under the headings, classification and regression models are defined separately. A brief introduction to the decision trees and learning algorithms that form the structure of the machine learning model developed in the application section has also been made. Two machine learning algorithms “The Classification and Regression Algorithm” and “Chi-square Automatic Interaction Detection Algorithm” can be used due to the purpose of the research and the characteristics of the data are further detailed in this section.

The fourth chapter consists of four main processes. Firstly, it has been revealed which social media platforms the container shipping companies actively use at most. For this purpose, container shipping companies listed in the Alphaliner top 30 are included in the research sample. The research continued on the LinkedIn platform as the review of all social media channels would produce superficial analysis unrelated to the research question.

Then, the process of data collection and content analysis takes place as a critical phase. In this section, the data restriction policy of the LinkedIn platform (LinkedIn, 2019) was encountered as an important barrier. Although the researcher communicated with LinkedIn administrators, it was concluded that platforms had dramatic data access restrictions to protect user information, especially after the Cambridge Analytica scandal (Schroepfer, 2018; Bastos and Walker, 2018). In this study, where ethical and legal issues are prioritized, a total of 4067 public messages and comments, excluding user information of companies, were received manually by the researcher and moved to analysis.

In this part of the study, both field experiments and a content analysis method were used. Various interviews were also conducted to increase reliability during the research process. In the study, LinkedIn data of the companies were collected in a natural environment. In other words, there was no emotional pressure on the formation

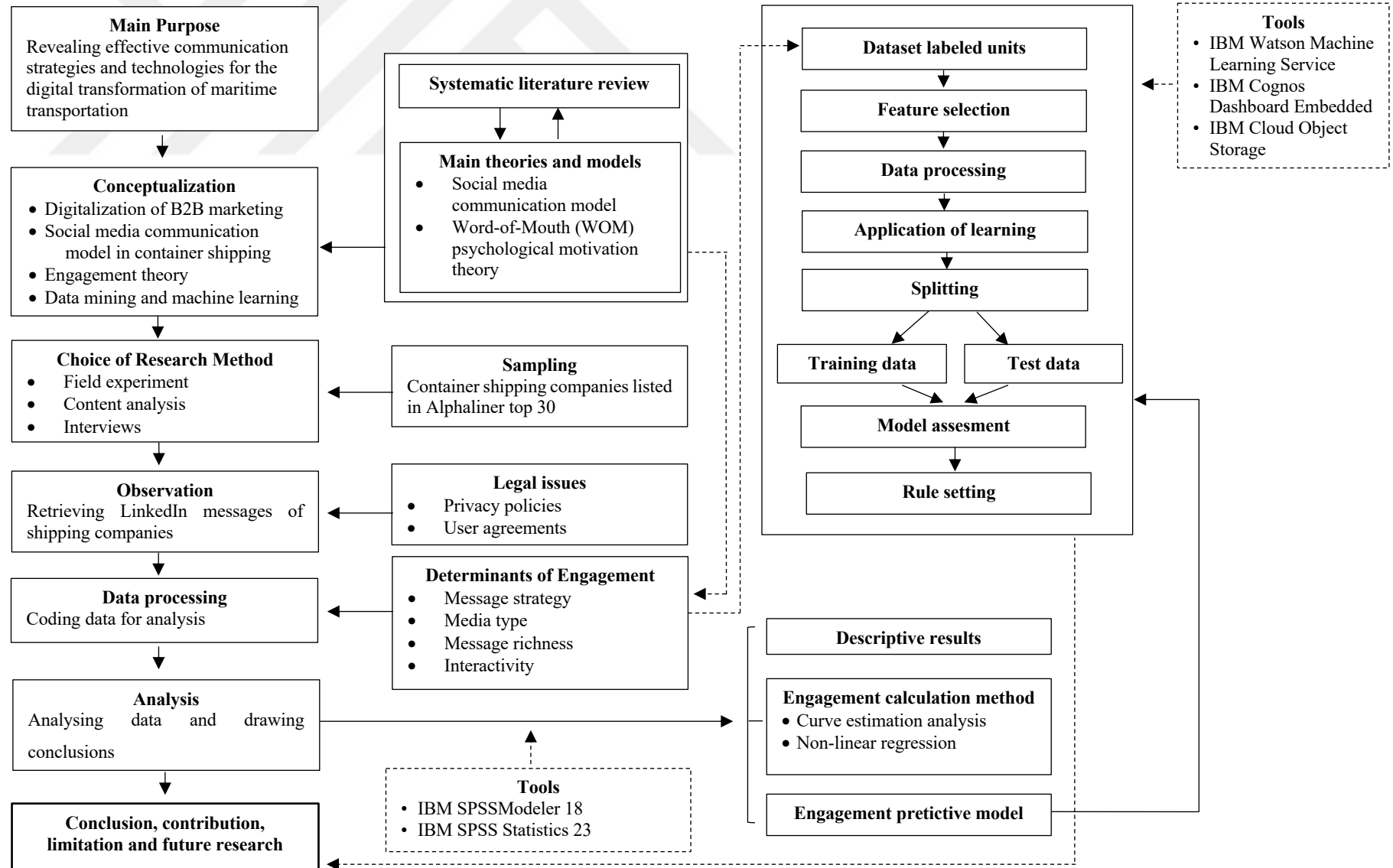
and collection of LinkedIn messages. As mentioned by Wrench et al., (2008) this type of research has maximized the validity of the research (Wrench et al., 2008: 451, 452). In field experiments, researchers examine how at least one independent variable leads to a change in a dependent variable in the natural environment. This influence is known as causality. Researchers do not have control over the independent variable because they cannot manipulate or influence it (Allen, 2017).

In the next section, a new approach to calculation of engagement, which is considered as one of the most important metrics used in understanding social media success, is proposed, as determined in the study of “Social media usage in container shipping companies: Analysis of Facebook messages”, which is a preliminary study of this research. In this section, an exploratory qualitative research process was carried out by consulting to the experts, who are academicians and practitioners, as well as by conducting the literature review. Exploratory research is used in cases where the knowledge that has reached a certain level of maturity previously needs to be explored anew because of changed so much (Stebbins, 2001: 7). Exploratory research can be carried out by detailed literature review and consultation with experts (Altunışık et al., 2005: 61).

In the last part of the study, a machine learning model was developed to predict highly interactive LinkedIn messages. Regression trees under classification and regression models have been the subject of these analyses. In the analysis process, a path suggested by the machine learning and data mining literature (Shearer, 2000: 14) was followed. The analyzes were carried out using IBM Watson machine learning services. Finally, the research findings are discussed and their theoretical and practical contributions are reported.

The research process below summarizes the critical steps in the thesis and the relationship between the content.

Research Process



CHAPTER ONE

DIGITALIZATION IN BUSINESS-TO-BUSINESS MARKETS

This chapter provides a brief introduction to the phenomenon of digitalization, focusing on B2B markets. For this, firstly, the B2B marketing theory is presented as a summary. In order to better understand the digitalization process of B2B marketing, it is necessary to take a look at the technologies behind digital communication. At this point, network, internet, and browser technologies come to the fore. In addition, understanding the place and importance of digitalization in the marketing literature also helps in understanding the concept of digital marketing in depth. This approach also gives the researcher a perspective on 360-degree digital marketing. This section, based on deductive understanding, allowed the researcher to identify gaps in the digital marketing literature and to understand current trends.

1.1. B2B MARKETING

B2B companies can be define as “businesses that market their products to other businesses, as opposed to B2C organizations that sell the products directly to individual customers” (Lacka and Chong, 2016: 81). Both B2B and B2C markets involve people who similarly undertake purchasing roles and make purchasing decisions to meet their needs. But, business markets differ from consumer markets in many aspects. The basic distinctions are the structure and demand of the market, the nature of the purchasing unit and the kinds of decisions taken and the decision process took (Kotler and Armstrong, 2018: 189).

Market structure, product specification, and product development process show significant differences between the B2B and B2C sectors. As an example, in general, products produced by B2B organizations are more complex and the production process takes more time. Industrial products are usually purchased by experts who consider a wide range of variables in decision process. Purchasing specialists look for more information on the industrial products to be purchased, and they generally analyze several options objectively. Moreover, the demand for industrial products is a derived demand, which means that the product demand for the industrial customers of the company stems from the end-consumer demand (Jussila et.

al, 2014: 608). Organizations involved in business transactions are less than consumers involved in B2C interaction and the nature of these interactions is more direct and denser than in B2C. Marketing process based on trust and a relationship level between industrial sides. For this reason, B2B marketing is considered to be of vital importance to the success of B2B companies (Lacka and Chong, 2016: 81).

Generally, business market customers can be divided into three categories: commercial enterprises- that is, businesses; institutions- ie universities; and the government (Hutt and Speh, 2012: 6). These groups buy a product for one of three purposes; re-sale, direct use in other products or traditional operations. Commercial marketing is usually based on long-term mutually beneficial relationships between marketing channel members. Suppliers and customers in B2B markets acknowledge that it is important to build a strong relationship based on cooperation and trust (Pride and Ferrell, 2014: 248).

As mentioned above demand for the industrial market is usually driven by trends in the end-customer (consumer) market (Rizomyliotis et al., 2017b: 4; Jussila et. al, 2014: 608). For this reason, B2B marketers are sometimes promoting their products directly to end-users in order to increase business demand (Kotler and Armstrong, 2018: 189). Many large companies that produce goods and services such as shipping, steel, production equipment or electronic chips cater only to business customers and never connect directly with their end-users. Some companies that produce products such as mobile phones, furniture, computers and digital programs are involved in both consumer and industrial markets (Hutt and Speh, 2012: 5).

Figure 1 shows the difference between B2B and B2C distribution channels. B2B companies sell their products directly to their customers through their own sales force, or they can market, sell and physically distribute their products using channel partners such as retailers or distributors. On the manufacturer's side, more intermediaries mean less control and more channel complexity. In addition, all sides in the channel are linked by various flow types. These contain the physical flow of products, property, payments, information, and promotion (Armstrong et al., 2015: 399).

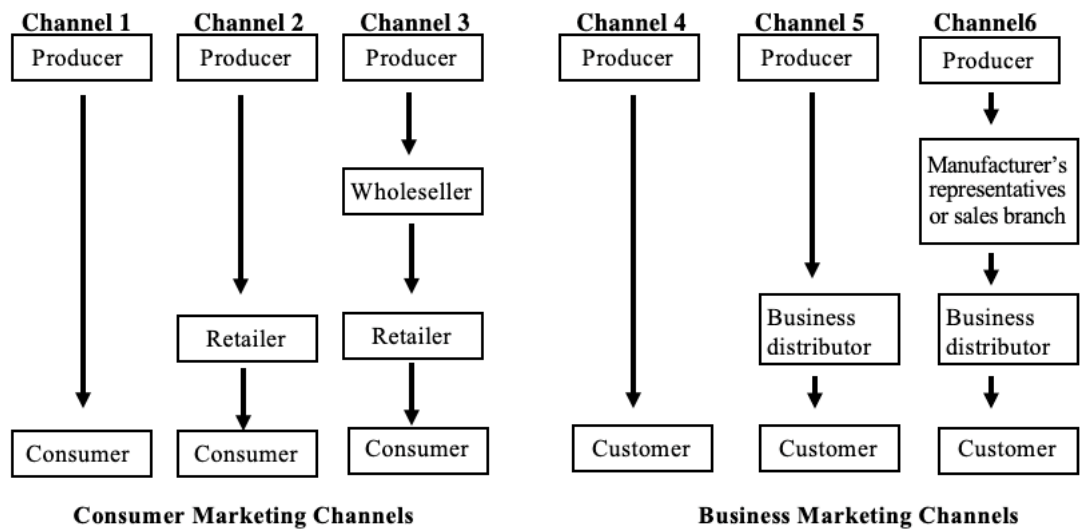


Figure 1: Direct and Indirect Marketing Channels, for Both B2C and B2B

Source: Armstrong et al. (2015: 399).

Today, in order to achieve success on these channels, B2B marketers must communicate clearly and effectively. Because B2B customers have recently gained more knowledge and understanding of digital marketing communications. They know what they need and have the ability to evaluate campaign messages in a good way (Rizomyliotis et al., 2017b). Therefore, these messages should be designed in a professional manner to directs the relationship.

Through marketing communication, companies can be the link of a real value chain that will create value at a lower cost. Likewise, communication can support the development of advanced product offerings, pricing decision and distribution process, and detailed measures to enhance the gap between value and costs. Marketing communication basically provides flexible and personalized activities to meet customer needs. In addition, the commercial value of the business is determined by the size of the expected cash flow, and digital marketing communication metrics have a feature to support these predictions (Rizomyliotis et al., 2017b: 6).

The disruptive power of technology can make some B2B applications outdated. The unpredictable impact of technology makes many B2B companies uneasy and also offers opportunities to facilitate marketing and communication with customers. Technology is seen as a driver of today's and tomorrow's B2B markets and marketing

systems (Wiersema, 2013: 473, 476). However, it should be noted that B2B firms still use printed media and they have not abandoned traditional promotions at the cost of digital media trends (Rizomyliotis et al., 2017b: 26, 29).

1.2. EVOLUTION OF DIGITAL MARKETING CONCEPT IN MARKETING LITERATURE

In the literature, it is observed that the digitalization of marketing has brought along many jargon and labels. For example, terms such as electronic marketing, web marketing, and internet marketing have been derived, and over time these terms have confused both the literature and the practitioner. For this reason, in this part, the concept of digital marketing has been introduced clearly and its difference with other terms has been clarified. In addition, it is thought that talking about the leading technologies of digitalization in marketing will make it easier to understand today's digital marketing technologies. In this part, the place of digital marketing in traditional marketing literature and its relationship with marketing theory is discussed.

1.2.1. Digital Marketing: Definition, Types and Elements

Digital marketing is seen as a digital channel used to transmit marketing messages regardless of whether they are online (Kannan and Li, 2017: 23; Kamal, 2016: 5300; Järvinen et al. 2012: 104). In other words, digital marketing is not only limited to the use of the Internet, but many other digital channels, tools, platforms can be used for marketing (Abud, ____). In light of this information, it can be said that web marketing, online marketing or internet marketing concepts are the types of marketing that are under digital marketing and require internet connection.

On the other hand, electronic marketing is seen as one of the oldest methods of transferring products from seller to buyer using one or more computerized ways. Electronic marketing appeared with the use of telegraphs in the 19th century and has become leading marketing force with mass media technologies such as telephone, radio, television (Ngai, 2003: 24). But later, with the widespread use of internet technology, internet marketing defined as “the use of the Internet as a virtual storefront

where products are sold directly to the customer” (Kiang et al. 2000: 383) has emerged (Ngai, 2003: 24). Similarly, online marketing represents marketing via the Internet using the website, online advertisement, and promotions, e-mail, videos and blogs (Armstrong et al., 2015: 554) and it can be said that online marketing and internet marketing is an umbrella term that includes marketing types such as web, mobile, email, social media and search engine marketing under the digital marketing. For example, social media is seen as an integrated technology, tool or platform of digital marketing to facilitate social interaction between customers and companies (Järvinen et al., 2012: 104). Social media complements the interactive side of digital marketing.

As mentioned before, digital marketing is seen as a generic term cover almost every single element of modern marketing practice (Kamal, 2016: 5300) and is the most preferred term in the contemporary marketing world. In Figure 2, the concepts of “digital marketing”, “online marketing”, “web marketing”, and “internet marketing” have been compared for the last five years according to the interest shown worldwide. As can be seen from the Figure 2, there is increasingly widespread use for the concept of digital marketing.

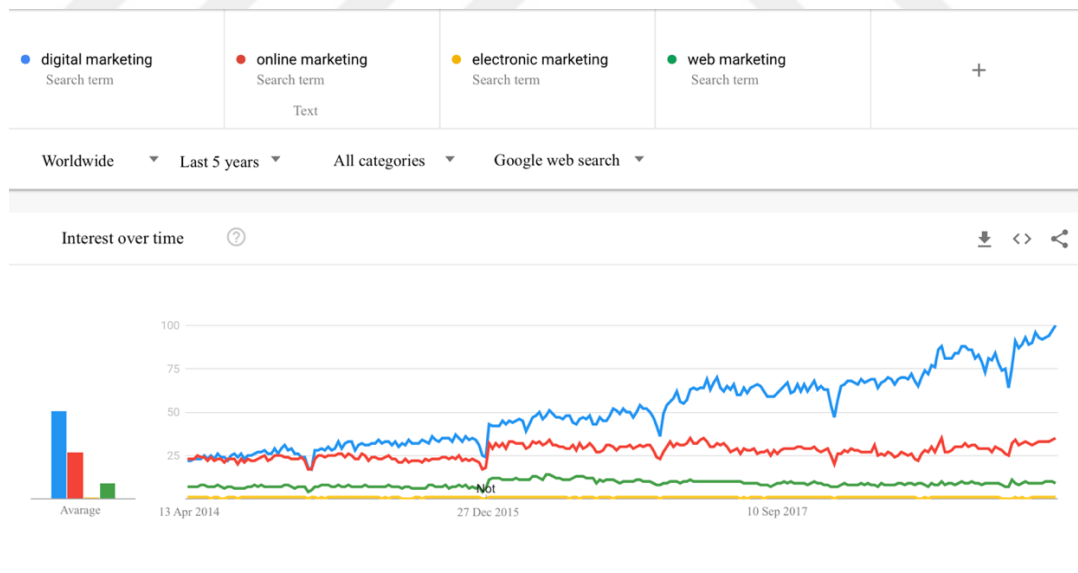


Figure 2: Comparison of the Concepts of Digital Marketing, Online Marketing, Electronic Marketing, and Web Marketing.

Source: Google Trends (09.04.2019).

Since this study adopts a holistic approach, the concept of digital marketing, which is accepted as the umbrella term, has been preferred. In this context, a comprehensive definition of digital marketing is required. The most primitive description with simple logic is “marketing of goods and services through digital channels.” However, this definition has evolved to more comprehensive ones. According to the “American Marketing Association (AMA)”, digital marketing can be seen as; “activities, institutions, and processes facilitated by digital technologies for creating, communicating and delivering value for customers and other stakeholders.” Gartner (2019), one of the leading research and advisory company, defines digital marketing as;

“a set of integrated techniques, technologies and information that enables marketing to create new products and services; enter new markets; improve the processes needed to engage in a dynamic conversation with people who are influencers and buyers; and ultimately target, acquire and retain customers.”

According to Kannan and Li (2017: 23) digital marketing is an umbrella term describing “the process of using digital technologies to acquire customers and build customer preferences, promote brands, retain customers and increase sales”.

Chaffey and Ellis-Chadwick (2016) define digital marketing with the purest form; “achieving marketing objectives through applying digital technologies and media”. The most accepted digital marketing definitions in the literature are presented in the following sections (see Table 1).

Digital marketing is applied in four different types according to the marketplace; “Business to Customer” (B2C), “Business to Business” (B2B), “Customer to Customer” (C2C) and “Customer to Business” (C2B). The first two of these are “consumer markets” and “industrial markets” are the most common (Mucuk, 2014: 251). The maritime transport, which is the subject of this study, serves an industrial market. Therefore, B2B marketing is discussed in more detail in the this study. But for now, it can be said that a large number of B2B firms see the use of

digital marketing tools as irrelevant for themselves (Järvinen, 2012: 108). However, the growing importance of digital communication tools is a well-known fact.

Table 1: Definition of Digital Marketing in the Literature

Author and Year	Definition
Kannan and Li (2017: 23)	“an adaptive, technology-enabled process by which firms collaborate with customers and partners to jointly create, communicate, deliver, and sustain value for all stakeholders.”
Royle and Laing (2014).	“is a sub branch of traditional Marketing and uses modern digital channels for the placement of products e.g. downloadable music, and primarily for communicating with stakeholders e.g. customers and investors about brand, products and business progress”
Karjaluoto et al. (2015a: 704)	“the use of new digital communication channels (or technologies/tools) to create an integrated, targeted, and measurable communication process that helps companies acquire and retain customers while building a deeper relationship with them”
Çizmeçi and Ercan, (2015: 154)	“sharing the content created according to customer groups, using layers in the digital media in order to reach consumers, on global networks at the right times in order to create brand/product awareness”
Joshi (2013)	“the method in which products and services are promoted through digital distribution channels”
Hadadi and Almsafir (2013)	“an e-marketing which is employing the internet and other communicating technologies to create a discussion between the firm and its customers”
Key (2017: 27)	“Internet systems that have the ability to simultaneously create, promote, and deliver value from producers to consumers through digital networks”

In this part of the study, it is also necessary to define digital media. Digital media is an electronic media that works using numeric codes. Digital marketing brings together all these digital media through online, mobile, and social media technologies to develop communication and exchanges with actual and potential customers (Pride and Ferrell, 2014: 316, 317). For example, Amazon.com, using its product-related digital media (photo, information content, e.g.) helps customers discover and purchase almost everything online, and it interacts directly with the customers through the website and mobile application (Armstrong et al., 2015: 548).

Apart from digital media, digital marketing has three essential elements; telecommunication infrastructure, software and products, and markets. The

telecommunication infrastructure is obtained from “Internet service providers” (TTNET, Superonline, etc.), “telecommunications services” and “private and official computer networks.” Change and development in this group are slow. In digital products (software, electronic services) and markets, innovations occur very quickly. Therefore, digital marketing requires to be able to keep up with digital product and market innovations to benefit from these innovations (Mucuk, 2014: 252).

It would be a wrong approach to see digital channels as an innovation, which fundamentally changes marketing, disrupts marketing theory, or causes a paradigm shift in marketing (Varnalı, 2013: 57). As mentioned earlier, digital marketing is just a new communication channel under the promotion mix. However, it should also be noted that it is one of the most effective communication method for marketing. It is seen as the rapid-growing form of direct marketing and includes digital technologies that engage customers at any time, anywhere through digital devices such as their computers, tablets or smartphones (Johnson and Kotler, 2017: 22). Marketers use the term digital marketing as a catcher to capture all digital platforms to reach customers. This area is developing gradually, and the digital world is still at an early stage of integration into the marketing strategy (Pride and Ferrel, 2014: 317). The following sections will examine the advantages and disadvantages of digital marketing communications.

1.2.2. Historical Review of Digital Marketing

In this section, it is aimed to understand the trend of digitalization, which is seen as the most important trigger of the transformation, on marketing communication. The following literature has been carried out to better understand the basic technologies that have contributed to the digitalization process of marketing today.

1.2.2.1. The Technologies Behind the Digital Communication

Technological developments have been the most important key element in marketing history. The emergence of new technology and its adoption by society causes it to be used as an innovative marketing tool. The traditional press (printing),

radio, TV and now the internet are the best examples of these marketing tools. In order to understand internet technology that leads to the digitalization of marketing, it is necessary to go back and examine the early communication technologies. The story of electronic communication begins with a telegraph (Ryan, 2014: 5). However, it is a well-known fact that information is transmitted physically by humans or animals.

It is not a new phenomenon to reach an information source or to interact with people in remote places (Sørensen, 2011: 18). It is an excellent example of Pheidippides in 490 BC to tell the news of victory that it runs 26.2 miles from Marathon to Athens (Lucas, 1976: 122), one of the best examples of the importance and cost of access to information and connectivity. Throughout history, people have tried many different methods to reach and connect to remote information. Many of these connection methods have been developed especially for military use (Sterling, 2008). For example, pigeons have been used to transmit messages since ancient times and have been proved useful in World War II (Via and Rejan, 2010: 4, 25). However, the physical transport of information by humans, horses or pigeons has brought many problems in most cases. For example, in 1858, it took 40 days for Indian Mutiny news to reach London (Solymar, 1999: 3). Something faster and more reliable than a human or horse was clearly required at that time. This situation would last until the invention of the telegraph, the first electronic communications network on earth (Ryan, 2014: 7).

Standage (1998) states that the first invention that determined the fate of the telegraph was made by French scientist Jean Antoine Nollet. According to the story, Nollet tied a couple of hundred monks with a long cable and exposed them to the electric shock with a primitive battery. With this experiment, Nollet pointed out that the signal could be transmitted very quickly with an electrically operated signaling device. Although painful, this experiment laid the foundation for the communication revolution. In Standage's terms, "the oddballs, eccentrics and visionaries are the earliest pioneers of the online frontier" (Standage, 1998: 15-18).

The signaling device that uses electricity was invented in 1791 by the Frenchman Claude Chappe. This device, which is used for long-distance message transfer, is called "Télégraphe" (Standage, 1998: 23, 25). However, this system was very different from the telegraphs that came to mind today. It is an information

transmission system that provides visual signals using a winged body (called semaphore) on a high structure (Solymar, 1999: 37). In 1830, the US scientist Joseph Henry took the issue a step further and demonstrated the potential for electromagnetism for long-distance communication. Samuel Morse, who developed Henry's invention using his Morse code, invented the first electronic telegraph in history (Ryan, 2014: 7). The electrical telegraph is a revolutionary invention that has radically changed the communication method of humanity.

In the 1840s, when electrical telegraphs began to spread, information of approximately 4 or 5 words per minute could be sent (Solymar, 1999: 4). This invention has brought a huge commercial success to Morse. At the end of the second year following the invention, 2,000 miles, and at the end of the fourth year, 12,000 miles of telegraph wire was operated by twenty different companies (Standage, 1998: 85).

After the telegraph that remained the fastest way of long-distance communication for almost 40 years, the next invention that profoundly influenced the world of communication has been the "Telephone." The inventors of the new technology were Elisha Gray and Alexander Graham Bell, who applied on the same day for the patent. But Bell beat Gray to the patent office by two hours (Solymar, 1999: 100). There are also debates about the fact that the phone was originally invented by Antonio Meucci, and that Bell copied the idea (Beauchamp, 2010; Schmidhuber, 2008; Campanella, 2007; Catania, 2004; Bargellini, 1993).

The next major invention in communication was wireless communication technology. The Italian Guglielmo Marconi was a curious student in radio waves, realized that Hertz waves, which the existence is known by everyone, could be used for communication. In 1895, Marconi took the first successful results of his research in his laboratory on the attic of his house and transmitted a radio signal from one end of the room to the other. One year later, Marconi patented his invention called wireless telegraphy and then he was awarded the Nobel Prize for his invention (Solymar, 1999: 130, 134). The rapid development and spread of the Telegraph have had a positive impact on many sectors. Companies have been able to reach foreign markets more easily. It has provided managerial facilities, especially for international enterprises (Nye, 1997: 1073).

Wireless telegraphy also paved the way for the invention of the wireless telephone. But at that time the telegraph seemed more advantageous than the telephone because of that the telegraphy was provided a permanent record of the messages. The disadvantage of the telegraph was that a messenger needed to transmit the message to the telegraph office. The Universal Private Telegraph Company was established for this purpose. This issue was solved with the invention of the teleprinter by Krum. The teleprinters were running automatically, and there was not needed to skilled operators both at the transmitting and at the receiving ends (Solymar, 1999: 167).

There have been many inventions in the transmission of knowledge as seen, and these inventions have continued to this day. The next section summarizes the internet technology and its components, the most important invention of the modern world.

1.2.2.2. Network, Internet and Browser Technologies

The story of the internet begins in 1957 when the “Soviet Union (SU)” launched the “Sputnik” satellite. However, the US government focuses on science and technology investments in order not to fall behind the Russians, and in 1958 the US government set up the “Advanced Research Project Agency (ARPA)”. ARPA (later DARPA¹), in 1966, starts the ARPANET project to connect powerful computers of government and research organizations. On November 21, 1969, DARPA connected two computers in Los Angeles and Stanford. In 1971, the number of US institutions under ARPANET increased to 15 and in the coming years, this number increased exponentially (Ryan, 2014: 9, 10).

The idea that social interaction can be achieved through network communication was first introduced in 1962 by the concept of "Galactic Network" developed by Licklider from MIT (Leiner et al., 2009: 23). With the expansion of ARPANET, the idea of sending e-mails, the first digital tool of social interaction, over the network has emerged. In 1971, ARPANET engineer Ray Tomlinson was able to send his first network email between two computers. Tomlinson has decided to use the

¹ ARPA changed the name to “Defense Advanced Research Projects Agency (DARPA)” in 1971, it back to ARPA in 1993, and than it back to DARPA in 1996.

@ sign behind the user name in order to avoid any confusion of messages over the network. He later explained why he prefers it; “the @ sign seemed to make sense. The purpose of the @ sign (in English) was to indicate a unit price (for example, ten items @ 1.95 U.S. dollars). I used the @ sign to indicate that the user was <at> some other host rather than being local” (Tomlinson, 2012).

The term of the Internet was first used in 1974 by the US computer scientist Vinton Gray Cerf (known as one of the “internet fathers” and is still Chief Internet Evangelist at Google) (Ryan, 2014: 11). The network messaging program written by Tomlinson was expanded by Robert Khan in 1972 and selectively read, forward, and file utilities were added (Kahn et al., 1997: 133). Khan then worked with Cerf to detail the protocol designs of computers on the network and standardize their communications. In 1973, they (known as fathers of the Internet) created the next generation “Transmission Control Protocol (TCP)” (Leiner et al., 2009: 25). This protocol was later combined with the “Internet protocol (IP)” and become the world's most popular network protocol, called TCP/IP (Tukade and Banakar, 2018: 123).

Another critical invention at that time was the “Domain Name System (DNS)”. In 1983, Paul Mockapetris and Jon Postel developed the DNS to convert IP addresses and names (Guillard, 2006: 1). The invention of DNS has made it possible to use a domain name consisting of a string of letters instead of the hard-to-remember IP numbers and to make it easier for users to find their way on the Internet.

Cerf and Khan’s TCP and Paul Mockapetris and friends' Domain Name System (DNS) have triggered the invention of the “World Wide Web (WWW)”. WWW is a universal information space operating on the Internet (Grosskurth and Godfrey, 2006: 2) and it was invented by British scientist Tim Berners-Lee in 1989 to encourage the sharing of information among physicists at the CERN research facility in Geneva, Switzerland (Berners-Lee et al., 1994: 298). Berners-Lee later explained the invention of the WWW as follows; “I just had to take the hypertext idea and connect it to the TCP and DNS ideas and – ta-da! - The World Wide Web” (W3.org, ____). Thus the first website was also online on August 6, 1991, by Berners-Lee (see info.cern.ch).

WWW has made it possible for documents written in a language called the “HyperText Markup Language (HTML)” to be transferred from a unique address called “Universal Resource Location (URL)” using the “HyperText Transfer Protocol

(HTTP)” (Bainbridge, 2004: 819). However, in that period, most people were not able to access this extensive information network (Zahay, 2015: 8). But with the invention of the WWW, this situation has begun to change. In August 1995, only four years after the first website was online, 18,957 sites were online. In August 1996, this number reached 342,081 (Ryan, 2014: 13). At the time of this study, this number has exceeded 1.6 billion.

It is necessary to think of the Internet as a network that connects various technologies (Zahay, 2015: 8). However, as an early form of networked communication, the telegraph and the telephone provide an essential idea to understand the working principle of the computer network (Nye, 1997: 1067), with the spread of the internet, especially invention of the world wide web, the network has become even more critical. In network technology, relationships are visualized to form a network with nodes and lines. These nodes can represent different things. In Social Network Theory, these nodes and lines represent connections between individuals. In Communication Theory, these nodes represent the areas in which the information on the network is processed before moving to another node (Zahay, 2015: 8, 9). The network that established with the nodes and lines visualized by network theory allows the transfer of information between the two systems. A browser can be considered as an interface used to provide this connection. Browser is a program that accesses documents on the remote server and displays them in the browser window (Grosskurth and Godfrey, 2006: 3) by navigating the nodes of the internet.

Today, browser technology has become the most widely used software application in history and has become a platform where billions of dollars of internet trade are being done (Grosskurth and Godfrey, 2006: 2). Therefore, this technology has a direct impact on the growth of digital marketing (Zahay, 2015: 9).

1.2.3. Digital Marketing Concept in Marketing Literature

The concept of digital marketing is mentioned together with direct marketing in marketing literature. Direct marketing is seen as a channel of promotion (marketing communication) which is an element of the marketing mix. It is a well-known fact that the marketing mix is one of the most widely used and popular models of marketing

strategy. In light of this information, it can be concluded that the brief description of marketing strategy and the integrated relationship between marketing mix and marketing communication are essential guides in understanding the place of digital marketing in marketing literature.

1.2.3.1. Marketing Strategy

Marketing strategy can be defined as “the decisive decisions in the creation, communication and/or delivery of products that determine an organization's important choices regarding products, markets, marketing activities, and marketing resources, and propose value in exchanges with the organization, in order to achieve certain goals” (Varadarajan, 2010: 119). Marketing strategy is the marketing logic by which the company unit expects to create value and create valuable relations with customers. Under the guidance of marketing strategy, the company sets segmentation, targeting, differentiation and positioning decisions and implements integrated marketing mix. Businesses should carefully design marketing analysis, planning, implementation, and control processes to develop the best marketing strategy and marketing mix (Kotler and Armstrong, 2018: 74).

In other words, the marketing strategy guides how to achieve marketing objectives and gives an overview of what the business will do in a particular market. The selection of the target market and the creation of the marketing mix are the two most essential elements of a marketing strategy (Mucuk, 2014: 47; Candemir et al., 2011: 57). By dividing up the total market, companies can choose the best segment and can design the plan that they will offer the most valuable service to the customers. This process includes segmentation, targeting, differentiation, and positioning (Armstrong et al., 2015: 58).

Market segmentation is based on the common needs of potential customers or similarities in the behavior of consumers in the market. When the market segmentation is done, each segment consists of consumers with similar properties (Altunışık et al., 2002: 124). Once a company has identified market segments, it can choose one or more of these segments. This selection process is called market targeting, and it involves evaluating each segment and selecting one or more of them to enter. The company

should choose a portion that is the most profitable of itself and the most valuable service for the customer (Armstrong, 2015: 59). With targeting, companies have the opportunity to match the profiles of their potential customers with the right offer and increase their relevance to the target market, thereby increasing their response (Smith and Zook, 2011: 384).

Differentiation and positioning are examined under competition strategy in some sources. Because the companies usually tend to differentiate and position their products in order not to face the price competition of new entrants (İslamoğlu, 1999: 253). The effective positioning process begins with differentiation (Armstrong et al., 2015: 61) because the products of the companies must be perceived as different from the competing products. Product differentiation defines as “the process of creating and designing products for customers to see them as separate from products of competitors”. Product differentiation is carried out by various methods. Features of products such as quality, design, and support services are some of these methods (Pride and Ferrell, 2014: 402). And finally, positioning is defined as "the place a product occupies in consumers' minds relative to competing products." This leads us to the brand concept and companies should not forget that the brand is formed in the minds of the customers (Johnson and Kotler: 2017: 209).

Segmentation and targeting are one of the most essential parts of the marketing strategy, and they are in almost every level of the marketing plan, in situation analysis, in strategy development, in objectives and of course in marketing communication (Smith and Zook, 2011: 229). This study is conducted within the scope of digital marketing communication. Considering the integrated structure of marketing communications, it is necessary to look at the general description of the marketing strategy. Segmentation, Targeting, and Positioning are deemed to be one of the most famous models used in marketing strategy (Smart Insights, 2019). It is a well-known fact that this model is also one of the most useful models of marketing communication. Therefore, segmentation, targeting and positioning decisions should be dealt with in more detail within the scope of digital marketing communication. In the next section, marketing mix and marketing communication, which is one of the most critical components of marketing strategy, are examined within an integrated structure.

1.2.3.2. Marketing Mix Considerations

The idea of the marketing mix was born for the first time in “The Management of Marketing Cost,” published by James Culliton in 1948, with the term “Mixer of Ingredients.” This concept, which was put forward by Culliton, has attracted and developed interest over time by the world of marketing science. In 1964, the idea started to be used in the article “The Concept of Marketing Mix” published by Neil Borden in “Journal of Advertising Research” (Sümer and Zeliha, 2006: 166, 167). Borden stated that the elements of the marketing mix could be listed under 12 topics; “product planning, pricing, branding, distribution channels, personal sales, advertising, promotion, packaging, display, service, physical distribution, fact-finding/analysis” (Broderick and Pickton, 2005: 15), and these elements could be listed in different forms (Sümer and Zeliha, 2006: 167).

In 1964, McCarthy further developed Borden's idea and defined the marketing mix as a combination of factors to ensure the satisfaction of the target market. McCarthy shortened 12 elements of Borden's marketing mix to four main headings: product, price, promotion and place (Goi, 2009: 3). If we need to briefly explain McCarthy's 4Ps, in order to reveal the value proposition that is subject to marketing, the company must first create a market offering (product) that relieves need. Next, it is necessary to decide how much (price) to request and how to make the offer available to target consumers (location). Finally, it should attract consumers' attention, communicate about the offer, and convince customers of the value of the offer (promotion) (Johnson and Kotler, 2017: 13). In Figure 3, marketing activities are listed under the marketing mix.

Especially in the 1980s, many researchers started to propose new "P" s to the marketing mix. One of the most widely used recommendations today is the 7P approach of Booms and Bitner in service marketing. In 1980, Booms and Bitner add three Ps (participants/people, physical evidence and process) to the original marketing mix (4Ps) to apply it to service marketing (Goi, 2009: 3). The first element of service marketing is people and is also called as participants. Most of the services are dependent on direct and personal interaction between customers and employees of a company, such as making haircuts or spend time in the amusement park. The nature

of these activities strongly influences the customer's service quality perceptions. Customers generally evaluate the quality of the service according to the service providers' performance. Successful service companies give importance to the training and motivation of their staff who are in direct contact with their customers (Lovelock and Wright, 1999: 14). The physical environment refers to the business opportunities that the company uses to carry out marketing activities. The issues such as the size, usefulness, design, and technology of the area where the service is provided to the customer are evaluated under this combination (Öndoğan, 2010: 8). Process management is a marketing mix that provides solutions for problems arising from the non-storage and homogeneity of services. With the process management, the service is available at the time that the consumer needs it and is presented to a certain standard. In other words, process management ensures the availability of the service against the simultaneous production and consumption of the service. This allows enterprises to offer a variety of service alternatives when demand falls or rises (Sümer and Zeliha, 2006: 169, 170).

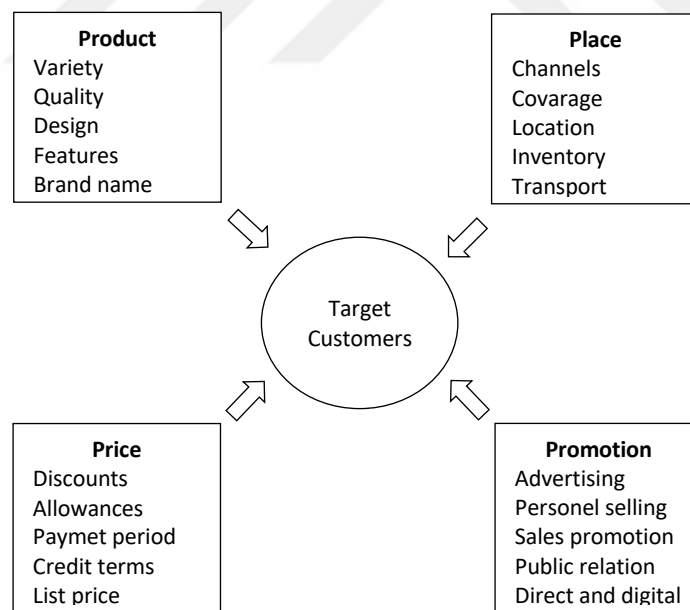


Figure 3: The 4Ps of the Marketing Mix

Source: Johnson and Kotler (2017: 50); Kotler and Keller (2016: 37); Armstrong et al. (2015: 62).

In the literature, similar to the 4P of marketing, different mixes were introduced in the customer dimension. For example, with the market-oriented businesses, customers' perspective has come into prominence, and 4C of consumers (customer solution, customer cost, communication, and convenience) have been introduced (Mucuk, 2014: 33; Kotler and Armstrong (2018) suggest that marketers should consider the 4As before building 4Ps. The 4As refers to the evaluation of a product from the buyers' perspective. These evaluations are called Acceptability, Affordability, Accessibility, and Awareness — the 4As is closely related to the traditional 4Ps. Design of the product affects the acceptability; price affects affordability; the place is directly related to accessibility and also promotion affects awareness. However, these issues are out the scope of the study and will not be detailed here.

In the next part, the promotion element of the marketing mix is under the spotlight. Thus, another step has been taken towards the goal of understanding the place of this study, which deals with digitalization in the dimension of communication, in marketing theory.

1.2.3.3. Marketing Communication

Marketing communication, in other words, promotion, have different categorizations in the literature. For example, Pride and Ferrel (2014) considers the marketing communication mix under four headings which are “advertising,” “personal selling,” “public relations” and “sales promotion.” In this distinction, the internet was dealt with as a transit vehicle that provided non-personnel communication under the advertising tool (Pride and Ferrel, 2014: 574). However, along with technological advances (online, social media), direct marketing has gained importance, and it has been accepted as the fifth element under the marketing communication mix (Mucuk, 2014: 181). This tool was later called as "direct and digital marketing" (Armstrong et al., 2015: 468; Johnson and Kotler, 2017: 409; Kotler and Armstrong, 2018: 422). Kotler and Keller (2016: 246, 247) added the “events and experiences,” “online and social media marketing,” “mobile marketing,” “direct and database marketing” categories instead of direct marketing and introduced the eight basic modes of communication.

In this study, Kotler and Armstrong's (2018) five-way distinction which is the newest and most widely accepted will be used. They have used the concepts of direct marketing and digital marketing together. According to Kotler and Armstrong (2018: 425), the five major categories of marketing communication are defined as follows:

- **Advertising.** "Any paid form of nonpersonal presentation and promotion of ideas, goods, or services by an identified sponsor".
- **Sales promotion.** "Short-term incentives to encourage the purchase or sale of a product or service."
- **Personal selling.** "Personal customer interactions by the firm's sales force for engaging customers, making sales, and building customer relationships."
- **Public relations (PR).** "Building good relations with the company's various publics by obtaining favorable publicity, building up a good corporate image, and handling or heading off unfavorable rumors, stories, and events."
- **Direct and digital marketing.** "Engaging directly with carefully targeted individual consumers and customer communities to both obtain an immediate response and build lasting customer relationships."

Each category has its specific channels to accomplish communication with customers. As an example, advertising requires broadcast media (radio or TV), print media (newspapers), online, outdoor displays (billboards and posters). Sales promotion includes consumer promotions (discounts), trade promotions (displays and demonstrations), offering added value or incentive programs. Personal selling consist of sales presentations and meetings, trade fairs, and other incentive programs. PRs include annual reports, press kits, brochures and event sponsorships. Direct and digital marketing includes mail, e-mail, web sites, catalogs, online media, social media, search and display ads, mobile marketing, and more (Kotler and Armstrong 2018: 425; Kotler and Keller 2016: 246, 247; Pride and Ferrel 2014: 576, 577).

1.2.3.4. Direct marketing and its Relations with Digital Marketing

Direct and digital marketing refers to establishing a direct engagement with target customer(s) to achieve an immediate response and create lasting customer

relations (Armstrong et al., 2015: 547). Digital marketing has emerged as a new channel under direct marketing (Mucuk, 2014: 247). However, with the rapid increase in the value of commercial transactions on digital platforms, digital marketing has rapidly gained popularity. In this context, it has become one of the most critical components of the promotion mix. Although in some studies digital marketing is examined under a separate heading under the promotional mix, it is often associated with direct marketing (Kotler and Armstrong, 2018; Johnson and Kotler, 2017; Armstrong et al., 2015). Even in some sources, digital marketing is defined as the internet-based version of direct marketing (Kotler and Armstrong; 2018: 513). In this study, digital marketing is categorized as direct marketing due to the mentioned relationships and in this context, firstly, direct marketing, which is the starting point of digital marketing, will be elaborated.

Direct Marketing Association (DMA) is defined the direct marketing as “ an interactive system of marketing which uses one or more advertising media to effect a measurable response or/and business transaction at any location” (Scovotti and Spiller, 2006: 192). In direct marketing, the presence of two-way communication (interactive system), measurable response facility and the flexibility of the interaction at any place (by mail, phone or fax) stand out (Saxena, 2009: 491, 492). At this point, direct marketing should not be confused with personal sales which is the oldest profession of marketing. Personal selling involves salespeople (sales representatives, agents, broker, sales consultants, etc.) to interact with individual customers by telephone, face-to-face or other means (Johnson and Kotler, 2017: 468). Direct marketing uses several channels to reach customers; direct mail, catalog, telemarketing, radio and television, and kiosks (Kotler and Keller, 2016: 286). In fact, it can be said that in direct marketing, companies are aiming to develop a communication network that customers can reach the company by using communications channels or by the information contained therein.

Direct marketing discipline has emerged with mail order which is primarily a distribution process rather than communication (Tapp, 2014: 8). Using direct marketing, companies find the opportunity to tailor their offers according to customers' interests and needs. In this way, they perform customer engagement, brand community, and sales (Armstrong et al., 2015: 547, 548). Direct marketing is seen by

marketers as an effective way of promoting and selling products in a highly competitive market (Saxena, 2009: 492) and it also differs from other communication elements (personal selling, advertising, sales promotion, and public relations) as it achieved the process of creating demand and meeting demand in one step (Mucuk, 2014: 241).

Traditional direct marketing channels include face-to-face selling, mail order, catalog, telemarketing, radio and TV, kiosk marketing (Johnson and Kotler, 2017: 505) and today marketers are using all these tools to create a customer database. In fact, the success of direct marketing is directly related to the development of these databases (Saxena, 2009: 492). Companies use this database in five ways for direct marketing; to identify prospects (business reply card, toll-free phone number), to know which customers should receive a special offer (up-selling, cross-selling), to focus customer loyalty (gift, discount) to reactivate customer purchases (birthday cards, off-season coupons) and to avoid serious customer mistakes (Kotler and Keller, 2016: 288).

Digital marketing can be associated with the ability of direct marketing to gain interactive features over time. The term “interactive” was first introduced in the mid-90s and it explains that marketing is not only a one-way communication of the world of mass communication but also a two-way conversation. It was first theorized by John Deighton and argued that marketing should become a conversation (Zahay, 2015: 5). A direct marketing database has become crucial for the development of interactive marketing. Because traditional data-base drove direct marketing tools such as radio, television has just empowered marketers, but the same thing does not apply to customers. Such communication tools were just providing one-way communication from the marketer to the customer. This, in some cases, caused problems on the part of the customers. With digital innovations, customers have also become part of marketing communications. In particular, with the development of social media, marketing communication has become an interactive one (Deighton and Kornfeld, 2009: 4). Figure 4 shows how direct marketing has evolved from mass communication to individual engagement.

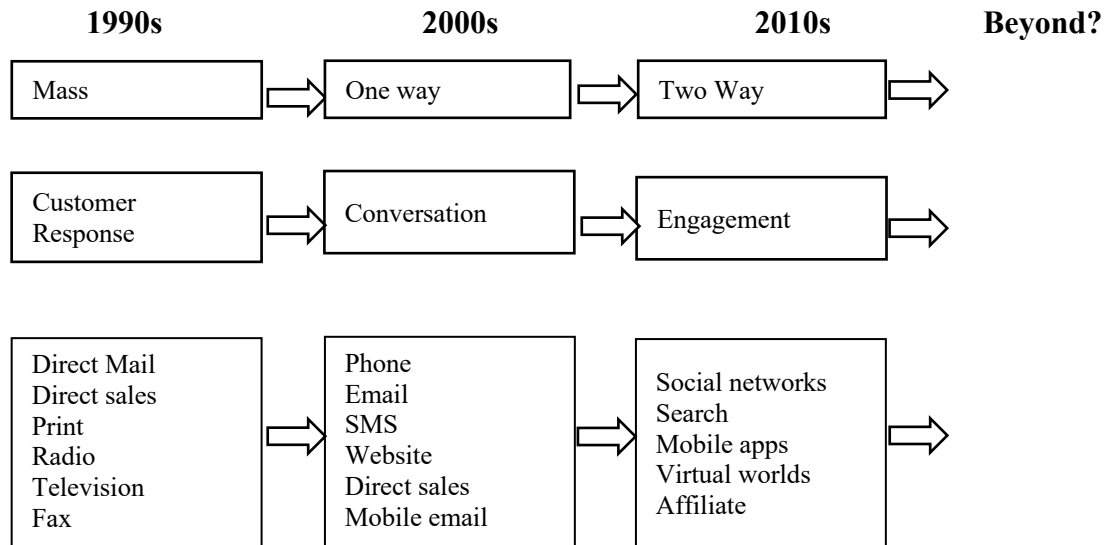


Figure 4: The Evolution of Direct Marketing and Media Terminology

Source: Adapted from Zahay (2015: 6, 15).

All these developments show how the term direct marketing has changed from a response measurement process to two-way communication and how digital marketing evolved from direct marketing. Figure 4 shows the popularity of communication tools over time. Mass media such as television or radio are still widely used today, but the main stars are new technologies such as social media and mobile. There is an uncertainty about what kind of communication tools will become widespread in the 2020s, but as a well-known fact, recently, machine learning, artificial intelligence, and blockchain technology are widely spoken. With the acceleration of mobility, it is no doubt that such technological innovations will deeply affect the digital marketing world.

As mentioned above, with technological progress, the world of marketing has included new technologies such as online, social media, and mobile technologies. Online marketing includes websites, online promotions, e-mail marketing, and blogs (Johnson and Kotler, 2017: 505). Figure 5 presents the main forms of direct and digital marketing. As it is presented from the Figure 5, although the tools used are different, both digital marketing and traditional direct marketing aim to engage with the customer and create a community.



Figure 5: Forms of Direct and Digital Marketing

Source: Johnson and Kotler (2017: 505)

Database marketing is seen as the most prominent intersection point of direct marketing with digital marketing. Digital marketing is based on direct marketing that uses a customer database to measure and track customer responses (Zahay, 2015: 5). In fact, with the rapid advances in internet usage and technology (e.g. social and mobile media, smartphones, smart watches) digital marketing has created a wind of transformation in direct marketing. However, most businesses still use direct marketing as an additional channel (Kotler and Armstrong, 2018: 512, 513).

To summarize, direct marketing and digital marketing serve the same purpose; building direct customer engagement and community. Digital marketing is a new form of direct marketing, especially after the internet has been invented and expanded. Some studies even consider digital marketing as a “new direct marketing model” (see Kotler and Armstrong, 2018; Armstrong et al., 2015). However, it should be noted that some of the traditional direct marketing channels are still in use today (such as telephone, television, catalog). However, it is a well-known fact that there is a serious trend towards digital channels. In this context, it is necessary to see digital marketing as a new channel of direct marketing, not as a substitute for direct marketing or as a new element under the promotional mix.

1.3. DIGITALIZATION IN B2B MARKETING

Current marketing and sales practices and theories are witnessing unprecedented changes. The rapid adoption of new technologies such as database marketing, sales force automation tools, network marketing, electronic commerce systems and the internet have led marketing in a more interactive direction. Moreover,

along with digitalization, the exchange of information between companies has been facilitated, such as the discovery of new customer problems, local and global market trends, competitive movements and joint sales activities (Avlonitis and Karayanni, 2000: 442, 443).

As mentioned before digital marketing can be handled in four different ways according to the marketplace; B2C, B2B, C2C and C2B. However, in digital marketing, the major market and development potential is on the industrial side (Mucuk, 2014: 251). For example, Dell Inc., it serves both the labor market (B2B) and the consumer market (B2C), but more than 80% of its sales come from B2B customers (Hutt and Speh, 2012: 6).

Industrial companies communicate with their customers through different channels such as direct calls, short text messages, search ads, online communities, emails and mobile applications (Freundt et al., 2013). However, today, B2B buyers can make most of their purchases online without seeing a sales representative. They can compile a list of potential suppliers and analyze the best solution- without a visit from a salesperson (Smith and Zook, 2011: 451, 452).

B2B businesses often organize promotional activities such as social media, email and search ads using mobile devices. For this reason, B2B businesses are expected to manage mobile, social media, email and search technologies effectively to transmit their advertising messages (Rizomyliotis et al., 2017b: 82, 83). In B2B markets, the website, email and social media are described as "the big tree". Microsites, video, image ads and searches (SEO and PPC) are less preferred. It is also stated that mobile and social media channels are the fastest growing channels. It is known that companies now invest less in old communication technologies such as extranets. All these reflect the customer-oriented objectives of the companies (Brosan, 2012: 155).

Because of the accessibility, ease of use and convenience of e-mail, webinars, blogs, and social media technologies, digital marketing has gained popularity in daily communication between two or more businesses. Similarly, a significant increase in the number of young employees in companies has had a significant impact on the adoption of digital technologies in the execution of B2B communication in many companies. Today, many young professional prefer digital content and tools in most of their daily activities (Rizomyliotis et al., 2017b: 80, 81). Nevertheless, digital

communication technologies are not accepted as B2C in B2B markets. In general, Table 2 clearly demonstrates how different the B2B marketing is to B2C. For example, the weak impact of social media on business revenues is clearly understood (Charlesworth, 2018: 28).

Table 2: The Most Popular and Effective B2B Marketing Channel

	Channels used in marketing activities (%)	Channels that have the most positive impact on income (%)
Email	88.6	8.3
Social media	85.0	3.1
Content marketing	81.2	9.1
Search engine optimization	78.0	9.1
Word-of-mouth/referrals	74.9	22.0
Conference/trade shows	74.5	9.1
Search advertising	59.6	6.7
Public relations	59.2	1.2
Outbound calling	58.0	8.3
Retargeting	52.5	0.8
Partner marketing	48.6	5.1
Display	47.5	0.8
Video	22.0	0.8
TV, radio and print	12.5	0.4
Other	5.5	4.3

Source: Charlesworth (2018: 29).

Brosan (2012) identified that there are seven main reasons for digital marketing budgets; to create deep customer relations, to increase brand awareness, to strengthen the position of “thought leadership”, to develop brand position, to better understand the target market, to launch products and to make sure that the organization lives the brand (Brosan, 2012: 156). Karjaluoto et al. (2015a) have gathered the purpose of digital prefer digital marketing; creating company and/or product awareness, developing brand image and acquiring new customers. The second objective is to increase the efficiency of communication with customers. And the third one is to foster customer communication and engagement. Lastly, to generate sales leads (Karjaluoto et al., 2015a: 704).

1.3.1. The Role of Digital Channels in B2B Marketing

Digital marketing technologies can be divided into three categories; online, mobile and social media. Online technologies include web, image, search and email marketing. These tools are also effective for B2B markets, but there may be some differences in practice. In the next chapter of the study, these technologies are discussed with their prominent characteristics within B2B and maritime transportation.

The role of digital marketing communication in the B2B market has increased significantly in recent years. It is no longer enough to have only good products to improve a company's sales volume and profits. Customers want to buy benefits rather than products. For example, a faster Web site that will increase customer satisfaction will maximize marketing communication benefits. Marketing communication gives B2B companies the opportunity to focus their offer not only on basic needs but also on benefits that differentiate their services from others (Rizomyliotis et al., 2017b: 5). Digital platforms provide many other opportunities in B2B markets such as finding suppliers, offering incentives, fulfilling orders, and tracking orders electronically. It also allows B2B buyers and sellers to trade in a single digital market area (e.g. alibaba.com)².

In B2B markets, websites are not usually used for sales purposes. Instead, inbound marketing and content marketing are used predominantly. There are four stages of this model used for customer acquisition (Chaffey and Ellis-Chadwick, 2016: 629);

Step 1. Inbound marketing focuses on search results, an online awareness and display ads to increase website visits

Step 2. Video, white papers, or educational materials are used to motivate the visitor to engage with the site and share personal data through social media.

Stage 3. Presenting content that is valuable to the visitor, provided that he or she is granted access to his / her personal information (permission-based) or shared on social networks.

Step 4. Monitor leads through personalized email sequences or phone calls.

² I forgot to include the citation of this sentence, and couldn't find it for hours. I'm sure i got it from a scientific study.

Content is at the heart of most company's customer engagement efforts. Content quality plays a critical role in customer acquisition rather than product sales. Tools such as blogs and social media and search optimization further increase the demand for such content. Today, the most preferred content production efforts can be listed in Table 3 (CEB, 2012: 18).

Table 3: Types of Content Produced by B2B Companies

Articles	Product demonstrations
Blogs and microblogs	Slide presentations
Case studies	Soundbites and comments
Videos and streams	Supplier comparisons
E-newsletters	Web interface
Industry events and trade shows	Web-based applications
Infographics	Webinars
Mobile applications	White papers, electronic books and reports
Online virtual environments	

Source: CEB, 2012: 18

Although the content creation method is not new to attract potential customers, the concept of content marketing has become even more popular in recent years. Content marketing can be defined as "a strategic marketing approach focused on creating and distributing valuable, relevant, and consistent content to attract and retain a clearly defined audience- and, ultimately, to drive profitable customer action" (Content Marketing Institute, 2019). Content marketing has been quickly adopted by marketers, with changes in search engine algorithms and demanding high-quality online content in parallel with social media (Charlesworth, 2018: 40, 41). According to the Content Marketing Institute and MarketingProf's comprehensive research in 2019, the objectives of B2B content marketing are presented in Figure 6 (Murton Beets and Handley, 2019).

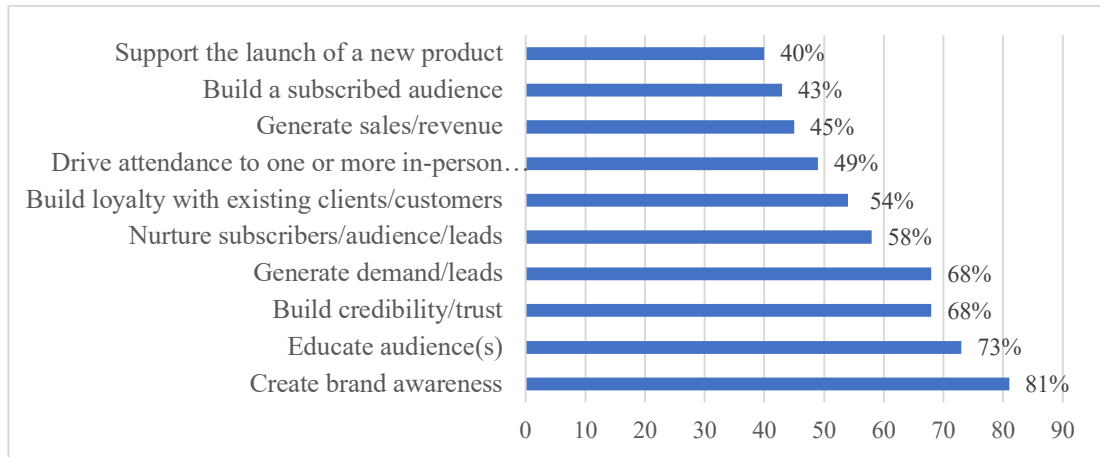


Figure 6: The Importance of Content Marketing Objectives for Organizations

Note: The results of the question of what the B2B marketers have accomplished by using content marketing in the last 12 months. 4% did not respond. Multiple answers are allowed.

Source: Murton Beets and Handley (2019: 36).

The use of online advertising such as banners to promote brand awareness is equally essential for creating demand in B2B marketing. For instance, global B2B brands such as IBM actively use this way on technology trade marketing sites (Chaffey and Ellis-Chadwick, 2016: 628). However, it is not possible to say that image ads containing banner and rich media ads are an effective method in B2B markets, as can be seen in Table 2. In fact, the effectiveness of Banner ads for B2B digital marketing is a topic that has been discussed for many years. Some people say they are extremely effective; others believe that there is nothing but a waste of time and money. With steadily decreasing clickthrough rates, banner advertising prices have decreased at regular intervals. The average clickthrough rate for all banner ads is about 0.5%. On the other hand, physical banners seem to be very useful for B2B marketing (Brown, 2015).

Nowadays, most of the B2B decision-makers begin their search with web search before buying a product and are not in contact with a salesperson until they conduct their own research (Blacharski, 2017). In this context, search engines have an important position in B2B digital marketing. In B2B digital marketing, search volumes may be lower, which means that a search ad strategy that is suitable for a small number of high-value customers is needed. B2B marketers can use Google's Keyword Tool to reveal the scale of market demand. Considering this limited demand in search volumes,

online PR can be effective in creating awareness and sales. Content marketing based on white pages and videos providing information and training is key communication tools, especially in the professional service markets. Infographics, charts, presentations, corporate photos/videos, staff interviews or guidance, customer testimonials, conferences and presentations on B2B products are the types of effective content that can be used to increase the position in the SERP (Chaffey and Ellis-Chadwick, 2016: 627).

E-mail marketing is seen as another most important digital technology to assist in the development of business relations and guiding in B2B communication and advertising. To build relationships, e-mail is widely used in B2B marketing. Leaving permission-based mailing lists or advertising in third-party e-newsletters is known to be the most effective method (Chaffey and Ellis-Chadwick, 2016: 628). A professionally-prepared B2B e-mail message not only generates sales but also provides a long business relationship. A B2B purchase decision cannot be taken by a single person in the company (Jussila et. al, 2014: 608); therefore, the e-mail message should not be sent to only one person, but instead should be for final decision makers in the company or for a few key people. For this reason, B2B firms must create an e-mail marketing strategy according to their overall marketing purposes so that they can conduct a successfully integrated message transmission (Rizomyliotis et al., 2017b: 83, 84).

Mobile technologies are also critical in B2B marketing. Because, most of the companies use mobile phones for their daily activities so that they can easily communicate their advertising messages to B2B customers (Rizomyliotis et al., 2017b: 82). SMS and MMS ads are used extensively in B2B marketing and this type ads have higher response rates than email or television, because all ads can be submitted individually. However, advertising is only a part of mobile marketing technologies. Other key critical mobile marketing technologies include; mobile advertising, location-based mobile services, mobile sales promotion, mobile entertainment services, mobile banking, mobile shopping and mobile internet (Barutçu, 2007: 28). According to Boston Consulting Group research, 80% of B2B buyers using mobile technologies at the workplace, and more than 60% have played an important role in a new purchase of mobile. In addition, 70% of B2B buyers have significantly increased

their mobile use over the last years, and 60% are expected to continue to increase mobile usages (Archacki et al., 2017).

1.3.2. Business Buyers with Digital Marketing

According to the basic relationship marketing literature, the ability to establish and manage long-term and close relationships is the key to success in business (B2B) markets. Developing high-frequency relationships that continue over time in B2B markets provides an important advantage for customers. Because gaining new customers is more costly than protecting existing customers. Considering the serious effects of strong and long-term business relationships on sales, market share and profit (Ordanini, 2011: 278), better understanding and close relationships with buyers are becoming more important especially in B2B markets.

The presence of buyers and sellers in B2B markets is well known, and so web-based communication and trade can be a much simpler process. Emotional motivations rarely affect the buying process. B2B buyers often show professional approaches that use economic selection criteria. Therefore, the promotion of B2B brands should be different from those used for B2C brands. It should also be noted that there is a tendency for more negotiation between the seller and the buyer in the price-setting process in the B2B market TV (Chaffey and Ellis-Chadwick, 2016: 624).

Marketing communication in the B2B sector is incredibly important not only to increase brand awareness but also to help decision makers make strong value judgments. Individuals are usually more likely to buy from somewhere they are familiar with; if companies do not appear and not getting a place in buyers' minds, they simply do not exist (Rizomyliotis et al., 2017b: 2, 7).

B2B marketing has generally been more formal (Rizomyliotis et al., 2017b: 7), but today it needs to be more social even if it protects this formality (Wiersema, 2013: 485). Another important aspect of B2B markets is that relationships are not always direct ways. 51% of large B2B customers rely on a advisor or colleague to help them identify and assess suppliers. The fact that companies introduce themselves to potential buyers and establish a trust relationship will make middlemen unnecessary. Therefore, suppliers that communicate with their potential buyers and deepen their relations come

forward (Brosan, 2012: 155). In traditional marketing, the decision-making department of a buying organization is called the "buying centre" and consists of experts and units involved in the decision-making process. This unit consists of the original users of the product to be purchased, those who make the purchase decision, those who impact on the purchase decision, those who make the actual transaction. The persons and units involved in the procurement centre are as follows (Kotler and Armstrong, 2018: 192).

- **Users** are members of the product to use. In most cases, users initiate the purchase offer and help determine product details.
- **Influencers** help identify the characteristics of the product to be purchased and also provide information to evaluate alternatives.
- **Buyers** have the authority to select the supplier and regulate the conditions of purchase and the main role is to select and negotiate vendors.
- **Deciders** have formal or informal authority to select or approve last suppliers.
- **Gatekeepers** control the information flows. Other door keepers include technical staff and even manager assistants.

Table 4: Characteristics of Business Buyers

Characteristic	Example
The business market customers consist of commercial companies, institutions and governments.	Dell's customers are Boeing, numerous universities and government units.
A single buying by a business customer is much larger than the individual ones.	While individual users purchase one unit of a software package from Microsoft, Citigroup can buy up to 10,000.
Demand for B2B products is due to the ultimate demand for end-customer products.	The demand for food sold in markets requires the logistics services of those products.
Marketing relations between companies tend to be close and enduring.	Maersk's relationship with some important customers goes back to decades.
Purchase decisions are usually made by a multilateral mechanism rather than by a single decision-maker.	A cross-functional team at P&G evaluates alternative notebooks and selects HP.
While providing services to different customers, companies and consumer marketers share the same titles.	Business titles are marketing manager, product manager, sales manager etc.

Source: Hutt and Speh (2012: 17).

In organizational markets, typically fewer customers are available, and these customers tend to buy products in bulk quantities. That's why B2B buyers have a great value for the supplier (Chaffey and Ellis-Chadwick, 2016: 624). There are many other significant differences in the buying behavior of customers in the consumer and business market. Sometimes products are the same, but basically a different marketing technics is needed to reach the organizational buyer (Hutt and Speh, 2012: 5). Table 4 summarizes the key characteristics of business market customers.

B2B companies use the Internet as a source of knowledge for their purchase and also as a transaction channel. For most B2B products, although the companies's online presence can play an important role in the commercial purchases, the website is rarely the real buying environment. The primary purpose of websites in B2B markets is lead generation. Lead Generation is the process of converting online and potential customers into a customer who is interested in a company's products (Durak, 2019). The purchase in a B2B transaction is very different from that in the B2C environment (Charlesworth, 2018: 21). Figure 7 shows the process of B2B buying.

The decision to buy B2B is more complex than the typical consumer buying decision and therefore targeted marketing is becoming more important. For example, lead generation and digital technology qualifications are widely used to increase the effectiveness of personal sales in B2B direct marketing. Tools such as Marketo, HubSpot, and Eloqua can facilitate lead nurturing and demand creation operation in B2B companies. B2B acquisitions usually contain a larger amount of money and so buyers need more information. In addition, purchasing decisions are taken by more than one decision-maker in the organization (Jussila et. al, 2014: 608) and purchases are usually repeated. Therefore it is very critical to understand who is involved in the purchase and collecting and processing lead nurturing information of potential customers (Zahay, 2015: 121, 122). A list of internal and external information that suppliers must collect about B2B buyers in order to earn repurchases is presented in Table 5.

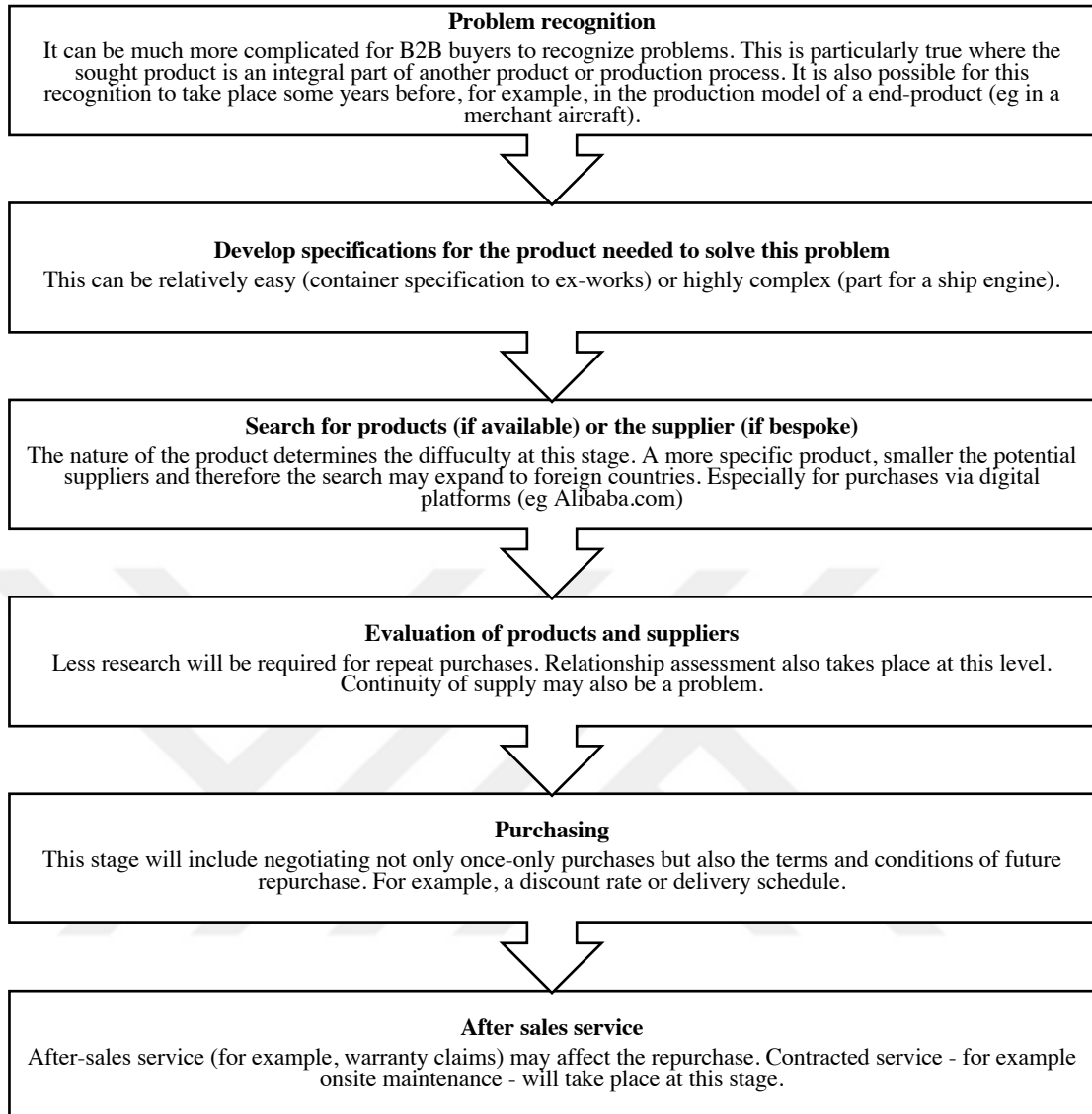


Figure 7: B2B Buying Process

Source: Charlesworth (2018: 22).

In addition, B2B buyers face risk when making purchases. B2C consumers generally do not take risks beyond the product price and this makes B2B buyers be more mindful in the purchase process. Also, it is proofing that marketing communication has become a powerful tool in terms of increasing sales (Rizomyliotis et al., 2017b: 6, 7).

Table 5: Types of Internal and External Information of Business Customers

Internal Information	External Information
Transaction history	Industrial Classification code
Purchasing address and contact	Size of the company
Shipping address and contact	Revenue of the company
Types of products purchased	Number of employees
The length of time as a customer	Geographic location
Buying center	
Stage in customer lifecycle and sales funnel	

Source: Zahay (2015: 121, 122).

In addition, B2B buyers face risk when making purchases. B2C consumers generally do not take risks beyond the product price and this makes B2B buyers be more mindful in the purchase process. Also, it is proofing that marketing communication has become a powerful tool in terms of increasing sales (Rizomyliotis et al., 2017b: 6, 7).

1.3.3. Advantages and Disadvantages of B2B Digital Marketing

In the last decade, the Internet has witnessed unprecedented growth as a global environment for communication and exchange (Schibrowsky et al., 2007: 722). This growth directly affected the world of marketing. Companies have shown a strong tendency towards digital channels. The reason for this trend is, of course, several advantages that digital communication channels provide to companies and consumers. In fact, it is also possible to talk about some disadvantages of the internet, in other words, the digital marketing channels. In this section, the advantages and disadvantages of digital marketing will be interpreted from the perspective of businesses and customers.

On the companies side, one of the significant advantages of digital marketing over offline marketing is that it is more easily measurable. Measurement provides clear information to digital marketers about understanding which marketing activities are more effective (Järvinen, 2012: 103). Another most crucial contribution of digitalization, especially social media, to the B2B marketing universe, is that it has

enabled active and two-way interaction between brand and customer. Through digital channels, companies have become able to collect customer feedback effectively and in real time and adapt their messages or products more quickly to the wants and needs of customer (Varnalı, 2013: 59).

B2B digital marketing is also seen as an effective vehicle for information exchange (Tiago and Veríssimo, 2014: 705) because it allows companies to quickly provide information about the product and themselves (Kotler and Keller, 2016: 275). B2B digital marketing is seen as a user-friendly tool for establishing a direct dialogue with customers and helping to evaluate suppliers and partners with whom to work (Tiago and Veríssimo, 2014: 705). At this point, marketers should also pay attention to the message content. Because the advantage of digital marketing communication can be turned into a disadvantage with the wrong connections. The perceived value of an ad message, especially on the customer side, is directly related to the level of being informative and entertaining of that message. If the message is misleading or disturbing, the value of the message will decrease (Varnalı, 2013: 31).

B2B digital marketing technologies can also be used for competitive advantage. Companies can efficiently perform targeting and positioning strategies by using digital tools (Kamal, 2016: 5302). For example, they can purchase ad space on relevant web sites (Kotler and Keller, 2016: 275) to reach their target customers more quickly, easily and less cost. Notably, the low input cost and specific targeting capability have turned digital marketing into a crucial competitive tool for companies (Key, 2017: 33). Digital marketing also facilitates small companies to compete with large organizations. Therefore, today digital initiatives are often associated with disruptive innovation.

Digital marketing has a significant difference in terms of communication costs compared to traditional marketing. In conventional marketing communication, mass media such as print advertisements, newspaper news, billboards or television and radio are used (Das and Lall, 2016: 6). However, the costs of communication activities using these tools are much more than the current digital marketing tools (such as social media, email, SEO). For example, the average cost of a newspaper ad is 32 U.S. dollars, while in a printed magazine this figure is 20 U.S. dollars (Nuanced Media,

2015). If the advertiser show this ad on Google, the average cost drops to 2.8 U.S. dollars (Adstage, 2018), on Facebook it falls to 1.26 U.S. dollars (Statistica, 2018).

Digital marketing provides an opportunity to refine strategies easily. Developing traditional marketing campaigns usually takes a long time, and it is difficult to take action if things do not work. In digital marketing, it works the opposite. If the digital marketing campaign seems ineffective, one can change the strategy instantly. For example, in the case of a deficiency, it is easy to improve the content type/itself or change the design of the channel. There is always a chance for adjustment in online communication (Das and Lall, 2016: 6).

The other significant benefits of digital marketing are promoting the internal and external relations of the companies and increasing the knowledge within the company. Companies can use digital marketing tools to monitor customers' consumption habits, preferences or detects adverse reactions (Tiago and Veríssimo, 2014: 705). For example, through the web, companies can easily track how many times their potential customers have visited a page or ad, how much time they spent, and where they went (Kotler and Keller, 2016: 275). Considering the 24/7 operating structure of digital platforms (Das and Lall, 2016: 6), it is seen that companies have an essential opportunity to develop their products, channels and even themselves.

Moreover, digital channels are seen as a useful technology for creating, consolidating, and maintaining brand awareness (Tiago and Veríssimo, 2014: 705). However most B2B companies think that digital marketing was irrelevant for themselves (Järvinen, 2012: 108) in fact, it has a direct impact on the brand awareness of the company. In particular, the absence of territorial boundaries in digital marketing (Girchenko and Ovsianikova, 2016: 25) offers companies the opportunity to promote their brand in international markets.

Some cases considered to be advantageous for companies also apply to customers. For example, digital marketing is a source of information for customers, and they can easily access digital markets and benefit from the wide range of products. The use of digital marketing communication offers many other advantages such as efficiency, convenience, richer and participatory knowledge, competitive pricing, and cost reduction. Especially online social networks tend to develop these advantages as customers can communicate more proactively. As an example, through online

networks, people can reach others' views on specific products (Tiago and Veríssimo, 2014: 704) and this also helps to make the right decision to purchase.

It is also possible to mention some disadvantages of digital marketing for both customers and companies. One of the most critical problems on the customer side is information pollution. Especially in the sectors with low entry barriers, high competition has caused confusion on the customer decisions. It has become more difficult for customers to reach the best and most affordable offers with the increasing of marketplaces. Although comparison sites are widely used to solve this problem (Kingsnorth, 2017: 9, 10), it is a well-known fact that information pollution is increasing day by day and adversely affects customers in most cases.

Since digital marketing communication is not face-to-face, it can be difficult to establish trust with sellers. In cases where a personal relationship between buyers and sellers such as life insurance sales is required, customers should be more careful. Besides, products that require physical examination may not be suitable for digital marketing. Digital marketing does not allow customers to touch, smell or taste products (Das and Lall, 2016: 10). Also, exposure to message bombing is seen as one of the most recent problems of digital marketing.

Deceptive techniques are seen as one of the most common threats to digital marketing from the companies' side. For example, bogus clicks made through software-powered web sites in an ad of the company may think that the ad is getting a valid result (Kotler and Keller, 2016: 275). The lack of control over message and distribution is seen as another fateful disadvantage of digital marketing (Cruz and Fill, 2008: 750). Advertisers may lose control of the online message; even they may be exposed to hacking attacks (Kotler and Keller, 2016: 275).

One of the issues that companies complain about is the difficulty in calculating the return of investments (ROI) in digital marketing. Because gauging the effectiveness of digital marketing is seen as a quite complex operation. Developing some standard metrics is needed to justify the money spent, especially. However, it should be noted that various methods are used to make these calculations (such as brand awareness, WOM buzz, customer satisfaction, user-generated content (UGC) and web analytics (Tiago and Veríssimo, 2014: 706) but it is not possible to say that it gives a precise result.

Table 6: Advantages and Disadvantages of Digital Marketing in Terms of Customers and Companies

	Advantages	Disadvantages
Customers	Increase knowledge Support decision-making process Easy to use Easy access to resources Accessibility Product diversity 7/24 accessible Customized offers Interactivity Rich payment option	Information pollution The lack of trust Not allow physical examination Risk of losing focus To be disturbed Screen out most message Privacy issues Slow internet connection
Companies	Increase knowledge Increase productivity Easy to use Easy access to resources Easy measurable Better outcome measurement Support decision-making process 7/24 accessible Interactivity Promotes external and internal relationship Improve information exchange (e.g. feedback) Real-time management Absence of the territorial limits Infinite audience Lower costs Easily refine strategies Opportunity to compete with large companies Contextual placement	Lack of control over message and distribution Can be hacked or vandalized Deceptive techniques such as bogus clicks High competition Gauging the effectiveness (e.g. ROI) Distruption threat by new entrants Easily copied by competitors Not yet embraced by all people Price competition Highly dependent on technology Inability to reach those who did not adopt technology The copyright

Source: Key, 2017; Kotler and Keller, 2016; Girchenko and Ovsiannikova, 2016; Das and Lall, 2016; Todor, 2016; Tiago and Veríssimo, 2014; Varnalı, 2013; Cruz and Fill, 2008; Järvinen, 2012.

While digital marketing is an advantage for small companies, in some cases, it can be a threat to large organizations. Digital channels have enabled small companies, especially start-ups, to compete with large organizations (Das and Lall, 2016: 7). Today, many large corporations are threatened by new digital companies. This

situation, which is explained by the theory of disruptive innovation, shows the disadvantage of digital channels on traditional companies.

There are many more details that can be written under the heading of the advantages and disadvantages of digital marketing. However, only the most important ones according to the author were evaluated within the scope of the study. Table 6 lists the advantages and disadvantages encountered in the literature.

In this section, digital marketing is handled within the scope of B2B theory with a holistic approach. In the next section, digitalization is detailed in terms of container shipping marketing. This review has been evaluated in terms of the technologies and strategies underlying digital marketing. Thus, more specific literature has been put forward for the purpose of the thesis.

CHAPTER TWO

TECHNOLOGIES AND STRATEGIES IN CONTAINER SHIPPING MARKETING IN TERMS OF DIGITALIZATION

2.1. DIGITAL TECHNOLOGIES IN CONTAINER SHIPPING MARKETING

With the growth of the digital economy, a new digital media channel is emerging almost every day (Varnali, 2013: 67) and digital marketing technologies become an even more critical tool. These technologies are also seen as part of the marketing communication strategy (Kannan and Li, 2017: 22). There are also various approaches to the classification of digital marketing technologies, both in the academic literature and in the use of professionals. Broadly, these technologies include SEO, PPC, website, inbound lead nurturing, content, social, and outbound e-mail (see Figure 8) (Deguire, 2019).



Figure 8: Digital Marketing Technologies Around Digital Marketing Communication Strategy

Source: Redesigned by author from Wheelhouse Advisor (2015).

However, as expected, it is not possible to use each of these digital marketing technologies in the maritime service markets. In this context, a new classification for

digital marketing technologies that can be used in the maritime sector is required in this study. For this, B2B digital marketing literature was used.

In accordance with this purpose, Zahay (2015) has classified digital marketing channels into four basic categories which consist of email, mobile, social and search and has put the website strategy at the center of the mix. However, in the marketing literature, it was observed that digital marketing was already examined under three main headings. These include online, social media, and mobile marketing (Johnson and Kotler, 2017; Kotler and Keller, 2016; Armstrong et al., 2015). According to this distinction, search, and email is examined under online marketing. More specifically, this study followed the online, social media and mobile classification, which is more appropriate to the maritime markets and also accepted in the marketing academic literature. In this context, the four foundation approach of Zahay (2015: 4) was adapted to this study as in Figure 9.



Figure 9: The Three Foundations of Digital Marketing Delivery Mix/Channel and Integration With Digital Marketing Strategy

Source: Adapted from Zahay 2015, Johnson and Kotler, 2017; Kotler and Keller, 2016; Armstrong et al., 2015.

In Figure 9, digital marketing strategy is located at the center of digital marketing channels (online, social and mobile) because these channels should be managed with an integrated approach to marketing strategy as mentioned before. Therefore, in this study, the integrated digital marketing approach is expected to

correspond to the holistic approach of container shipping sectoral publications. In the following sections, these digital technologies are discussed separately in the context of the digital marketing literature.

2.1.1. Online Technologies

Technology selection is a complex process for both researchers and practitioners in marketing. Especially in digital marketing, there is no systematic method to guide this process (Kiang et al., 2000: 384). In this context, it would be a more beneficial approach to evaluate channels one by one. Online marketing refers to the marketing of companies' websites, online advertising, email, video and photo contents. Social media and mobile marketing are also online, but these approaches will be discussed in separate sections because of their unique characteristics (Kotler and Armstrong, 2018: 516).

Marketers divide the media into two groups; paid and owned from earned (free) media. Paid media includes advertising and promotion efforts generated by companies. The earned media are the benefits that the companies get with PR and word-of-mouth methods (news, blogs, and social networking conversations) without having directly paid for anything (Kotler and Keller, 2016: 275). Online media includes a significant portion of paid media. However, it is a known fact that social media is also now gradually slipping into the paid media (e.g., Facebook ads). In this section, online marketing technologies discussed under four main headings; website, image ads, search ads and email.

Websites

Since its first online in 1991, websites have been considered the most critical component of the Internet. Although there is a shift towards social and mobile marketing, the website is still seen as the destination of marketing campaigns and should be found online (Zahay, 2015: 27).

Websites are the official showcase of companies in digital media, and it can be defined as the environment where the most reliable digital information is available to

ensure that the brand's corporate identity is seen (Çizmeçi and Ercan, 2015: 154). As Web 2.0 applications become more common, it is thought that these showcases have become less important. But Web 2.0 applications and corporate websites serve different purposes. It is better to see corporate websites as the headquarters of brands. Websites are seen as a trusted source of information by people about companies. For example, a university student visits the official website of the school to obtain reliable information about the school of his choice. That is why websites are still essential media that remains important (Varnalı, 2013: 68, 69).

The website is seen as the most valuable digital property and the only fully controllable channel of the digital world, which is in constant change (Ryan, 2014: 56). Website content usually consists of the company's corporate identity, products, contact information, history, vision and mission statements of company (Çizmeçi and Ercan, 2015: 154). Sometimes, however, companies use micro websites to support various product and campaign launches or social responsibility projects, apart from corporate websites. Micro websites are usually created to collect user data with fun content or to broadcast an event live. Such micro websites are perfect for supporting digital campaigns. Micro websites, which offer socialization, gamification and entertainment together to the user, usually achieve conclusive results (Varnalı, 2013: 69, 71).

According to literature, the marketing communication mix for websites consists of advertising, sales promotions, public relations, and direct marketing components. The purpose of web site advertising is to raise awareness, convey benefits, encourage trials, and encourage customers to action by providing information about products, prices, distribution, and company. The website may also include refunds/rebates, special offers, online shows and sweepstakes as sales promotions. In the context of public relations, news, speeches, training programs, and lobbying can also take place on websites. And finally, companies can also use websites to sell a product (electronic commerce) and to provide customer service (Perry and Bodkin, 2002: 134, 135). In light of this information, it is once again proven that a website was an integrated part of the company's marketing strategy and marketing communication. Companies design a website according to their objectives and target audience (Wsi, 2013: 24). A website has three main goals. These are acquiring new customers (traffic),

drive conversation (engaging with visitors), and generating revenue (Larson and Draper, 2017: Chp1, Sec2.). For these purposes, companies decide on the most appropriate type of website for themselves. For example; personal, social sharing, blog/publishing, digital community, specific mobile, booking, directory, marketing brochure, information, e-commerce or regulation websites are a few of them (Wsi, 2013: 22-24).

There are three main dimensions of global website design; the navigation design (how easy and accessible the content stream is), the visual design (how attractive and aesthetic the website graphics is), and the information design (how correct and comprehensive the data on the website is). These three design criterias are closely related to the usability of the website (Wang et al., 2015: 584). Another essential criterion to consider when designing a website is multi-device compatibility. A website must be designed to be compatible with the devices owned by users. For example, desktops, laptops, tablets, smartphones or smart TVs are the best examples of device diversity with different screen sizes where websites are visualized.

The ease of use of a website (fast downloading, navigation) and physical attractiveness (design, color, clarity) are the basic criteria for determining the performance of that site in the eyes of its target audience (Kotler and Keller, 2016: 275). Building a website is not the same thing as getting users to that website. Companies must aggressively promote their website with online and offline campaigns to attract the attention of target audiences. But today's internet users are quick to leave any website that does not measure up. Companies need to built high quality and valuable content to enable target audiences to come back to the website again (Kotler and Armstrong, 2018: 517).

Websites get traffic in three different types; direct traffic, referral traffic and search traffic. Direct traffic refers to the user visiting the site by entering the URL of the website into the browser. In the case of direct traffic acquisition, it is tough to be successful if the website does not have satisfactory content for the visitors. The referral traffic describes visiting the user by clicking on a link from another site. Companies usually need to provide banner, text or rich media ads (paid) on other websites to receive these clicks. Search traffic means that internet users come to the site using search engine results (Larson and Draper, 2017: Chp1, Sec2.). Companies can

manipulate search engine results with paid or organic methods. The methods of bringing traffic to the website with referral and search methods will be discussed in detail in the next section.

Display ads

Display ads are a marketing channel that enables the transmission of the brand message using visual elements such as logo, animation, video or photo. A brand message that can be given in tens of words can be delivered more effectively by using a single image. Display ads are a highly efficient type of ad to drive brand awareness and drive targeted traffic to the website. Display ads may also be called "banner ads" because they have a banner that is heavily used (Gökşin, 2017: 117).

It is believed that the first internet ad is a text-based link to a fee or barter-type agreement that is placed on a web site. This type of link directs the user to different website when it clicked. Text-based links are supported by visuals over time and are then associated with interactive animations and videos (Varnalı, 2013: 71).

Display advertisement or banners are rectangular boxes containing text, images or animation that advertiser pays to place on a relevant web page. With the size of the banner, the amount of fees paid to the ad space also changes. Because internet users spend about five percent of their time searching for online information, display ads can be said to be still a useful digital communication tool today. However, display ads should more remarkable and effective, better targeted and more closely monitored. Pop-up ads, which are a type of display ads, usually consist of video or animations that are opened on a website or page change. Because consumers have found that such pop-up ads are intrusive and distracting, many are using software to block them (Kotler and Keller, 2016: 277). Therefore it is not recommended to use it much.

Different terms are used to measure the effectiveness of display ads. Each time an advertisement is viewed is called to as an ad impression or page views. Some users may see an ad more than once, and they are increasing the number of impressions. But for marketers, it's also important how many people reach that ad. Naturally, the number of reaches is smaller than the number of impressions. Advertising costs are typically indicated by cost-per-mille (CPM) or cost-per-thousand as in other media. Furthermore, the rate of interaction is also an important criterion. The number of direct

responses and clicks generated by ads determines the interaction rate (Chaffey and Ellis-Chadwick, 2016: 519).

Giving the right message to the right user is the most important fact that affects the success of the display ad. In order to reach the right user, it is necessary to give the advertisement in the right place. Businesses can run their display ads according to different purchase types. First of all, specific targeting can be done in large advertising networks provided by internet companies such as Google and Facebook. A media area can also be purchased from a website that is intended to be advertised. Or programmatic purchases can be made with the developing advertising technology (Gökşin, 2017: 117). Each of these three different methods will be briefly explained below.

Display Networks

Display networks are platforms that bring publishers (website owners) and advertisers together (Gökşin, 2017: 118). Some of the most important display network networks are; Google display network (GDN), Facebook Audience Network Ads, Apple Advertising, Adknowledge, Yahoo! Network (WebFX, ____). Since they serve similar purposes, only GDN and Facebook Audience Network Ads will be mentioned in this section.

GDN is Google's own Ad Network and is also linked to YouTube, Blogger, and Gmail. Publishers add Google Adsense codes to their websites and access the GDN network and manage their ads through the Google Adwords panel. GDN offers businesses the ability to target users to text, visual and video ads by using relevant keywords and users' interest, location, behavior, and demographic information. Although GDN ads are charged at cost-per-click, their primary purpose is to increase brand recognition through advertising (Şengül, 2017: 99).

At this point, it is necessary not to confuse Facebook Audience Network Ads with the ads that Facebook receives on their platforms. Facebook Audience Network ads are shown on applications and sites other than Facebook (Facebook Business, ____a). According to a research conducted by Facebook, the conversion rate is eight times higher if an ad on Facebook is also provided in Instagram and Audience

Networks. Some of the aims of the Facebook mass network can be listed as follows; brand awareness, reach, traffic, engagement, applications, video or photos and conversation (Facebook Business, ____ b).

Manual Buying

Direct purchasing is a method of buying traditional digital media. The advertiser agrees with the publisher either by himself or through an agency and publishes his ad for a while in exchange for a certain budget. Bargaining is an essential factor in advertising price (Şengül, 2017: 91). The media purchase method allows advertising outside the standard. For example, “masthead” ads are one of the most effective advertising types. Masthead ads are placed horizontally at the top of the homepage of the publisher website and are usually booked by an advertiser for one day per country. One of the most valuable masthead sites on the Internet is youtube, and it offers this area to advertisers at a CPM basis (Search Engine Journal, 2019). One another manual buying type of ads is “page skin.” As the name implies, the web page in this format is covered with the advertising image. Sometimes, even if the website is dragged down, maximum visibility is maintained while remaining constant. Such ads cannot be removed by users and cannot be used with animated content (The Guardian Advertising, ____).

The most important points to consider when placing direct advertising; the ad must be visible, noticeable, remarkable, reasonable in size, and contextually relevant, namely compatible with the content of the page and the audience. It should also be noted that banner ads that use page take over technology in a highly aggressive and disturbing manner can cause severe discomfort on the part of users, even if the click rate is high (Varnali, 2013: 72, 73).

Programmatic

Programmatic buying is a way of analyzing data and buying media through technology. Because it is much faster and smarter than manual purchasing, it increases the efficiency of digital advertising investments. The system focuses on the users and their behaviors. The user data is analyzed very quickly, and the correct mass is targeted

and this increases advertising efficiency (Think with Google, 2016). Programmatic advertising is an increasingly common method. For example, according to Zenith's "Programmatic Marketing Estimates", 65% (84bn U.S. dollars) of money spent on advertising in digital media in 2019 will be realized through programmatic purchasing. This rate was about 10% in 2012 (Zenith Media, 2018).

Programmatic marketing briefly offers broad targeting, real-time action, personalized and effective advertising, useful measurement and tracking (Think with Google, 2016). Recently, as an essential change, Demand Side Platforms (DSPs) working with Real-Time Bidding (RTB) method are used in the process of advertising. RTBs, known as the new programmatic acquisition technique, increase productivity to automatically bid on the most cost-effective ad inventory in an auction. This method can be used to target individuals according to the content they are looking at, by using a technique known as behavioral targeting (Chaffey and Ellis-Chadwick, 2016: 516).

Video ads

Video content has an effective power to inform users and to have a fun time. Video content, which is a useful tool for telling mixed products and ideas, also has the potential to become a superior viral. The importance of video ads is increasing day by day with the increasing use of video playback devices, especially smart TVs (Gökşin, 2017: 123).

Video content has a growing importance in the world of marketing. At the beginning of 2017, 63% of the companies used the video as a marketing tool, and by the end of 2018, this figure increased to 87% (Hubspot, 2019). Video ads published on digital platforms like Youtube, Facebook is known to be more effective than those broadcast on television. According to a survey, traditional television ads attract 55% of viewers, while youtube ads attract 83% of viewers (Think With Google, 2017). The most important advantage of digital video ads according to TV ads is that targeting can be done and ROI calculation with campaign performance can be made very clearly (Şengül, 2017: 98).

Video content is also more useful than other content types to learn about a product. According to a study, when consumers want to learn about a new product,

68% of them stated that short video content related to that product is the best. The other tools that consumers preferred to obtain information were; text-based items (15%), infographics (4%), presentations and pitches (4%) electronic books and manuals (3%), respectively (Hubspot, 2019). The prevalence of video content usage also applies to B2B markets. According to the report of the Content Marketing Institute, in 2018, 64% of B2B marketers used more video and audio content than the previous year (Murton Beets and Handley, 2019: 25). These are some of the reasons why video content is popular in the world of marketing.

The digital video market includes platforms such as mobile, TV and a range of other technologies and devices (IAB, 2015). Video ads on these devices have many different types of impressions. Video ads can be divided into three categories as an industrial standard. These are (Google Ad Manager, ____);

- **Linear ads:** Video ads that appear before the video content (pre-roll), after (post-roll) or in the middle of the video content (mid-roll). Linear ads are the most popular type of advertising.
- **Non-linear ads:** Display ads (such as ad banners) that appear during video content, without disrupting playback.
- **Companion ads:** Displayed on the page around the video player.

Video ads are usually played in the stream. Besides, it is possible to divide the video ads into two categories; non-skippable and skippable. Non-skippable videos must be tracked to the end. Youtube calls the 5-second in-stream skippable ads as “TrueView,” 6-second videos that cannot be skippable ads as “Bumper” (Şengül, 2017: 98). Other relevant advertising and creative video types listed by the Interactive Advertising Bureau (IAB) are; 360-degree videos, autoplay video ads, interactive video, long video, native ad, out stream video ads, sticky video ad (aka adhesion ad), opt-in value-exchange ads, vertical video ads (IAB, 2018).

Search ads

If companies don't know who they are and who they are trying to target, then there is no point in offering themselves on the web (Zahay, 2015: 43). For that reason,

companies should first identify who they are and what they offer and display this information in a way that can be found on the web. But the web is so complex and crowded that special techniques are needed to achieve this visibility. As of the date of this study, approximately 1.7 billion websites are active worldwide (Internet Live Stats, 2019). Given that most of these websites contain hundreds of web pages, it is necessary to acknowledge that accessing specific information from this vast amount of data is beyond the limits of the human brain. Search engines are a crucial tool to process or organize this large information presence on the Internet (Larson and Draper, 2017: Chp2).

The main task of search engines is to provide qualified information to users at the right time. Search engines are in the process of continuous research, development, and correction to improve the quality of the services they offer, namely to optimize the importance and quality of the results they provide (Ryan, 2014: 140). Under this purpose, search engines use highly advanced and continuously changing algorithms during the search process. These algorithms serve the purpose of finding the most suitable site for the searched words, and therefore the sites which have regularly updated and reliable content can rank higher in the lists (Kılıç, 2010: 52, 53). Companies aim to appear at the top of search engine results to make their brand and products visible to customers and achieve competitive advantage. This aim leads us to the concept of search marketing.

The search marketing process is called “Search Engine Marketing” (SEM), and it is a key method to attract quality visitors to identified website. SEM can be defined as “promoting an organization through search engines to meet its objectives by delivering relevant content in the search listings for searchers and encouraging them to click through to a destination site” (Chaffey and Ellis-Chadwick, 2016: 484). Search engine ads should not be limited to Google and Bing services only. Users sometimes use social media platforms or third-party websites like a search engine (Charlesworth, 2018: 64). For example, people can look at Facebook or Foursquare reviews of businesses for a car repair service. Or, similarly, customers can search for the product they are looking for on third-party websites such as Amazon.com or Booking.com and read reviews about the features of the product. Such behavior should also be addressed in the context of search engine marketing.

There are two main types of SEM in the marketing activities that marketers interested in (Chaffey and Ellis-Chadwick, 2016: 484). These are paid search, often called pay-per-click (PPC) and unpaid search (organic) (see Figure 10). The pay-per-click process includes payments to ads that appear above or next to the Search Engine Results Page (SERP). This type of search marketing is called a paid call because the advertiser pays for the website (Google, Youtube, Facebook, etc.) that hosts the ad when people click on an ad. Unpaid search type has an organic or natural rank and is known as search engine optimization (SEO) (Zahay, 2015: 44, 45, 49).

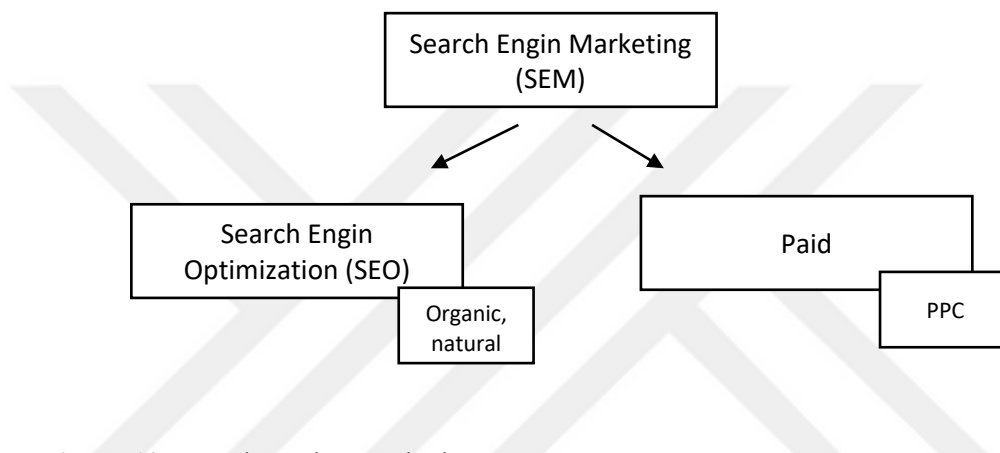


Figure 10: Search Engine Marketing Types

Source: Zahay (2015: 44).

At this point, it would be a correct approach to refer to a meaning confusion. Many practitioners and authors consider SEO as a separate title from SEM (e.g., Webstures 2020; Seotech, 2017; Leffler, 2018; Gökşin, 2017: 49; Şengül, 2017: 64). However, SEO is also a promotional activity and should be considered under marketing. Therefore search engine marketing should be defined as a key concept that hosting SEO and PPC as seen on Figure10.

Interestingly, most online-sellers at SEM do not willing to invest in SEO to achieve higher search results rankings. Instead, they prefer paid access (PPC). They say that SEO is more expensive and has no continuity than paid access. So in most SEM campaigns, PPC is a preferred strategy and usually does not include SEO (Sen, 2005: 9). This is also, in fact, a phenomenon explaining the cause of the confusion between SEM and SEO.

PPC

Search engines such as Google, Yandex and Bing have paid ad slots at the top and right of the page where organic search results are shown. But the display of these search ads on the results page is continuously being modified by search engines. For example, in 2018, the text ads for the websites shown on the right of the SERP have been completely removed, as users tend to look vertically at search results (Zahay, 2015: 45). Product lists and knowledge panel continue to be seen on the right side (Kim, 2018). Figure 11 includes a Google SERP screenshot for a keyword. As can be seen from the figure, PPC ads are at the top of the organic search results.

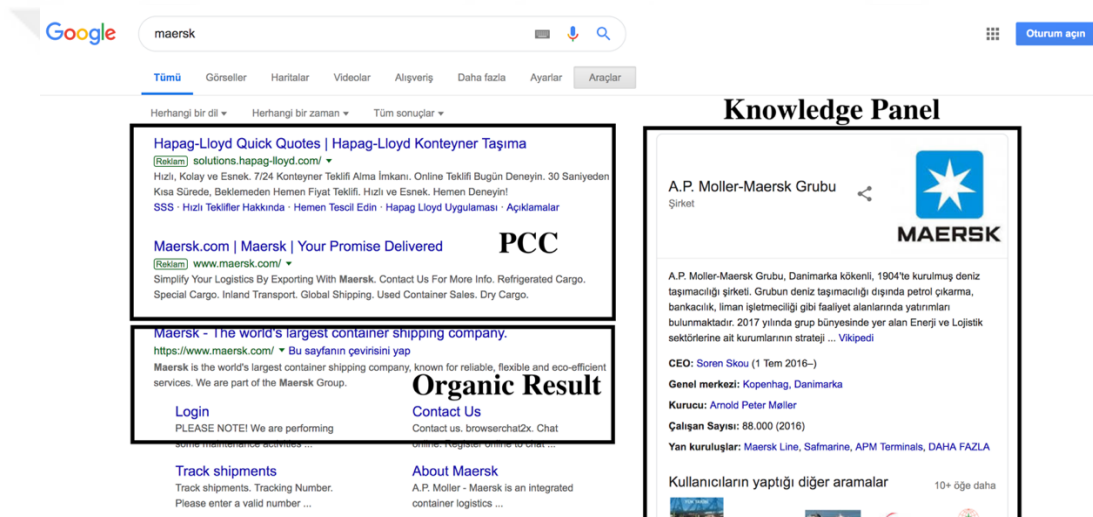


Figure 11: Google SERP for “Maersk” Search Term (29.04.2019)

The performance of search engine ads, which can be described as new generation banner ads, can be controlled in real-time. In search engine marketing, the question of which keywords will be used to reach the target audience most cheaply and effectively has led to the emergence of agencies serving in this field. With Google Adwords, Yahoo Overture, and Microsoft adCenter, it is possible to provide ads that are shown by keywords in these areas and are priced on clicks (Varnalı, 2013: 74). The most crucial advantage of PPC ads is that companies only pay when the user clicks on the advertisement to go to the website or call the company by phone (Google Ads, ____). There are no charges for Google display in SERP. This, in fact, provides a free brand awareness for companies.

Paid search (PPC advertising) should be handled with a strategic approach. Even though statistics indicate that 36 percent of clicks are made to links in the first four rows, if no one clicks the ad or the desired conversion is not received, there is no point in being even in the first position in paid search (Zahay, 2015: 45). In early pay-per-click programs, search engines were ranking ads based on the bids for keywords. But nowadays there are several criteria to carry out a successful paid search campaign. For example, understanding the quality score developed by Google is key to the success of a paid search marketing. The criterion for determining the quality score is “relevance” (Chaffey and Ellis-Chadwick, 2016: 497). Relevance refers to “how useful the information is for the customer's search”. Google looks at several things such as keywords, ads, and landing pages when determining relevancy. It's essential for companies to focus on relevance when creating a campaign because relevant ads offer more clicks, higher positions, and more success. Also, relevant ads reduce cost-per-click (Google Ads Help, ____).

SEO

Another factor affecting search engine rankings is search engine optimization (SEO), also called natural or organic listings. SEO is “a set of modifications and techniques that make it easy for search engines to crawl, index and understand the content of a website” (Zilincan, 2015: 506). A website must be understandable to both the user and search engines. Various visuals or redirects used on websites may increase the user experience, but may sometimes have a negative effect on search engines. Therefore, the site structure and content should be optimized for search engines as well. Although SEO has a very mixed world from site design to speed, it is possible to get top rankings in search engines results with little touches (Gökşin, 2017: 123) such as optimizing the content, titles, tags and subtitles (Varnalı, 2013: 74). Thus, companies have more visibility in search engine results.

According to the data obtained from a survey of over 250 keywords for 250 B2B and B2C companies, the relationship between Click-Through-Rate (CRT) and SERP ranking is visualized in Figure 12. According to the data of the study, 36% of clicks go to the web list in the first place of the natural SERP, while all of the websites on the second page receive about 15% clicks (Soames, 2011).

Click Through Rate (%)

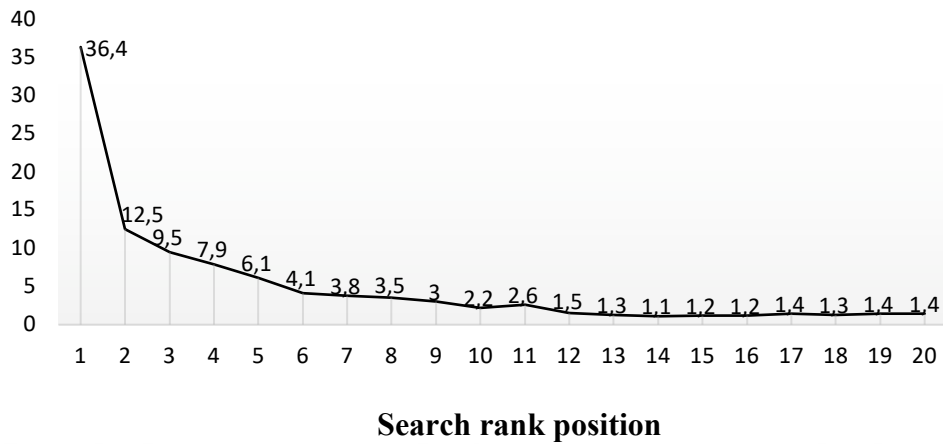


Figure 12: Organic Click Through Rate (CRT) By Search Position

Source: Data from Soames (2011).

According to March 2019 data, Google has 92.46% of the global search engine market (Statcounter, 2019a). Therefore, in this section, it is helpful to refer to Google's indexing logic briefly. Indexing is called to register a website's search engines in the database. Google indexes websites with robots (bots) that also known as spiders. These bots are part of the search engine algorithm and are available in different types. The most critical bots are DeepCrawl and FreshBot. For these bots to crawl the website healthily, the file settings of the Robot.txt must be constructed. Freshbots can visit a site 3-4 times a day and index the most popular and new content. DeepCrawl visits the website on average every week and indexes everything. The DeepCrawl bot has great importance in search engine ranking (Barışkan, 2016: 5). The indexing logic of search engines includes a deep and complex system. As it is out of the scope of the study, technical details about the search engines will not be given.

To develop an effective SEO strategy, it is necessary to understand the search algorithms well. For example, the Google search algorithm has a regularly updated structure. Core updates are usually done every year or every two years. Before 2003, search engine algorithms were quite simple. Page titles and keywords almost entirely determined rankings. Search engines were easily manipulated during this period. The Google Florida update at the end of 2003 was the first comprehensive algorithm

update. Together with this update, link-based factors became the focal point (Kingsnorth, 2017: 91, 92) and the SERPs were unintentionally changed (Demirayak, 2019). The Panda update in February 2011 was the most critical and complex algorithm in the history of Google.

The Panda update is designed to reward high-quality websites in the SERP (MOZ, ____). Search engine algorithms are still being developed and updated today. Google announced the most recent and significant update Florida 2 in March 2019 (Google SearchLiaison, 2019; Search Engine Journal, 2019) and the effects of this update began to emerge gradually at the time of this study.

As mentioned above the SEO market is continually changing due to the frequent updates made to search engine algorithms. However, there is always one aspect that not changed; SEO is made up of “On-Page” and “Off-Page” optimizations (Rende, 2018). On-Page SEO includes elements that are directly under the control of a website owner. The main On-Page SEO items are content, titles, meta descriptions (tags), URL structure, titles, visual optimization, page load speed, structured data, site map and social sharing integration (Zilincan, 2015: 506). Especially the original content has now become the center of search engine algorithms. Companies use a variety of methods to produce SEO-friendly content, and many agencies have been opened to focus on providing these content for brands (Barişkan, 2016: 19). The content can be blog posts, videos, white pages, reports, news, articles, social media posts or any media that getting the message across. Another critical element is the URL with a meaningful title tag. The title tag offers the opportunity to describe the keywords and brand name to the business, and appears in the blue bar in the search results, depending on the browser (Zahay, 2015: 51).

Tags are another critical part of successful SEO. For example, search engines recognize images from tags, and therefore images must be identified by well-matched alt tags (Heijmans, 2018). Alt tags appear after the image tag and contain an expression associated with the image. As an example; `<img src = “logo.gif” alt = “Company name, company service” />` (Chaffey and Ellis-Chadwick, 2016: 497). Spiders recognize these alt tags and index the image for the SEO. It is also a well-known fact that search engines reward websites rich in visual media. The most basic organic search factors (both on-page and off-page) are summarized in Figure 13.

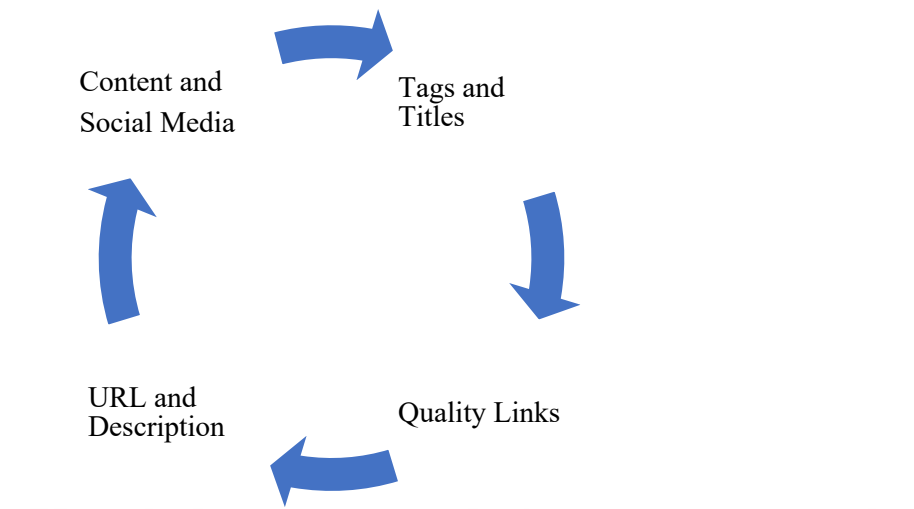


Figure 13: Main Factors for SERP Ranking in SEO

Source: Zahay (2015: 52).

On the off-page SEO side, links have always been the most crucial element of the search engine results. Even in 1998, Google's founders, Brin and Page, have noted that the number and quality of links on a page is a great way to identify the relevance of a page to searchers, particularly when combined with keywords on that page (Brin and Page, 1998: 116). Building a high quality and natural backlink profile, social sharing signals and social bookmarks are the most critical factors affecting off-page SEO (Rende, 2018). Off-page SEO is impacted by readers, visitors, and publishers and cannot be controlled directly by the publisher (Zilincan, 2015: 506).

One of the most mentioned topics in the world of SEO is black and white hat techniques. Black hat technique aims to stand out in the SERP without obeying search engine rules and manipulation methods such as Hidden Text, Link Farms, Keyword Stuffing and Scraping are used (Singh, 2013: 50). The white hat technique represents the SEO by the rules of search engines (high-quality content, links, tags, URLs, etc.).

As mentioned earlier, search engine marketing is a specialty in itself and has a deep technical richness. SEM is a key element of digital marketing that must be considered, but its technical details do not serve the purpose of this research. The study will continue with e-mail marketing in the next section.

E-mail

E-mail is seen as the first digital marketing tool that emerged in the 1990s. This channel made marketers communicate directly with the customer and made them respond more quickly to the customer. E-mail is known as a useful digital tool used to manage processes on the Internet, such as being a member of a site and is also provided easy access to data on response rates and the effectiveness of various marketing offers (Zahay, 2015: 14).

E-mail is a form of digital marketing and has an increasing use because it is much cheaper than other marketing tools. Email marketing offers two times more investment returns than digital marketing tools such as web banners (Ellis-Chadwick and Doherty, 2012: 843). Another reason for the adoption of e-mail by companies is the possibility of targeted distribution of promotions like discounts and various coupons and affordability by small and medium-sized companies (Moustakas et al. 2006: 44). The e-mail also offers companies a flexible and inexpensive tool to test and distribute sales and promotional messages to existing and potential customers (Marinova et al. 2002: 61). Further reasons of email using can be listed as follows; to share information about products, to promote products, to guide customers to the web site, to build a brand, to tell the status of orders. Digital marketers today use many different e-mail techniques such as newsletters, community building, and reward programs (Merisavo and Raulas; 2004:499).

Email is also the digital channel most commonly adopted by internet users. In fact, many research reports state that e-mail has become the most popular digital service among firms to reach customers (Merisavo and Raulas; 2004:499). But especially today, e-mails sent by companies for marketing purposes can sometimes cause some problems on the customer's side. For example, irrelevant e-mails that are frequently sent out, without a strategic approach by companies, can disturb customers. Such e-mails are called spam (unsolicited e-mail) and junk mail. Annoying e-mails are not attractive to existing or potential customers and may have a negative impact on the brand of the companies. This leads us to the concept of "permission marketing," which is one of the most discussed topics in the e-mail marketing studies (Marinova et al. 2002: 62).

Sending unsolicited emails to randomly selected consumers without their permission is a violation of spam laws in many western countries. Anti-spam laws are also applied in Turkey (Ryan, 2014: 244). In the regulation published on 15 July 2015 under the “Regulation on Commercial and Commercial Electronic Messages,” it is stated that communication permission should be obtained from the users to send e-mail for commercial purposes (Resmi Gazete, 2019).

Managing email marketing requires action on many fronts. The first task, the company must create a list of e-mail addresses. E-mail addresses must be collected together with the permission to send emails to consumers, and then the e-mail content must be generated. A good e-mail marketer optimizes several aspects of email content to maximize customer response and ROI. All e-mail messages must be sent to the recipient's inbox and should not be blocked by spam filters. Because in some cases even when users have permitted to e-mail them, a spam filter might prevent a firm's email from being delivered (Larson and Draper, 2017: Chp9).

E-mail marketing consists of four steps. Every step taken to construct a proper e-mail marketing strategy should be planned, by the desired goal. In Figure 14, this plan is visualized. According to the figure, primarily the purpose of e-mail (announcement, feedback, such as a new feature presentation) and the content should be specified. The headline of the e-mail is the most important criterion at this point because hundreds of emails come to the e-mail box of the users. For the user to open the e-mail, he/she must have a headline that attracts attention first (Gökşin, 2017: 71,72). For example, intriguing topics, that offer a specific opportunity, or that include a state of urgency, can attract the user's attention (Allen, 2019).

Similarly, the content of the e-mail is critical because if the content is not simple and clear, the user will want to close the e-mail and delete it from the e-mail box. Customization also affects the structure of marketing emails. While some companies are designing short, quick, anonymous messages designed to respond immediately, others create long, complicated, sender-defined messages to interact with the potential customer more interactively (Ellis-Chadwick and Doherty, 2012: 848).



Figure 14: E-mail Marketing Process

Source: Gökşin (2017: 71).

In the second stage, e-mail should be tested on all devices, especially mobile devices. In the segmentation and transmission section, the preparation is about making sure that the content is sent to the appropriate audience. Thus, people other than the target audience will not be disturbed. Measuring the success of the e-mail that is sent will be useful in taking the appropriate actions in addressing the following e-mail (Gökşin, 2017: 73,74; Şengül, 2017: 103).

There are different scales to measure success after sending an e-mail. The three of them are essential (Chaffey and Ellis-Chadwick, 2016: 526).

- **Delivery rate:** Used to understand the rate of unsolicited e-mails due to an invalid e-mail address or spam filter.
- **Open rate:** Shows how many individual have opened an email. Open rate is measured by dividing the number of individual who opened the email to the total number of people sent to the email.
- **Click-through rate:** The click-through rate is calculated by dividing the number of individual who clicked the link sent by e-mail to the total number of individual sent to the email.

Email is the leading digital channel of information exchange for buyers and sellers and has become a critical part of network marketing. It is a rational option for B2B companies to use E-mail marketing (Liu, 2012: 24). However, according to a study, 59% of B2B companies do not use e-mail marketing, while the average frequency of sending is one e-mail every 25 days (MacDonald, 2018). In the B2B markets, where sales cycles are long, regular emails sent to B2B clients can convince them for sales. For example, a software company can assure its customers by

presenting the software demo together with a content that explains the benefits of the product. However, an e-mail offering promotional opportunities will be less valuable for B2B buyers, as they often negotiate contracts with sellers on an individual basis (Larson and Draper, 2017: Chp9, Sec2).

To summarize, e-mail marketing has a significantly lower cost and higher ROI than other marketing activities. E-mail marketing seems to be easier to manage than other marketing channels like SEO. However, it still requires a strategic perspective and creativity. On the other hand, academic publications related to e-mail marketing are minimal. Notably, there is a need for guiding studies for creating and sending permission-based e-mails in addition to business facts.

2.1.2. Mobile Technologies

According to Mobile Marketing Association (MMA) mobile marketing is “a set of practices that enables organizations to communicate and engage with their audience in an interactive and relevant manner through and with any mobile device or network.” MMA draws attention to the concepts of “set of practices” and “engage.” According to the definition, practices include marketing aspects such as activities, processes, standards, advertising, direct response, promotions, and relationship management. Engagement in the definition represents activities such as initiating relations, creating events and promoting social interaction among members (MMA, 2009). According to another description made by Shankar and Balasubramanian (2009: 118), the mobile marketing is “the two-way or multi-way communication and promotion of an offer between a firm and its customers using a mobile medium, device, or technology.” Based on these two definitions above, in simple terms, mobile marketing is the marketing communication activities made by mobile smart devices (e.g. phones and smart watches).

Especially the integration of smart devices with communication increases the power of mobile marketing every day. There has been a sharp rise in the adoption of mobile devices by internet users in recent years. The main reasons for the rapid adoption of smartphones include the following activities and behaviors; access e-mail,

search the internet, social networks, play games, listen to music, multitasking, read, watch videos or movies, get direction and so on (Mishra and Garris, 2015: 10).

According to the Turkey Statistical Institute (TÜİK)'s survey which was conducted in 2018, 79.4% of households in Turkey have a mobile connection. This rate was 72.4 in 2017 (TÜİK, 2018a). According to another study made by TÜİK, while 19.2% of households used desktop computers in 2018, 98.7% used mobile phones or smartphones (TÜİK, 2018b). Other researches around the world also support the rapid adoption of mobile technologies. According to Statcounter (2019b) statistics, the worldwide desktop market share rate is 52.25%. Figure 15 compares the last 10-year desktop and mobile market share ratios.

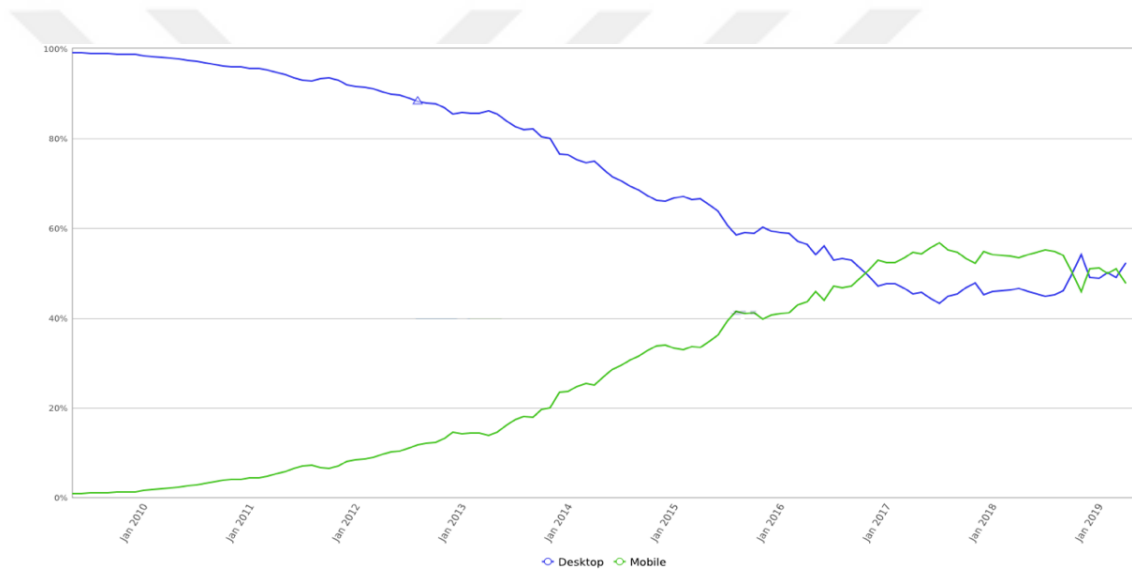


Figure 15: Desktop and Mobile Market Share Worldwide from May 2009 to May 2019

Source: Statcounter (2019b).

The rapid adoption of mobile devices also severely affected mobile marketing spending. In 2014, the world mobile advertising spending, which was 29 billion U.S. dollars, increased to 147.6 billion U.S. dollars in 2018 and expected to reach 231.3 billion U.S. dollars by 2021 (Statistica, 2019b). This rapid increase in mobile advertising spending confirms the “mobile-first” discourse, one of the leading trends in the digital marketing sector. Specially in recent years, it is expected that mobile markets will grow even more with the rapidly developing wearable technologies (Şengül, 2017: 106, 107).

The mobile channel is a subset of digital marketing and also includes different advertising channels in itself. “Short Message Services (SMS)”, “Enhanced Message Services (EMS)”, “Multimedia Message Service (MMS)”, “Interactive Voice Response (IVR)”, “Video IVR” and location-based message submissions are the leading types of push-type mobile advertising media. Application notifications, mobile app ads (such as Adwords and Facebook Ads), service ads can be listed as other mobile advertising methods (Varnalı, 2013: 77, 78). QR codes, which also mean "quick response" codes, serve as an essential bridge between online and traditional marketing. It is often used by cameras on mobile devices. The most popular area of use is to direct the user to the desired URL. QR codes are also intriguing, and there is no additional cost to adding a QR code to offline channels (Gökşin, 2017: 138, 139).

Notably, the increasing trend toward mobile use is offering significant opportunities for growth (Key, 2017: 33). In the early years of the smartphone revolution, marketers hesitated to use mobile tactics such as mobile search, display ads, and apps. However, especially with the emergence of application stores, they develop tactics targeting smartphone users. Mobile ads and apps allowed companies to reach the right people in the right place and at the right time (Mishra and Garriss, 2015: 8). According to Statistica (2019b), 53.9 percent of all retail e-commerce in 2021 is expected to be produced through m-commerce.

The purpose of the mobile can be listed as follows; creating a brand and product awareness, interacting with online communities, gaining valuable ideas about consumer behavior, providing customers with deeper and more personalized brand experience, more effective targeting, loyalty programs, and competitions, etc. (Ryan, 2014: 282). Mobile applications have two essential features that enable companies to grow; trust and user experience. Trust is “the ability to rate the quality of a product”. These ratings give customers the confidence to pursue products. Similarly, the high level of user experience provides fast and secure purchasing and payment capability for customers (Key, 2017: 28).

One of the essential criteria to be considered in mobile marketing is responsive designs. Responsive web design enables users to dynamically control the presentation of the website based on the properties of the screen that it’s being viewed on (AdSense Help, ____). Responsive design contents can take shape according to the dimensions

of the browser size and can work on all devices. The mobile-friendly website also has a significant impact on SEO. Google prioritizes websites that have an excellent mobile site performance in their search results. Besides, a mobile-friendly web site makes it easy for users to take action on their mobile devices and improves customer conversion rate (Gökşin, 2017: 130, 131).

One of the most necessary components of mobile marketing is mobile apps which is a piece of software that is installed on the phone or downloaded from the internet (Ryan, 2014: 296, 297). Smartphone owners download mobile applications in addition to using websites for knowledge. Users accept applications to be more convenient, faster and easier to browse. Application icons allow quick and easy access to the content of a brand, so it is especially useful for frequently used services (Mishra and Garris, 2015: 43).

Application stores and mobile boom are described as a revolution in digital platforms. This revolution is seen as a new case of attacking gold (Ryan, 2014: 296, 297). It is proven that branded-mobile applications are a rapidly growing marketing channel, especially in the sharing economy. Branded-mobile claims refer to “a specially created software interface that a user downloads for the sole intent of branded engagement with a firm via entertainment, knowledge, and exchange” (Key, 2017: 28).

As in other marketing channels, measurement and analysis of these measurements (KPIs) are also invaluable in mobile marketing. The basic KPIs used in mobile marketing campaigns are; total number of downloads, number of application users, new users, frequency and process of visits, rewind rates, segmentation by device types, clickthrough rates (Ryan, 2014: 300, 301). As with desktop display advertising, it is critical to understand ROI in mobile advertising better. Cost per mille (CPM) and CTR are the leading criteria for measuring and benchmarking the effectiveness of mobile ads. Both metrics are not perfect, but tracking these data can provide insight into specific ad formats (Mishra and Garris, 2015: 84).

Mobile phones were invented to facilitate communication. But people's obsession with communication has led to the development of social media networks. Social networks have been the most popular applications on mobile devices. Although most of the social networks, such as Facebook and Twitter, started on computer

desktop screens, they continuously see more usage from mobile devices (Mishra and Garriss, 2015: 8). According to eMarketer, 90% of time spent on social networks happens on mobile tools (Wurmser, 2018). Social media is discussed in the next chapter as the third principal component of digital marketing in this study.

2.1.3. Social Media

Social media is the newest communication channel of the 21st century, although its origin is based on the billboard in the 1970s (Kingsnorth, 2017: 150). Today, social media is widely used by people, especially with the development of mobile technology (Mishra and Garriss, 2015: 57). Although academic studies related to social media are still at the embryonic stage, knowledge production in this area is increasing rapidly (Salo, 2017: 116). However, the broad definition of social media is beyond the scope of this study. Therefore, this section is focused on summarizing social media from a technological and strategic viewpoint. Therefore, firstly, the current social media technologies (tools and sites) will be mentioned, and then, especially in the B2B area, their usage will be discussed.

Social media is defined as “any website or application that allows users to create and share content or participate in social networking”. When people talk about social media, only the best known social networks (Facebook, Twitter, Youtube, etc.) come to mind. However, these are only a small part of a much larger channel (Kingsnorth, 2017: 150). Social media includes a wide range of sites and tools such as social networking (Facebook), business networks (LinkedIn), video sharing (YouTube), photo sharing (Instagram), user or company blogging (blogger, medium), microblogging (Twitter), collaborative websites (Wikipedia), commerce communities (Letgo) (Mangold and Faulds, 2009: 358). There are different approaches to the classification of social media channels in the literature. Some of these classifications are presented in Table 7.

Social media penetration is growing in the world. In 2017, 71% of Internet users were social media users, and these numbers are expected to increase. Social networking is seen as the most popular online activity with high user engagement and increased mobile opportunities. In 2019, it is estimated to be approximately 2.77

Table 7: Categorization of Social Media Channels

Mangold and Faulds (2009)	Social networking (Facebook)
	Business networking (LinkedIn)
	Creativity works sharing sites
	Video share (Vimeo)
	Photo share (Instagram)
	Music share (Soundcloud)
	Content share combined with assistance (Piczo)
	General intellectual property share (Creative Commons)
	User-sponsored blogs (Cnet.com)
	Company-sponsored websites/blogs: (Apple.com)
	Company-sponsored sites (click2quit.com)
	Invitation-only networks (ASmallWorld.net)
	Collaborative websites (Wikipedia)
	Virtual worlds (Second Life)
	Commerce communities (Amazon.com)
	Podcasts
	News sites (Current TV)
	Educational (Udemy)
	Open source software communities (Linux.org)
	Bookmarking (Digg, Reddit)
Safko (2010)	Social networks
	Publishing (Blogs, Wikis)
	Photo share (Flickr)
	Audio share (Podcasts)
	Video share (YouTube)
	Microblogging (Twitter)
	Livecasting (Justin.Tv)
	Virtual worlds (Second Life)
	Gaming (World of Warcraft)
	Productivity applications (SurveyMonkey, Slack)
	Collectors (FriendFeed)
	RSS (FeedBurners)
	Search (Technorati)
Kaplan and Haenlein (2010)	Mobile social media (Apps)
	Interpersonal (Skype)
	Collaborative Projects (Wikipedia)
	Blogs
	Content Communities (SlideShare)
	Social Networks (Facebook)
	Virtual Games (World of Warcraft)
	Virtual Worlds (Second Life)

billion social media users worldwide (Statistica, 2019c). Figure 16 shows the ranking of the most popular social media sites and apps around the world by the number of active users as of April 2019. As the market pioneer, Facebook platform was the first social media to exceed 1 billion registered accounts and has 2.32 billion active users per month. The sixth-ranked photo-sharing application, Instagram, has 1 billion monthly active users (Statistica, 2019d).

Social media is a large formation on a global scale. Although applications such as Facebook and WhatsApp are widely used in North America and European countries, the situation in Asian countries is very different. For example, China had 673 million social media users in 2018 and the Chinese-origin WeChat, a WhatsApp-style messaging service, has more than 1 billion users, as shown in Figure 16. The micro-blog site SinaWeibo, which uses a Twitter-like model, has more users than Twitter. Similarly, QZone is a social network similar to Facebook, and its use is quite common (Kingsnorth, 2017: 151).

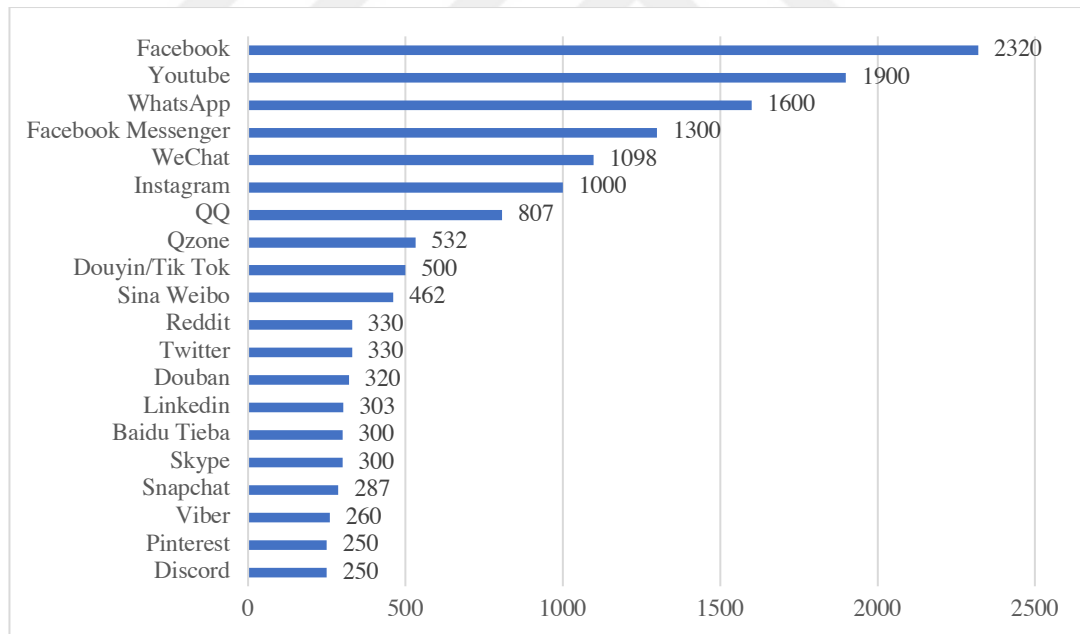


Figure 16: The World's Most Popular Social Media Sites and Applications as of April 2019, Sorted by the Number of Active Users (Millions)
Source: Statistica (2019d).

These platforms managed by companies themselves or sponsored organizations such as social media agents and allow companies to talk to their customers and stakeholders. Such communications usually include suggestions, requests or complaints. In some cases, these conversations can be viral and reach hundreds of thousands of individuals outside the control of companies (Mangold and Faulds, 2009: 357, 359). Social media is seen as an extension of word-of-mouth marketing (Kozinets et al. 2010: 71), and strategically designed messages can motivate network members to share the content and can encourage WOM communication about the brands (Swani et al., 2017:78).

Social media has also changed the communication habits of companies through new technologies (Mangold and Faulds, 2009: 357). Customers rely less on traditional marketing sources such as catalogs, trade publications, and trade shows that the digital platforms to stay informed. This trend directly affects the salespeople and sales channels roles in the marketing effort (Wiersema, 2013: 476). Social media differs from traditional communication with its unique and dynamic features such as users' ease of involvement and engagement. However, the message itself is still a key factor in the successful completion of communication (Sasser et al., 2014: 18). Thus, it will be more beneficial for marketers to develop communication strategies that encourage network fans to share their own content. In other words, the crafting of driving messages by marketers can promote the WOM communication of brands (Swani et al., 2017: 78). However; it would not be a right approach to view social media as a substitute for traditional marketing. Marketers should see social media as a complement to conventional marketing methods (Weinberg and Pehlivan, 2011: 282).

A social media site is much more than just a website. From a technological side, most of the social media sites can be seen as software apps or internet services that provide users access to different permission levels and then allow the management and storage of various forms of UGC (Chaffey and Ellis-Chadwick, 2016: 34, 35). Especially with Web 2.0 technology, content and page format are separated from each other and users can easily upload content to the internet without extra technical equipment. Web 2.0 is based on the Extensible Markup Language (XML) infrastructure as technology and philosophically based on the view of free, democratic and participatory media (Vernalı, 2013: 60). Web 2.0 applications are Internet-based

applications that allow the content to be easily created and shared by users through this technological infrastructure (Kaplan and Haenlein, 2010: 61).

Messaging is a more useful method, especially when it provides content that interests and informs the user. Application Programming Interfaces (APIs) for exchanging data with other internet service interfaces are another a critical feature of social media which enable them to be more beneficial and let users extend their reach and influence by incorporating comments into other sites (Chaffey and Ellis-Chadwick, 2016: 34, 35).

It is a well-known fact that today social media has made a significant impact not only on people but also on companies. In spite of the B2C markets seem to have quickly adapted themselves to social media technologies, researches indicate that B2B markets still have difficulties in this regard. Some of the reasons for this trouble are explained by industrial companies' late adaptation to technological innovation, limited customers in the market, long sales periods, and have multiple decision makers (Holliman and Rowley, 2014: 274; Leake, et al., 2012; Siguaw et al., 2003: 544; Zeng et al, 2003: 39, 40). However, in today's rapidly changing communication environment, B2B firms need to create an effective social media strategy to protect their brand, competitiveness, market share and build strong customer relations (Nunan et al., 2018: 31; Andersson and Wikström, 2017: 1100). Therefore, businesses should primarily determine the most appropriate channels for social media, such as social networks and/or content sharing platforms, in line with their target groups, and decide what kind of marketing communication activities they will be involved in.

Social media is seen as the communication channel to enrich customer relationship, highlight the brand and support sales by B2B companies. Similarly, it is also used as a recruiting and job seeking, providing product information and service tool (Andersson and Wikström, 2017: 1103). However, on the academic side, even though the production of knowledge is accelerating in this subject, the studies in the B2B area are still at an embryonic stage (Salo, 2017: 116). Therefore, it is expected that this study will contribute to the gap for the role of social media in B2B markets, especially in container shipping companies.

Social Media Advertising

Social media advertising is the key issue to be addressed in terms of the scope of the study. Because, especially on the B2B side, if companies want to use popular social media sites or tools effectively, social media ads should be well understood. Rather than demonstrating a technical approach to social media advertising, the levels of engagement on popular social media sites will be summarized in the context of social media advertising.

As mentioned in many studies (Sasser et al., 2014: 18; Swani et al., 2017: 78), social media message itself is critical in ensuring communication with users. Companies achieve communication objectives through the message they send. As a well-known fact, the number of users on popular social media channels such as Facebook or YouTube directly affects the level of this achievement. However, the engagement rates have gained a different dimension with social media advertisements.

There are two types of social media communication: “organic” and “paid”. Organic social media is the communication built by the company on a social media platform. The company does not pay for it, and the consumer's engagement or resharing (WOM) is seen as earned media. “Paid” content is as it sounds: the company pays for the content. Both social media communications are used by many companies as complementary to the existing communication program. However, in recent times, due to the algorithmic changes made by social media sites, organic access has become increasingly difficult (Fulgoni, 2015: 232).

As an example, Facebook's founder Mark Zuckerberg announced in January 2018 that they had made some important changes in the News Feed algorithm. Accordingly, in order to encourage more meaningful interaction among people, News Feed demonstrations will be linked to a standard, and publications from the business, brand, and media will be shown less (Facebook, 2018a). Another noteworthy announcement by Zuckerberg is that they will show more local news in order to provide people with more reliable and relevant content. According to this, the share of local publishers will be displayed more in order to increase civic engagement on Facebook (Facebook, 2018b). With this algorithmic change made by Facebook, the messages of the companies now have less organic reach than before. In addition, the number of followers in Facebook accounts no longer directly affects this organic

access. With this new "pay-to-play" model of Facebook, the rate of organic engagement of companies decreased significantly. As a managerial implication of the study, companies are now required to promote their messages with Facebook ads if they want to reach more people, even their current fans. So at this point, companies' Facebook engagements are more related to Facebook advertising budget than fan numbers.

The good news for companies is that Facebook ad is seen as one of the most cost-effective as platform in the digital marketing industry. It is a well-known fact that digital media advertising is quite low compared to traditional media. For example, the average cost of a newspaper ad is 32 U.S. dollars, while in a printed magazine this figure is 20 U.S. dollars (Nuanced Media, 2015). If the advertiser show this ad on Google, the average cost drops to 2.8 U.S. dollars (Pratskevich, 2018). The average CPM (depending on the country) of the Facebook name is 1.26 U.S. dollars (Statistica, 2018). That is to say, companies should not hesitate to use digital platform ads, especially Facebook.

Another point to be remembered here is that the digital world is continuously changing and developing. For example, Facebook's 2018 News Feed algorithm update mentioned above is an extension of the change made in 2014 (Facebook Business 2014a, 2014b) and 2016 (Facebook Newsroom, 2016). Therefore, in order to establish a successful communication on social media platforms, companies should follow the updates of the relevant social media site or tool in terms of the operation policies. Thus, it will be possible to adapt the marketing communication strategy of the company to the functioning of the relevant social media technology.

Including each of these technologies in the subject of the research would be to obtain superficial results. In this context, the scope of this research was continued only with social media technology. There are several reasons for continuing the research with social media technology. The most important of these is that the use of social media in the maritime sector is subject to a noticeable increase year by year (Denktaş-Şakar and Sürücü-Balci, 2019; Dwivedi et al., 2019; Kovac, 2016; Minsky and Quesenberry, 2015; Katona and Sarvary, 2014; Agerdal -Hjermind, 2014). Thus in the next section of this study, which adopts a deductive approach, social media technology, and strategies in maritime transportation are discussed.

2.2. THEORETICAL BACKGROUND OF SOCIAL MEDIA COMMUNICATION

This study is based on the Social Media Communication Model and Word-of-Mouth (WOM) Psychological Motivation Theory. However, in literature, there are many other theories and models that form the theoretical background of social media communication. However, in literature, there are many other theories and models that form the theoretical background of social media communication. Since the explanation of each of these is out of the scope of this study, the most frequently used theories and models in the literature will be briefly introduced in the next section. Then, Social media Communication Model and Word-of-Mouth (WOM) Psychological Motivation Theory were discussed.

2.2.1. Main Theories and Models in Social Media Communication

Since sites like Facebook, Twitter or LinkedIn are relatively new, there are few theories that can help companies use social media effectively (North, 2015: 6). Nowadays, theories about social media are generally extensions of previous theories. For example, the rapid growth of social media has required companies to integrate into crisis management and communication processes. Therefore, Coombs (2014) updated the “Situational Crisis Communication Theory”, which he previously discussed (Coombs, 2007), and transformed it into a Social Mediated Crisis Communication model (Coombs, 2014).

Another theory that can be associated with the use of social media is “Uses and gratifications theory” (U&G Theory). Communication scholars disagree about the exact roots of this approach, introduced in the 1940s (Ruggiero, 2000: 4, 5). Katz and Foulkes (1962) stated that the main purpose of U&G theory is to understand why individuals are actively seeking and using certain environments to meet specific needs. U&G Theory deals with how individuals choose media that enables them to achieve gratification such as information acquisition, entertainment and reward (Dolan et al. 2016: 262).

Adaptation theories such as “Diffusion of Innovation Theory”, “Technology acceptance model (TAM)”, “Theory of planned behavior (TPB)” and “Theory of reasoned action (TRA)” are also commonly used in social media studies. The reason why these theories are popular in social media studies is to question the acceptance of social media by people and businesses as innovative technology. Companies use technology to increase their productivity. However, in some cases implemented technologies are not accepted and used by the users (Venkatesh et al., 2003: 426). This may cause the companies to waste investment and loss of labor and capital. The question of whether the acceptance of technology can be predicted has kept experts busy for a long time. Technology adaptation theories are effective theories that can be used to question the acceptance of social media, especially in B2B markets such as maritime transport.

The Theory of Reasoned Action (TRA) is introduced by Fishbein and Ajzen (1975) and has become leading theory in the field of social psychology (Trafimow, 2009: 501). TRA model explain casual relations between beliefs and evaluations, attitudes, norms, intentions and behavior of a person.

Technology acceptance model (TAM) introduced by Fred D. Davis in 1986 and it widely accepted in literature of technology usage. According to Davis et al. (1989) if we correctly understand why people accept or resist using new information technologies or computer systems, it can be better predicted, explained and also increased user acceptance by better designing and developing methods. However, at that time, Swanson (1988) emphasized that clarifying why people accept or reject new computer technologies is one of the most challenging topic in information systems literature. TAM describe computer usage behavior by using TRA as a theoretical basis. It point out relation between “perceived usefulness” and “perceived ease of use”, and “users’ attitudes”, “intentions” and “new technology adoption behavior”. But it should be noted that TAM is less general than TRA because of it developed to exert only to computer usage behavior (Davis, 1986; Davis et al., 1989: 983; Mathieson, 1991: 173).

Theory of planned behavior (TPB) developed by Ajzen (1991) to shows the relations one’s beliefs and behavior. TPB is an extension of the Fishbein and Ajzen (1975)’s TRA and there is not significant difference which is better at predicting computer system adoption intention (Grandón et al., 2011: 292). However original

model (TRA) has become leading theory in a short time, it was incapable to deal with behaviors over which users have incomplete volitional control. Hence Ajzen (1991) added a new variable to the TRA which is called perceived behavioral control (PBC) and called this new model TPB. This adding construct reflects perceptions that individual and situational barriers to the performance of an individual's behavior may exist (Grandón et al., 2011: 292)

The foundations of the theory of innovation originated from the work of economist Joseph A. Schumpeter. Schumpeter (1939) saw innovation as distinctly different from the invention (Robertson, 1967: 14). On the one hand diffusion of innovation studies were initiated by a group of independent researchers in the 1940s and 1950s (Rogers, 2003). Diffusion of Innovation Theory (DOI) (also called Innovation Diffusion Theory) introduced by Rogers in 1962. Rogers (1983) defined the diffusion as “the process in which an innovation is communicated through certain channels over time among the members of a social society”. In other words DOI indicate the adoption of a new system or technology among company employees (Rogers, 2003). Innovation diffusion is provided by users to accept and use new things (Chen and Tan, 2004: 75). Rogers (1983) initially explain the adoption of an innovation through five dimensions (perceived characteristics of innovations) which are “relative advantage”, “compatibility” “complexity”, “trialability”, and “observability”.

Some of other theories and models that are most frequently used in social media communication studies are as follows; Social Exchange Theory (Shiau and Luo, 2012; Beck et al., 2014; Hamoud et al., 2016), Social Interaction Theory (Lee-Kelley et al., 2004; Fischer and Reuber, 2011; Harrison, 2013), Social Influence Theory (Leenders, 2002; Cheung et al., 2011; Zhou and Li, 2014), Media Richness Theory (Kaplan and Haenlein, 2010; Mandal and McQueen, 2013), Social Identity Theory (Sanderson et al., 2016; Wang, 2017; Fujita et al., 2018), Network Theory (Merchant, 2012; Peters et al., 2013; Saxton and Wang, 2014).

There are many more theories and models in the literature that can be associated with social media. In the early stages of this study, technology acceptance models were examined in detail to question the acceptance of social media technology in the maritime industry. However, the fact that digital transformation spread rapidly

and the maritime sector was also affected by this transformation, changed the perspective of the study. Therefore, it is believed that it would be a more correct approach to conduct a study that will answer the question of "how to make better use of this technology?", instead of doing a study for the acceptance of social media technology. Accordingly, the social media communication model and the Word-of-Mouth (WOM) Psychological Motivation theory have been the approaches forming the theoretical background of this study. In the next section, these two approaches are discussed and explained in detail.

2.2.2. Social Media Communication Model

Communication simply can be defined as “the transfer of information between different points in space or time” (Madhow, 2008: 1). The traditional theory of communication model (Shannon and Weaver, 1949) sees communication as “a process of dissemination of information”. According to this process, communication is a “flow of information that a sender disseminates a message to receivers by revealing its meaning within the message” (Van Ruler, 2018: 368). Shannon and Weaver (1949) communication system consists essentially of five parts (see Figure 17). An information source (sender) which produce a message, a transmitter operating on the message to create a signal appropriate for transmission over the channel (encode), the medium (channel) used to transmit the signal from the transmitter to the receiver, a receiver that reconstructing the message (decode) from the sign and the person or thing for whom the message is intended (destination) (Shannon 1948: 4).

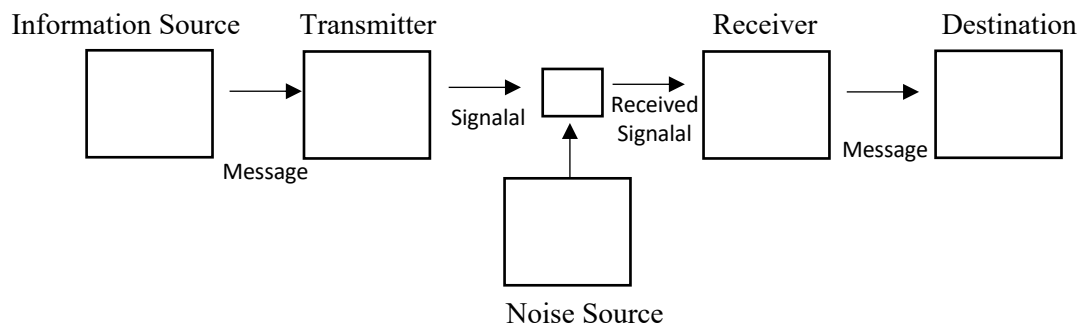


Figure 17: Schematic Diagram of General Communication Systems
Source: Shannon (1948: 4).

This simple communication theory has undergone various changes over time. For example, in the mid-90s, two-way communication (interactivity), theorized by John Deighton for the first time (Zahay, 2015: 5), made an important contribution to literature, particularly in understanding today's social media communication. In this study, Shannon and Weaver's (1949) traditional (mathematical) communication model updated by two-way communication is used to understand social media communication between container shipping companies (marketers) and their buyers and networks. Figure 18 illustrates the social media communication model that is the subject of this study. Source represent the marketer of the container shipping companies, the channel (medium) is social media, the receiver is the audience of the company's social media channel. Encoding and decoding is handle in there level in this study. Level I represent social media message of the company without interaction. In this level source (marketers) only encode the message and sent it out to the receiver (channel followers). Level II involves receiver reaction to the decoded message. At this level, receivers (followers and network of friends) encode and send their message within the methods allowed by the relevant social media channel when they are motivated for the reaction. This reaction signals can be changed according to social media channel user interface. For example, Twitter offers users a "reply", "retweet" and "like" button, while Facebook and LinkedIn use a "reaction", "comment", and "share" button. Level III corresponds to a full two-way interactive process in which the source responds to the feedback it receives. At this level, the source encodes a message in response to the feedback it receives from the receiver.

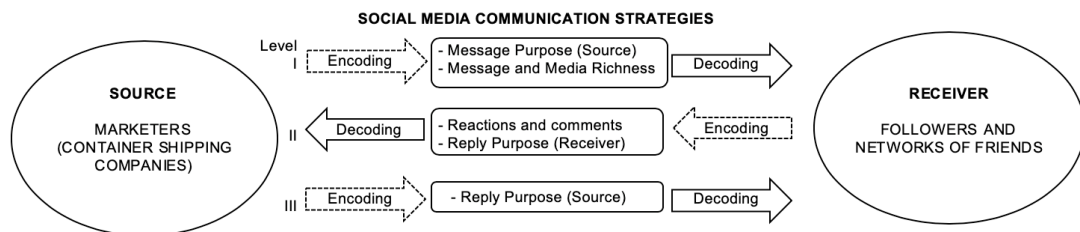


Figure 18: Social Media Communication Model of Container Shipping Companies

Encoding processes of level I, II and III are the main focus of this study. Accordingly, the messages shared by the container shipping companies on social

media channels, the response of their followers and friends to these messages, and the responses of the companies to these reactions, if any, will be examined.

2.2.3. Word-of-Mouth (WOM) Psychological Motivation Theory

Word of mouth (WOM) refers to the communication of goods, services or businesses between individuals. Because such communication does not involve commercial concern, consumers tend to rely more on WOM in their purchase decisions. On the other hand, WOM can be an opportunity and a threat to companies. A positive WOM can strengthen the brand of the company, while a negative WOM can destroy the prestige of the company overnight. It is therefore essential to understand how WOM works to strengthen communications and create a competitive advantage in companies (Shen et al., 2016: 75).

In traditional communication models, the sender (source) encodes or creates a desired message, which is sent to the recipient through a specific medium. The recipient then decodes the sender's message (Sasser et al., 2014). If this communication process is to be successfully completed, the sender's encoding process must mesh with the receiver's decoding process (Kotler and Armstrong, 2018). Regarding successful marketing communication, it is also critical that the transmitted message. There are six elements that determine the likelihood of a message spreading by WOM: simplicity, unexpectedness, concreteness, credibility, emotions, and story form. Except for credibility, the other five features relate to how to design the message (Heath and Heath, 2007).

Social media is different from traditional communication due to its unique and dynamic features, such as the ease of user involvement. Nevertheless, the message itself is still a key factor in successful communication (Sasser et al., 2014). Thus, it is more beneficial for marketers to develop communication strategies that encourage network members to share their content. In other words, the crafting of motivating messages by marketers can promote WOM communication of brands (Swani et al., 2017). People engage in WOM communication for many reasons. Most research in the literature has approached WOM as a function of brand experiences and personal characteristics of the transmitter (Alexandrov et al., 2013).

There are three main motivations for transmitting brand content: social, emotional, and functional. These motivations are mainly based on needs, such as sending signals to others regarding one's expertise, uniqueness, or social status, sharing feelings about brands, and providing and supply information (Lovett et al., 2013). Motivations can also include the pursuit of economic incentives and social benefits (Swani et al., 2017). Marketers can encourage motivations through these social media channels by creating contents that integrate appropriate branding cues, message appeals, sales tactics, and information level (Swani et al., 2017).

2.3. SOCIAL MEDIA MARKETING IN CONTAINER SHIPPING

Business-to-business communication has recently undergone significant transformations to adapt to the ever-changing market conditions of businesses. In fact, not only marketing communication has changed, but also the ways in which B2B companies such as container shipping companies communicate with their customers have changed. In time, a power shift occurred from the organizations to the customers (Karjaluoto et al., 2015a: 703). Consumer trends affected by social media, web and mobile technologies have quickly shaped B2B marketing communications. Digital platforms have pushed B2B marketing communications to higher levels and provided multiple ways to deliver desired messages to targeted destinations. Digitalization has also provided companies a significant competitive advantage (if it is used correctly) (Rizomyliotis et al., 2017b: 80).

Social media marketing in container shipping markets is growing very fast and is seen as a new area to attract commercial customers. For example, Maersk, the world's leading container transport and forwarding company, serves commercial customers from 374 offices in 160 countries. Maersk line is also seen as one of the successful digital marketers. Maersk Line uses social media accounts very actively, including Facebook, LinkedIn, Instagram, Youtube and Twitter. Maersk Line has a noticeable engagement with more than 3 million fans on Facebook and its employees state that they use social media to be closer to customers (Kotler and Armstrong, 2018: 198, 199).

However, large number of B2B companies see the use of social media as irrelevant for themselves (Järvinen, 2012: 108). Evidence from B2B companies indicates that approximately 60% of company managers find social media unnecessary or doubt the effectiveness of sales generation and brand development (Wang, et al., 2016: 56). The main reasons why B2B businesses are not sure about using social media are listed below (Bernard, 2016: 955);

- They perceive it to be irrelevant to their customers' purchase decisions.
- They are worried about controlling what is said by employees.
- It is seen as a meaningless burden that will disturb employees.
- They want to stay away from the risk of lobbying or pressure against them.
- They do not have the ability to use social media in the organization.
- They perceive it can only be a tool used for B2C marketing.

Nevertheless, the advantage of digital channels in terms of cost, effectiveness and efficiency and the quality of service has led to rapid adoption on the industrial side (Kırcova, 2008: 47-48). Social media can be very effective technology in delivering the content to the targeted customer and it also creates new relationships and supports the relations that have been established before. Container shipping marketers use social media for various purposes, such as recruitment and product detail research and development. In this context, social media is seen very useful marketing technology for shipping companies in developing customer relations, increasing sales and brand building (Andersson and Wikström, 2017: 1098, 1104).

As mentioned before there are different categorization of social media platforms in literature. For example, Krishnan and Rogers (2014) segmented social media platforms and listed the ten most essential segments as follows; (Krishnan and Rogers, 2014: 75-87).

- Blogging communities (Blogger, WordPress)
- Crowdsourced platforms (Reddit, Digg)
- Discussion forums (Flyertalk)
- Gaming communities (Zynga)
- Live streaming (Ustream, Justin.TV)

- Micro-blogging (Twitter)
- Sharing networks (YouTube, Flickr)
- Special-interest platforms (AllRecipes)
- Social platforms (Facebook, LinkedIn)
- Rating and reviews platforms (TripAdvisor)

In container shipping markets, social media communication is generally more effective on LinkedIn, Facebook and Twitter because of the professional outlook of businesses. LinkedIn provides a channel to share a company's content or activities, while Facebook and Twitter provide the opportunity for discussions about a firm's products. Thus, social media is not only transmitted the product information to another company but also provides real-time discussions and important feedback (Rizomyliotis et al., 2017b: 82; Guesalaga, 2016: 78).

As a B2B marketplace in digital media communication, one of the concerns of container shipping companies is the lack of control over social media messages. Therefore, they have to monitor chat sites to be aware of what is said about them (Wiersema, 2013: 476). Moreover, the difficulty of determining return on investment (ROI) is seen as one of the significant obstacle to investing in B2B social media marketing (Järvinen, 2012: 108). That's why engagement metrics are the most common way to measure the success of social media posts. Therefore, in the following sections, the social media engagement literature is discussed in more detail.

2.3.1. Social Media Strategies in Container Shipping Markets

Container shipping is characterized by a standard B2B service market where technological innovation is adopted late, with long sales cycles and multiple decision-makers (Holliman and Rowley, 2014; Leake et al., 2012; Ramos and Young, 2009; Siguaw et al., 2003; Zeng et al., 2003). On the other hand, even though container shipping line operations permits the presence of a small number of service providers in the market with its capital intensive nature, the intensity of competition among these players is quite high (Yap and Zahraei, 2018). There are various ways to get out of this challenging competition in the international logistics market where container shipping

companies operate. One of the most important methods is to follow customer-oriented market strategies (Shin and Thai, 2015) that require the best understanding of customer needs and provide solutions. The most beneficial solutions provided by companies to shippers and freight forwarders, which are major customers of container shipping (Balci and Cetin, 2017), will increase customer satisfaction and competitiveness in the long term.

Today, many organizations use digital transformation to get better customer experience and advance competition. It is seen that companies exhibit a digital maturity to develop customer-oriented market strategies (Kane et al., 2015). Digitalization has become an essential driver of competitiveness in container shipping as well as in many other sectors (De Martino, et al. 2013). It is observed that digitalization, which is an important challenge of transactions in the supply chain, is rapidly adopted in the container shipping sector. For example, shippers and other actors in those chains have moved away from paper-based communication to electronic communication (Maersman et al., 2016). The same applies to the use of social media, which is an important element of digitalization (Probst et al., 2018; Hansen and Sia, 2015), although it has not yet reached full maturity.

Container shipping, with its customer-oriented structure, is actually suitable for social media communication. However, in the past, some claimed that because B2B means “Boring-to-Boring”, social media is unnecessary for B2B companies and that they have no place on social media (Agerdal-Hjermin, 2014). As the case of Maersk proves, social media offers many opportunities to shipping lines, such as strong brand reputation, competitiveness, increased market share and strong relationships between suppliers and customers (Nunan et al., 2018; Spekman and Dotson, 2010). In 2012 and 2013, Maersk won several prestigious awards in the field of digital communication with its successful social media strategy. Maersk's social media campaigns focused on increasing public engagement rather than direct sales (Dong, 2015).

Social media can also be used as a communication tool to support sales, recruitment, job seeking, and provide product information (Andersson and Wikström, 2017). For example, Maersk Line has taken into consideration four areas in determining its social media strategy; communication, customer service, sales, and internal use. The first objective of the company was to be closer to its customers

through social media. They emphasized brand awareness rather than direct sales. However, over time, they have seen that social media can be used to make sales (Katona and Sarvary, 2014).

2.4. SOCIAL MEDIA ENGAGEMENT

Engagement can simply be described as “a user-initiated action” (Gluck, 2013: 8). The concept of engagement has been studied in many areas, such as psychology (Hallberg and Schaufeli, 2006), education (Kahu, 2013) and management (Saks, 2006). In the field of marketing, customer engagement with the brand came to the fore (Hollebeek, 2011). Accordingly, customers engage with a company or brand through multiple communication channels and service encounters such as communication with staff and physical store visits (Dolan et al., 2016: 265).

In literature, there is various models have been proposed for the level of social media engagement. These models differ according to the communication goals and management strategies of the organizations (Heldman et al., 2013: 6). For example, engagement can be seen as the level of direct messaging with the customers for one business, while for another business, it may represent to what extent the social media message reaches the audience. In this study, the subject of engagement is approached within the framework of the interaction of individuals with social media contents.

Engagement is considered by digital marketers as the most important metric for measuring social media success. 80% of digital marketers see social media engagement as one of the top three metrics (others; target audience size (61%) and website traffic (56%)) (Pick, 2016). Therefore engagement seen as the heart of the social media strategy (King, ____ a).

Another importance of engagement is that it is a critical indicator to understand the return of social media investment. For B2B companies, it still seems difficult to measure ROI. According to Webbiquity, a B2B marketing blog, 46% of B2B marketers are not sure whether social media is generating revenue for their business. The results of the research show that only 13% of B2B companies can quantitatively measure the impact of social media (Pick, 2016). Although it is not always possible to

calculate the ROI of social media economically, engagement measures are a very useful tool for understanding the success of digital activities.

In light of this information, it can be said that engagement measurement in social media communication has critical importance. Therefore, in the next section, approaches to measure social media engagement are discussed. Later, social media contents, which are the main determinant of the engagement, are discussed within the theoretical scope. Furthermore, social media engagement is at the focus of this study. LinkedIn engagement is discussed in more detail in the application part of the study.

2.4.1. Engagement Measures of Social Media Communication

Although some researchers have tried to use surveys or laboratory experiments to measure the natural impact of social media shares on followers and fans, such methods do not seem to be effective (Saxton and Waters, 2014). For instance, Paek et al. (2013) measured social media engagement with 13 items on a five-point Likert type scale adapted from Calder et al. (2009). The weakness of this method is that the data to measure social media participation is derived from surveys (Bonsón et al., 2017). Instead, the most effective way to understand the impact of the shares on the public is to interpret social media indicators, such as page views, likes, shares, and comments. In the literature, many methods and formulas have been developed to measure social media interaction in this way.

Bonsón and Ratkai (2013) developed a set of metrics to evaluate engagement on social media platforms. These metrics use three different tools available on Facebook: like, comment, and share (P3, C3, V3). P3 refers to the popularity of a Facebook account's content in terms of the mean number of likes per post. C3 measures the commitment level to the account's content in terms of the number of comments per post. V3 indicates the virality of the content in terms of the mean number of shares per post. The sum of these values measures the overall engagement (E) of the relevant content. Table 8 shows the metrics and formulas used.

Table 8: Categorized Metrics of Social Media Engagement

Category	Label	Formula	Measure
Popularity (P)	P1	Num. of posts liked/total posts	% of posts that have been liked
	P2	Total likes/total posts	Mean num. of likes per post
	P3	$(P2/\text{num. of fans}) \times 1,000$	Mean num. of likes per post per 1,000 fans
Commitment (C)	C1	Num. of posts commented/total posts	% of posts that have been commented on
	C2	Total comments/total posts	Mean num. of comments per post
	C3	$(C2/\text{number of fans}) \times 1,000$	Mean num. of comments per post per 1,000 fans
Virality (V)	V1	Num. of posts shared/ total posts	% of posts that have been shared
	V2	Total shares/total posts	Mean num. of shares per post
	V3	$(V2/\text{num. of fans}) \times 1,000$	Mean num. of shares per post per 1,000 fans
Engagement	E	$P3+C3+V3$	Stakeholder engagement index

Source: Bonsón and Ratkai (2013).

There are different formulations in the literature to calculate the level of engagement of social media messages (Yew et al., 2018; Sağlam, et al., 2016; Vadivu and Neelamalar, 2015; Buhalis and Mamalakis, 2015). However, the basis of these formulas is obtained by dividing the total interaction to the number of followers, as in Bonsón and Ratkai (2013).

2.4.2. Determinants of Engagement of Social Media Communication

This section reviews the literature on public engagement on social media to gain a fuller understanding of previous publications and shed light on future directions for the research community.

Most quantitative studies in the literature evaluate social media engagement in terms of media and/or content type. Luarn et al. (2015) classified Facebook posts as ‘informational’, ‘entertainment’, ‘remuneration’, and ‘social posts’. Similarly Cvijikj and Michahelles (2013) examined Facebook messages under the categories of entertainment, information and Remuneration in their research.

Dektaş-Şakar and Sürücü (2018) are used five main codes to determine the content of Facebook messages. These codes are “celebration; corporate social responsibility; advertisement; industrial information; and combined content”. They are

also are coded Facebook messages by media type as follows “photo; video; link; and combined media”. Combined media includes photos and links together (Dektaş-Şakar and Sürücü, 2018: 9).

North (2015) examined twitter messages according to their purposes in six categories: ‘pure information’, ‘Information with clear PR’, ‘sales or promotion’, ‘customer service’, ‘job recruiting’, and ‘non-informational’. Pure information is about the news that doesn't include the company itself or its product. PR information includes information about the image management of the business. Sales / promotional information is product promotion to create sales. Customer service is a message that worries about users. Finding jobs are messages that offer employment opportunities. Non-informative messages are content that does not have any commercial purpose (good wishes or celebrations, etc.) (North, 2015: 165).

Çalışkan and Esmer (2018) conducted an exploratory study to reveal the content of the social media messages of the ports. They conducted an inductive content analysis to bring out meaningful themes for messages on Facebook, Instagram, Twitter and LinkedIn. As a result of content analysis, they revealed 19 different types of content. Some of these content types; photos and videos of the port, ships, and workers, service information, social responsibility, safety and security issues, investment news, innovative solutions, etc. (Çalışkan and Esmer, 2018: 67).

Swani et al. (2017) categorized social media posts into four main groups; brand cue (corporate or product), message appeal (functional or emotional), selling strategy, and level of information searched. They suggest that B2B and B2C marketers should use different sharing strategies to increase the engagement of their posts (Swani et al., 2017; Swani et al., 2014; Swani et al., 2013).

In this study, the distinction of Swani et al. (2017), which has a more theoretical background in categorizing social media message strategies, was taken into consideration. In the next section, the theoretical structure behind this distinction is detailed. In addition to the message strategy, the media type, message richness and interactivity topics used in the categorization phase are also defined in the light of the literature.

2.4.2.1. Message Strategy

The message strategy has a critical impact on the behavioral engagement of consumers on social media. Businesses aim to engage customers by using various content strategies through social media channels. In this context, the message strategy is a basic issue to be considered before creating content. Especially in B2B markets, social media advertising messages should always be short, clear and open so that most of their customers do not spend much time on social media. For this reason, B2B businesses must prioritize the content of social media communication and identify measures and strategies to effectively conduct and maintain social media accounts (Rizomyliotis et al., 2017b: 82; Guesalaga, 2016: 78).

Companies that are successful in social business intelligence achieve this success by setting a series of strategies and targets. The same applies to the use of social media. Accordingly, when establishing a social media strategy, businesses should first determine what purpose they will use social media. Some of the purposes of social media use of businesses are as follows; brand awareness, customer services, lead generation, recruit new employees, public reaction, educate, monitoring etc. (King, ____ b:24; Krishnan and Rogers, 2014: 39). Each of these objectives requires a unique content strategy. In the following section, these content types are discussed under basic strategies according to their objectives.

2.4.2.1.1. Brand Strategy

Brands convey information to people outside the business that will assist in evaluating the business and its activities. Branding provides businesses with a personality, allowing them to differentiate from other businesses. This can be achieved through emotional engagement with consumers, which is a condition for success, especially in highly competitive markets (Baştuğ et al., 2020: 2).

Traditionally, branding was considered unnecessary in the B2B side (Leek and Christodoulides, 2011: 830), but with the advancement of technology, branding has become increasingly important for B2B businesses. For example, the brand's

information efficiency, risk reduction, value-added and image creation functions are some of the reasons for this importance (Kotler and Pfoertsch, 2006: 2, 8).

Many companies in the modern economy seek to differentiate themselves through their corporate and product brands (Mudambi, 2002). Especially in B2B markets, companies mostly tend to promote their brand at a corporate level (Turley and Kelley, 1997). Corporate branding is basically about communicating with the firm's core values and acting accordingly. Companies are separated from competitors by creating trust and preference with corporate branding (Mäläskä and Nadeem, 2012: 31). The product brand, on the other hand, represents the efforts by which the business highlights its tangible assets.

B2B marketers focus on corporate brand (eg IBM, Intel) rather than product brand (eg Downy, Dove, Nutella). Corporate name branding activities, generally following an umbrella branding approach, the names of all products pass under the corporate brand name (Swani, 2014: 20).

Businesses can, for example on LinkedIn, create a brand page and provide consumers with ongoing information and content about the business itself or its products. This reveals the social media marketing phenomenon, which is the digital transformation of marketing communication (Cvijikj and Michahelles, 2013: 843). In social media communication, businesses share content by creating brand communities to strengthen their brands; their followers can interact by liking these contents (De Vries et al. 2012).

2.4.2.1.2. Message Appeal

The most critical element of creating an social media message is the decision to use a functional appeal (rational) or an emotional appeal. Emotional content expresses themes such as attraction, fear, humor, romance, game/competition. Functional messages, on the other hand, represent product features and quality, performance, economic signs, comfort, ease of use, profitability and other more concrete features (Swani, 2014: 21, 22).

Emotional values can significantly affect industrial buying decisions (Andersson et al., 2013). Especially entertainment posts often aim to have a positive impact on the user (De Vries et al., 2012) without referring to the relevant brand or

product (Luarn et al., 2015). Cvijikj and Michahelles (2013) found that entertaining messages cause more likes, comments and sharing levels compared to informative contents.

Remuneration, as a social media-specific motivator, refers to rewards and economic incentives (e.g. money, prizes) to increase interaction with people (Men and Tsai, 2013; Muntinga et al., 2011). Social posts include question and statement type shares to increase the level of interaction with users (Luarn et al., 2015; Muntinga et al., 2011). These posts offer users the opportunity to respond, and through this type of bilateral communication, companies can achieve value in many subjects.

However, in B2B markets, companies more widely using functional (rational) appeal messages (Turley and Kelley, 1997). The organizational buying process is quite complex and involves comprehensive problem solving (Brown et al. 2011: 196). The information available in the environment allows B2B buyers to accurately identify the best alternative (Keller and Staelin, 1987). In this context, it can be said that functional messages are critical in B2B social media communication.

2.4.2.1.3. Direct selling strategy

B2B companies have the opportunity to turn a simple user into a fan or loyal customer by using advantage of direct communication on social media. In addition to bringing customers closer to the brand, social media can increase their sales by using special discounts, offers, and even direct sales channels (Tsimonis and Dimitriadis, 2014: 338). Social media usage has positive impacts on the sales process and sales performance in the B2B context (Rodriguez et al. 2012). However, there are doubts about sending direct sales messages.

Direct calls to purchase (hard sell) means to “explicit commercialism encouraging prospective customers to make an immediate purchase” (Swani, 2014: 24). Although sales promotions are an important message strategy in the literature, major global brands are not very interested (Tafesse and Wien, 2018: 251). Because B2B markets are made up of knowledgeable, professional buyers. That's why B2B transactions usually take a long time. The marketing communication process should

be well planned because a purchase may take months or more to complete (Rizomyliotis et al., 2017b: 6).

When B2B buyers perceive that a company is using its social media channel for aggressive sales purposes, their concern in the site is likely to fall to the point where they may never back (Spekman and Dotson 2009). This is due to the longer purchasing cycles and meticulousness involved in processing the complicated information that buyers are looking for when making purchase decisions. Therefore, B2B buyers are reluctant to respond directly to calls to purchase (Swani, 2014: 24).

2.4.2.1.4. Information Strategy

Information-based posts provide information about brands, products or events to enable customers to make better choices (Muntinga et al., 2011). The ability of a message to provide information to viewers significantly affects the acceptance of the message. Also, one of the most important reasons for consumers to use the internet is the need to access information. On the other hand, seeking information on a topic is one of the main satisfaction of consumers joining online communities. Consumers' desire to receive information directly from brands is a motivating factor in their use of social media (Dolan et al., 2016: 263).

Nowadays, many B2B companies are in the process of balancing marketing communications between printed and electronic media. Because B2B buyers are less reliant on trade fairs, catalogues, commercial publications or intermediaries for information. This shift is changing the role of salespersons and sales channels in customer decision-making and buying behavior (Wiersema, 2013: 476).

According to data in the official blog of LinkedIn, the types of content LinkedIn members are most interested in are industry trends and news. Moreover, the most important reason why they engage with the contents is their educational and informative features (O'Connor, 2017).

Swani et al. (2014) reported that B2B companies use informative shares more frequently than commercial selling shares. Because B2B buyers tend to be experts in their field, and they engage in more analysis during the purchasing process. The informative message strategy presents real information about products and services in

clear and concrete terms. It provides consumers with information on how to solve the functional problems of products and services or how they can meet their functional needs that are not met (Tafesse and Wien, 2018: 244). Therefore, B2B buyers see technical information from the manufacturer as an important part of the purchasing process. That's why B2B businesses tend to provide relevant information through a variety of sources to make it easier for potential buyers to make an informed purchase decision. Today, B2B buyers have just begun to realize the value of the internet communication and especially social media as a new way of information (Swani, 2014: 25, 26).

2.4.2.2. Media Type

Another popular way to categorize social media shares is the type of media, such as photos, videos, status update, or link. Media type influences the vividness, richness, and interaction of the online content at various levels (Coyle and Thorson, 2001). The media types of shares are also highly variable. For example, some shares provide informational photo about products and brands (Cvijikj and Michahelles, 2013) while others can be funny videos and anecdotes to gain attention (Luarn et al., 2015).

In the literature, there is no clear view of the relationship between media type and engagement rate. For instance, Tafesse and Wien (2018) found that text and photos type contents generated a higher level of engagement than both text and video type messages. Denктаş-Şakar and Sürücü (2018) found that Facebook photos provide a higher level of engagement compared to videos and texts type posts. Kim et al. (2015) stated that photos generate more consumer responses than text-based posts and photos perform better than videos. On the other hand, they have been found that video posts produce better consumer responses than text messages. Su et al. (2014) found that photo messages are more likely to be reshared by followers than non-photo posts. Cvijikj and Michahelles (2013) reported that photos and status posts received higher engagement than videos and links. Despite contradictory results, most of the findings support that a post's vividness or media type directly affects the level of engagement (Sürücü-Balci et al. 2020: 4).

2.4.2.3. Message Richness

In social media communication, it is possible to examine the richness of the messages in various dimensions. In this study, the richness of the message was handled within the scope of the hyperlink usage, the number of hashtags, the reshare status and the number of words.

The first clue about the richness of the message is the use of hashtags and the amount of use. Hashtag is a new form of communication that associates a user-generated tag with an event or context using the "#" symbol. It is possible to combine internet resources across websites with shared hashtags (Chang, 2010: 1).

In literature, it is stated in the messages that the presence of hashtags is generally good indicators of high engagement levels (Naveed et al., 2011; Suh et al., 2010). The use of a hashtag in social media messages is important for various reasons. For example, it helps to identify which types of messages echo among the targeted audiences. Thus, it can be determined which topics provide more interest and interaction. Thus, key messages can be repeated to engagement in future messages (Saxon, 2015: 21). Moreover, it is easier to reach users who are curious about a particular subject through hashtag channels. In addition, the patient monitoring method may be useful in detecting issues that have negative reactions on social media channels.

Reshare is seen as an act of copying or rebroadcasting. Reshare brings new people back to a specific topic and invites them to this topic without addressing directly (Boyd et al., 2010: 1). The applicability of resharing activity differs according to social media platforms. The most popular reshare channel is Twitter. On Twitter, the name of this action is referred to as "retweet". On Facebook and LinkedIn platforms, the messages can be republished via the "share" button.

The number of links in the message is called the referral count. In literature, it is stated that link usage has a positive effect on engagement (Saxton et al., 2015; Naveed et al., 2011; Suh et al., 2010) but the use of a large number of references causes low engagement (Rowe and Alani, 2014).

The number of words can be handled within the context of message complexity. Daft and Lengel (1986) examined the impact of large amounts of

information on communication efficiency. He stated that the analyzability and variety of information is a key factor in determining the appropriateness of the message. Analyzability represents the complexity or level of information of the message. Variety is about the existence of unexpected and novel events in the message. Messages with a small amount of information and low variety are easy to analyze, but the structure of the message is weak and insignificant. Messages that contain large amounts of information and have a high variety are very difficult and complex messages to analyze (Daft and Lengel, 1986: 563). Accordingly, it can be assumed that the number of words representing the amount of information affects the complexity of the message and consequently has a significant impact on social media engagement.

2.4.2.4. Interactivity

In the literature, debates have been conducted for the definition and measurement of interaction for many years (Ariel and Avidar, 2015; Kioussis, 2002; Schultz, 2000; Jensen, 1998; Moore, 1989; Rafaeli, 1988). The concept of interactivity is difficult to define because interactivity concerns not an only human conversation but also human-computer interaction mediated by hardware and software. Nevertheless, to summarize simply, interactivity is any form of communication between two or more parties (North, 2015: 21, 22).

The interactive message strategy has a feature that does not work in traditional advertising with its two-way nature (Berthon et al., 2012), but enables businesses to talk to their customers one-on-one through the possibilities of social media (Tafesse and Wien, 2018: 244).

There are two main views on interaction in the literature; functional approach and contingency approach. The functional approach states that interaction affects three factors; the speed at which the contents can be manipulated, the range of paths at which the contents can be manipulated, and mapping (Li and Li, 2014: 652).

The contingency approach reveals a message-based perception of interactivity (Li and Li, 2014: 652). According to this approach, participants are looking for ways to transfer information to each other in a communication environment (Kelleher,

2009). Rafaeli (1988) proposed an interactivity model that examines interaction under three headings. Accordingly, communication includes non-reactive, reactive and interactive responses. Non-interactive message, the first message type of the model, there is a one-way message between the sender and the receivers. Reactive messages are two-way, that is, receivers also become sender status and reacts to the previous messages. In the third type, interactive messaging, both parties (the sender and the receiver) are exposed to a two-way message flow. That is, the sender responds to the reply after receiving a reply to his message (Ariel and Avidar, 2015; Rafaeli, 1988: 119). The literature agrees that the high level of interactivity affects the engagement of the message positively (Blasco-Arcas et al., 2013; Chu and Kim, 2011; Wu, 2005; Teo et al. 2003; Rafaeli, 1988).

Interactivity is also discussed in Figure 18 under the social media communication model. Accordingly, level I represents non-active communication between marketer and receiver. Level II corresponds to reactive communication, including the response of the receiver. For the LinkedIn platform, this response can be either reaction or comment. Level III is the message of the business that responded to the receiver's response.

CHAPTER THREE

CLASSIFICATION AND REGRESSION MODELS IN MACHINE LEARNING

There is a close relationship between machine learning and data mining. While machine learning, which is a sub-branch of artificial intelligence, is concerned with data education and modeling and analysis, data mining involves the process of discovering significant correlations and trends by eliminating large-scale data. This also applies to the classification and regression models that are the subject of the research. Classification and regression models use machine learning methods and data mining processes to make predictions through data.

In the classification and regression models, which are also seen as a predictive model in data mining, the data are subdivided into prediction processes. As the name implies, these models are divided into two types according to the state of the dependent variable to be estimated. If the value to be estimated is a nominal variable, classification models are used, and if it is a continuous or ordered value, regression estimation models are used. In this part of the study, firstly, the subject of machine learning and data mining is summarized. Then, classification and regression models under the machine learning and data mining models were examined. Within the scope of the study, decision trees, one of the classification and regression models, are discussed and the C&RT and CHAID models used in this study are detailed.

3.1. DATA MINING

Data mining can be defined as “the process of discovering meaningful patterns and rules from large amounts of data”. In this discovery process, useful and valuable information is created by combining techniques in machine learning, statistics and databases. The technology behind the data mining process (neural networks, decision trees, genetic algorithms and visual techniques) is in constant development (Çalış et al., 2014: 3).

There are diverse definitions of data mining in the literature. For example, Jacobs (1999) defined data mining as a data analysis process that extracts information that raw data alone cannot provide. According to Larose (2005), data mining is the

process of discovering significant new correlations, patterns, and trends by eliminating large amounts of data stuck in storage environments by using statistical and mathematical techniques and pattern recognition technologies. According to another definition, data mining is the work of linking and using meaningful data from databases where a large amount of information is stored, which will enable future predictions in line with the purpose (Savaş et al., 2012: 4).

Data mining is used effectively in many different sectors. For example, marketing (Domingos, 2005; Barbier and Liu, 2011), which is the subject of this study, finance (Albashrawi and Lowell, 2016), banking (Hassani et al., 2018), sports (Bunker and Thabtah, 2019), health (Serrano et al., 2016) and economics (Helbing and Baliaetti, 2011) are some of the areas where data mining is widely used. As can be seen from the subject titles of the referenced studies, data mining is generally a very useful method for detecting abnormalities and frauds in the related areas.

The steps followed during the data mining process are usually as follows; (Shearer, 2000: 14):

1. Problem identification,
2. Preparation of the data,
3. Development and evaluation of the model,
4. Using the model,
5. Model monitoring.

Figure 19 visualize the stages of design and development of typical data mining processes. The arrows in Figure 19 show the most substantial and frequent dependencies between the phases. The outer circles symbolize the circular nature of data mining itself. The cycle also states that lessons learned from the solution can trigger new business questions (Shearer, 2000: 14).



Figure 19: Stages of Design and Development of Data Mining Processes

Source: Atkinson et al. (2008: 5).

The stage of defining the problem involved in the data mining process includes for what purpose the project will be done and how to measure the success levels of the results. In order to prevent problems that may arise during the establishment of the model, the data should be rearranged, that is, the data should be made ready for the model. The preparation of the data consists of "collection", "*appraisal*", "*assembly and cleaning*", "*sample selection*" and "*conversion*" stages. On the other hand, in order to find the most suitable model for the problem described, it is necessary to try and install as many models as possible. Data preparation and model building stages are a repetitive and monitored process until the model, which is thought to be the best, is reached (Savaş et al., 2012: 8).

3.1.1. Data Mining Methods

Many techniques and methods are used in data mining. Which method is used in research depends on the definition of the problem and the structure of the data. For this reason, there is no such thing as the best model, the most successful algorithm or

technique in data mining (Saygılı 2013: 22). The success of estimating and describing algorithms and methods depends on the subject of the research.

Data mining is divided into two as descriptive and predictive models. However, some methods may have both descriptive and predictive features. In estimation models, it is about establishing a model by using known data and estimating unknown data from this model. Descriptive models, on the other hand, aim to provide information from the available data that can be used in strategy development and decision-making processes. Descriptive models are mostly used to reveal hidden relationships between data (Akman et al., 2011: 37).

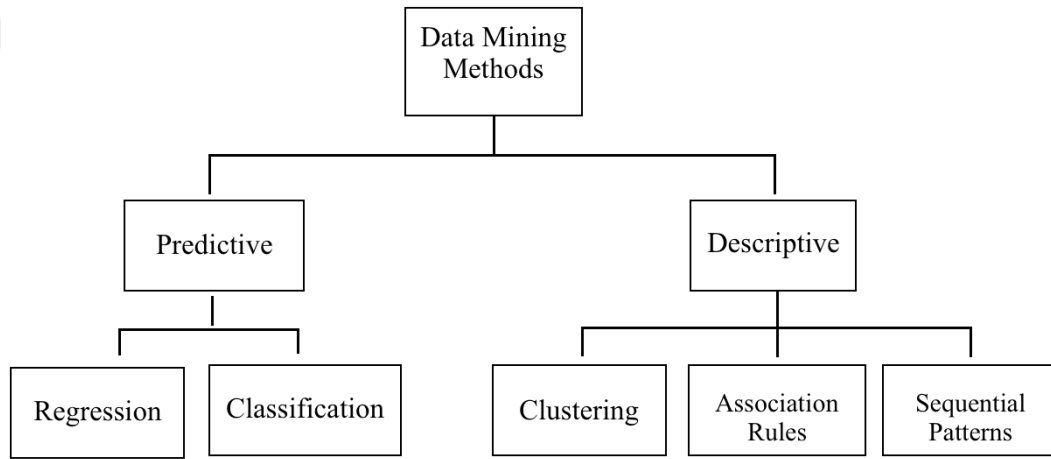


Figure 20: Descriptive and Predictive Technics is Data Mining

On the other hand, data mining models are grouped under three main headings according to their functions. These are (Akpınar, 2000: 5);

- Classification and Regression Models,
- Clustering Models and
- Association Rules and Sequential Patterns

As seen on Figure 20, classification and regression models are predictive, on the other hand clustering, association rules and sequential-time pattern models are descriptive models (Akpınar, 2000: 5). Since the purpose of this study is prediction, the classification and regression models will be detailed in the further section

3.2. MACHINE LEARNING

Machine learning theory is an important sub-branch of both artificial intelligence and statistical science. The origin of machine learning can go back to the beginning of artificial neural networks and artificial intelligence research in the 1950s. The oldest definition in the literature was made by A. L. Samuel, one of the pioneers of computer games and artificial intelligence (Michie, 1968: 19). Samuel (1959) defines machine learning as a “field of study that gives computers the ability to learn without being explicitly programmed” (Tandon and Tandon, 2018: 939). However, this definition is misleading because the algorithms themselves adapt not in the learning process but in the function they are encoded. In other words, this is achieved by a series of educational data of the input-output relationship of a computer program (Schuld et al., 2015: 173). More specifically, machine learning is (Robert, 2014: 62);

“a set of methods that can automatically detect patterns in data, and then use the uncovered patterns to predict future data, or to perform other kinds of decision making under uncertainty (such as planning how to collect more data!”

In general, what computers do in machine learning is learning from the natural experience of humans and animals. Machine learning uses computational techniques that “learn” directly from the data without using a predetermined equation model. The data used in machine learning consists of a number of variables (features) (Baruaa, et al., 2020: 2).

The main purpose of machine learning is to increase the level of automation by mechanizing the information obtained from the experiences and thus to replace the manpower which is more inefficient in terms of time (Jackson 2002: 272). However, such methods have become more important nowadays because computers are increasingly interacting with humans. For example, the spam mail filter used in e-mail technology is a machine result that learns from user behavior and external databases. This machine is just one of the different situations where learning affects humans'

everyday lives (Schuld et al., 2015: 173). The most common examples of machine learning in human's daily life are as follows (Çatak, 2014: 26);

- Displaying the results related to this search criterion after entering the search term in search engines (Google and LinkedIn Search Engine)
- Cross-marketing by examining the buying behavior of customers (Amazon and Netflix)
- Automatic document translation processes; foreign language translation processes such as Google translate.
- Face recognition and voice recognition operations can be performed with algorithms used in the image and sound classification and robotics (New generation smartphones and Siri).

Machine learning not only provides new tools but also offers a way to solve a different problem. Machine learning (supervised) revolves around the problem of estimation: generate a prediction of from X. The attractive point of machine learning is that it manages to come up with generalizable forms. In fact, the greatest ability of machine learning stems from its success to discover a complex structure that was not mentioned before (Mullainathan and Spiess, 2017: 87, 88).

Machine learning can be used for predictive purposes in traditional data sets as well as in big data, that is, machine learning model can be used for both low and high size data (Mullainathan and Spiess, 2017: 89). But in IoT (Internet of The Things) scenarios, supervised machine learning can be difficult to implement. IoT devices are inadequate in terms of computing in the processing of the comprehensive data set for learning in a dynamic environment (Sharma and Wang, 2019: 26).

In the next section, an overview of machine learning models is presented. In the literature, there is a wide range of work-related to machine learning methods. Considering the focus of this study, the most basic ideas of machine learning methods are defined. However, these comprehensive machine learning models in the literature have been developed from the basic models discussed in the next section.

3.2.1. Machine Learning Methods

In the theory of machine learning, the method of learning can be examined in three different categories: supervised learning, unsupervised learning and reinforcement learning methods (Baruaa, et al., 2020: 2). The supervised learning method has the purpose of creating an output that has been previously observed and mapped out using known data. In the unsupervised learning method, it is aimed to find the hidden structure in the data without any label and make an association. In other words, it is aimed to reveal the connections that exist between the data, but not visible (Nalçakan et al., 2015: 2). In reinforcement learning, a reward is given to the system if a correct result occurs. Likewise, it gives a penalty for wrong results (Bilgin, 2018: 20). Reinforcement learning techniques enables a number of agents to interact with the environment and includes an environment of states (Sharma and Wang, 2019: 27).

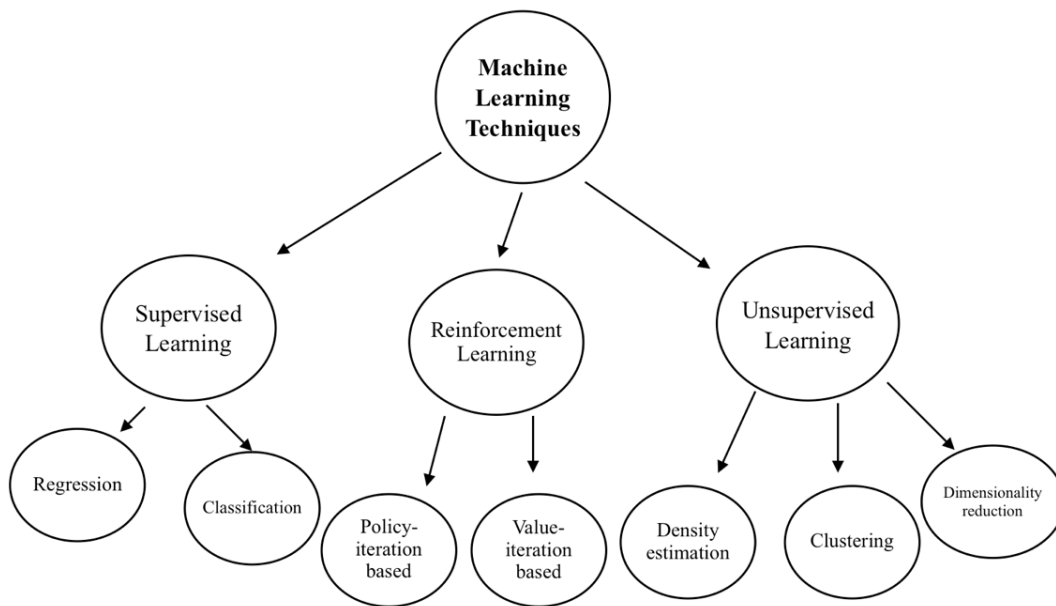


Figure 21: Classification of Machine Learning Methods

Source: Adapted from Sharma and Wang (2019: 26).

As can be seen in Figure 21, there are subgroups under each machine learning techniques. These sub-groups list the models that can be used according to the aim of

the research and the type of variable under the relevant learning category. All of these machine learning techniques are briefly mentioned in the next section.

3.2.1.1. Supervised Learning

In supervised learning, which is also the subject of this study, the data trained with the help of an algorithm is controlled by test data. Supervised machine learning focuses primarily on prediction and is addressed in two subgroups as regression and classification. Regression is controlled learning used for the prediction of quantitative variables. Classification is a type of supervised learning related to modeling and prediction of qualitative variables (Akay, 2018: 46).

In this system, the data to be used for training are pre-labeled. In other words, the data to be used in the analysis process and the classes (categories) belonging to the data are pre-determined. The system learns this labeled data and interprets it with test data. Supervised learning is widely used in many areas such as handwriting definition and visual classification (Pariltay, 2019: 9). The prediction process is based on the majority label for the classification model and the average label for the regression model (Baruaa, et al., 2020: 2).

Some of the classification and regression algorithms are Decision Trees, Naive Bayes, Artificial Neural Network, Support Vector Machine and k-Nearest Neighbor (k-NN) algorithms (Akpınar, 2000: 6). These algorithms are summarized in the following sections under classification and regression models.

3.2.1.2. Unsupervised Learning

In machine learning based on unsupervised learning, algorithms aim to reveal functions using the unlabeled data set. These algorithms reveal hidden patterns on the data. The data set used does not have a target variable and therefore there is no error or model selection assessment (Çatak, 2014: 31).

In unsupervised learning, the most common techniques are Basic Component Analysis (PCA) and Clustering. PCA is a dimensional reduction technique that converts a number of correlated variables into fewer uncorrelated components. PCA

can be used to extract or synthesize the properties of the data. It can also be used in both exploratory and predictive data analysis. Clustering, on the other hand, divides the dataset into groups (sets) (Baruaa, et al., 2020: 2, 3). The aim of the clustering method is to combine the samples generated by the same distributions (Ryabko, 2019: 29). In this method, while the data is divided into clusters, the distances between them are measured by techniques such as Euclidean distance, Pearson distance, and Spearsman sequence correlation.

3.2.1.3. Reinforcement Learning

The reinforcement learning process is to approach the most appropriate action-value function within the framework of a series of rewards/penalties, making use of past experiences. The aim here is to choose actions in a way that will maximize the next cumulative reward (Mnih et al., 2015: 529). Unlike supervised learning, there is no reply in reinforcement learning. In lieu, the agent decides what to do to perform a specific task. The most common reinforcement learning methods include Q-Learning, state-action-reward-state-action (SARSA) and deep Q networks (DQNs) algorithms (Baruaa, et al., 2020: 3).

3.2.2. Relationship Between Machine Learning and Data Mining

Data mining enables the retrieval of confidential information within database systems that contain large datasets. These operations are performed by combining many disciplines such as statistics, mathematics, data technology base and modeling techniques (Saygılı 2013: 18). Therefore, data mining is seen as an interdisciplinary field. As can be seen in Figure 22, main disciplines that data mining relates to include machine learning, databases, statistics and visualization (Gahegan and Brodaric, 2002: 2, Mehra et al., 2015: 37).

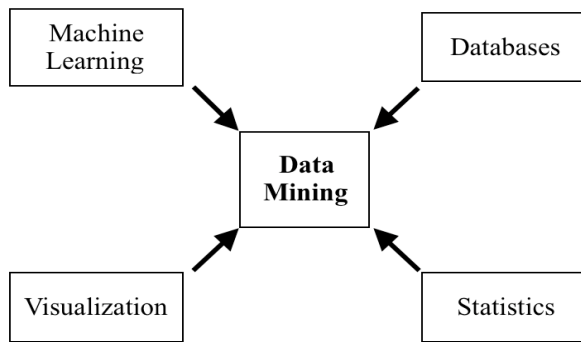


Figure 22: Disciplines Related to Data Mining

Since this study focuses on decision trees within the framework of machine learning, which data mining is related to, these all disciplines mentioned will not be detailed in this study. However, different disciplinary perspectives on data mining and information discovery activities summarized by Gahegan and Brodaric (2002) are presented in Table 9.

Table 9: Summary of Different Discipline Perspectives in Relation to Data Mining

	Databases	Statistics	Machine learning	Visualization
Finding	Association rules	Analysis of local pattern and global inferential tests	Neural networks and trees	Exploratory visualization and visual mining
Reporting	Lists of rules	Summary statistics, power and significance	Likelihood estimation, information gain	A stimulus in visual domain
Representing	Schema update, metadata	Fitted statistical techniques, local or global	Graphs, functions and rules	Shared between the scene and the observer
Validating	Weak significance testing	Statistical significance tests	Learning with validation	Human subjects testing
Optimizing	Decreasing computational complexity	Data reduction and stratified sampling strategies	Stochastic searches and gradient ascent techniques	Hierarchical models and adaptive techniques, grand tours

Source: Gahegan and Brodaric (2002: 2)

On the other hand, machine learning and statistics are seen as the most important areas where data mining is concentrated. In particular, the methods involved in machine learning form the core of the methods used in data mining algorithms. These two disciplines aim to determine the patterns between the data (Saygılı 2013: 18).

Machine learning aims to solve the target problem by developing algorithms and techniques that computers are easy to learn. It does not aim to work on a specific data set in this process. Data mining, on the other hand, works for identification, classification, prediction or clustering on “real” data using machine learning methods. In machine learning statistical analysis, it can be used in researches without any modeling. In this way, models specific to certain situations can be introduced instead of just data-specific results. Data mining, on the other hand, can be used for researches with its own ready and controlled databases (Coşgun and Karaağaoğlu, 2010: 162).

3.3. CLASSIFICATION AND REGRESSION MODELS

Regression and classification models, previously mentioned in Figure 20 and Figure 21, are under the prediction models in data mining and supervised learning models in machine learning. In this study, the classification and regression models under the machine learning method and data mining process are focused on. For this reason, in this part of the study, the basic functioning of the classification and regression models and the algorithms used are discussed.

The main distinction between classification and regression models is that the predicted dependent variable has a categorical or continuous value. However, with the techniques that allow for predicting categorical values such as multinomial logistic regression, both models are getting closer to each other and it is possible to use the same techniques as a result (Akpınar, 2000: 6). The main learning algorithms used in classification and regression models under the supervised learning techniques are as follows (Sharma and Wang, 2019: 26);

- Artificial Neural Networks,
- Support Vector Machine
- K-Nearest Neighbor

- Naive Bayesian Classifier
- Decision Trees

K-Nearest Neighbors (kNN) algorithm is a non-parameter learning algorithm for classification and regression. In this algorithm, when a new data point x comes in, k data points closest to x are defined in the training data. Support Vector Machine (SVM) is established on statistical learning theory and has the ability to locate decision boundaries, allowing optimal separation of classes (Pal and Mather, 2005: 1007).

Another prediction algorithm artificial neural networks (ANNs) are non-linear mapping structures that emulate the function of the human brain. ANNs are seen to be a highly flexible and universal prediction function for any data set (Lek and Guégan, 1999: 65). Neural networks have the ability to optimize the relationship between inputs and outputs through distributed computing, training, and processing. Moreover, ANNs are capable of training rather complex models when large amounts of data are provided (Jiang et al., 2010: 617).

Naive Bayes algorithm is a method that aims to predict the probability of future events using data from past events (Boschetti and Massaron, 2016: 206). Naive Bayes algorithm, which is based on Bayes theory and is used mostly in text classification, aims to predict the probability of future events by using data from past events. This technique, the basis of which was developed by the 18th-century mathematician Thomas Bayes, introduced the probability of occurrence of events and how these possibilities should be reviewed with the information added (Bulut, 2019: 44).

And finally, decision trees are a tree-shaped decision algorithm, whose classes are learned by using the inductive method from sample data (Sun and Li, 2008: 2). The decision tree algorithms under regression and classification models are the focus of this study. In the following sections, decision trees algorithms are discussed in more detail.

3.4. DECISION TREES AND LEARNING ALGORITHMS

Decision trees were proposed by Breiman and Friedman in 1973 and are based on creating a tree by grouping the variables. Decision trees are a tree-formed decision

structure type whose classes are learned by means of the inductive method from the known data (Sun and Li, 2008: 2). Decision trees proceed by “applying simple decision-making steps, dividing large amounts of records into very small groups of records”. With these division operations, the members of the result units become much more akin to each other (Dondurmaci, 2011:46).

Decision trees emerging as a finding of machine learning (Gahegan and Brodaric, 2002: 2), as the name suggests, is a predictive technique with a tree appearance. With its tree structure, it is one of the most popular prediction techniques that can create rules that are easy to understand and can easily be integrated with information technology processes (Ozekes, 2003: 68). Decision trees are widely used in classification and regression models because they are (Çalış et al., 2014: 3; Özgür ve Erdem, 2012: 43);

- low cost in data mining,
- easy to understand and interpret the out comes,
- easily integrated to the databases
- more comfortable to visualize the results and,
- reliable

Decision tree models are a useful tool that predicts or classifies future observations according to a set of decision rules. Decision trees serve to create new classifications with maximum accuracy by establishing rules with pre-tagged data (eg voters against non-voters, or bacterial species). The decision tree uses the if-then algorithm to make this process more understandable. With learning algorithms, it is possible to classify according to people's age and other characteristics according to credit risk or purchasing status (IBM Knowledge Center, ____f). Decision tree models perform the prediction process by dividing the data set into sub-categories. As a result, partitioning is graphically represented as a decision tree (Loh, 2011: 14). Figure 23 visualize a simple decision tree model for buying a new car.

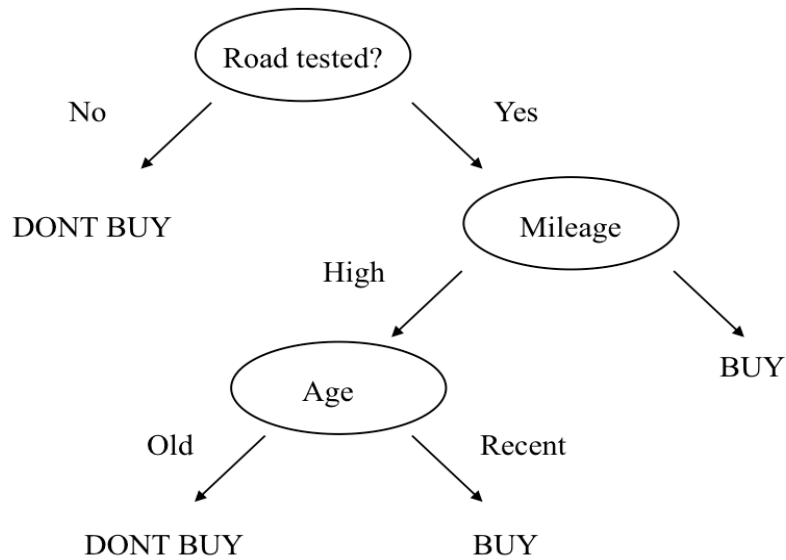


Figure 23: A Simple Decision to Buy a Car

Source: IBM Knowledge Center (____f).

Accordingly, the car purchasing algorithm can be coded as follows (IBM Knowledge Center, ____f).

IF tested = 'yes' AND mileage = 'low' THEN-> 'BUY'.

The most important step in the formation of the land tree structure is to determine the criteria according to which the branching will be done. There are several approaches to this in the literature. The most important of these are knowledge gain and knowledge gain rate (Quinlan, 1993), Gini index (Breiman et al., 1984), Twoing rule (Breiman et al., 1984) and Chi – Square probability table statistics (Mingers, 1989) approaches (Kavzoğlu et al., 2012: 26).

The classification and regression tree not only investigates the structure of the relation between the dependent and independent variables; it also helps to understand the interaction of independent variables with each other (Kayri and Boysan, 2008: 169). Decision trees can be seen as segmenting the original dataset. Segmentation of customers, products and sales areas is widely used in marketing (Ozgulbas and Koyuncugil, 2006: 330). There are also studies in the literature on the segmentation of maritime transport markets (Balci and Cetin, 2017).

Classification (such as logistic regression and cluster analysis) and regression models are used extensively in the analysis of scientific research data. However, such models require some assumptions (normal distribution eg) and limit the possibilities of statistical analysis in many areas. Decision trees, which do not require any assumptions on the research data set, are a powerful alternative to such statistical classification and regression techniques (Saitoğlu, 2015: 56, 57) such as regression, logistics regression and discriminant analysis. Decision trees are also unaffected by outliers, heteroscedasticity, collinearities, or distributional errors that affect the parametric analysis. Outliers are split into one node and have no effect on the split (Yohannes and Hoddinott, 1999: 11).

Classification trees are used for arguments with categorical variable properties, while prediction error is measured with incorrect classification cost. Regression trees are used for dependent variables with continuous or ordered discrete values. In regression trees, the prediction error is calculated by the squared difference between observed and predicted values (Loh, 2011: 14). Accordingly, the Classification and Regression Decision Tree method should be examined under two subtitles according to the type of dependent variable; Classification Trees and Regression Trees. In the next section, the working principles of classification and regression trees are detailed. Then, an overview of learning algorithms in decision trees is given and learning algorithms used in regression trees are detailed.

3.4.1. Classification Trees

Classification Trees are non-parametric statistical method to estimate the values of categorical dependent variables and they do not require any assumptions of distribution of independent variables. Dependent variables can be categorical, interval or continuous (Yohannes and Hoddinott, 1999: 10, 11). In addition, since the results of the analysis are presented visually, they can be easily interpreted without the need for much statistical information. Due to such advantages, classification trees is seen as a powerful alternative to many statistical methods such as multiple regression, logistic regression, discriminant and cluster analysis (Küçükoğlu, 2010: 5).

In a classification tree model, there is a training sample of n observation on a categorical variable that takes the prediction variables ($X_1, \dots, X_p$). Main purpose is to determine a model to estimate Y values from new X values. Theoretically, the solution is a division of the X space into k discrete sets, $A_1, A_2, \dots, A_k$, so that if X belongs to A_j , for $j = 1, 2, \dots, k$, the estimated value of Y is j . If X variables take ordered values, differential analysis and the closest neighbor classification are used. These methods give bounds that are not easy to interpret if A_j 's piecewise linear and nonlinear p sets are large (Loh, 2011: 1, 2). The main purpose in classification studies is to produce a correct classifier and to reveal the predictive structure underlying the problem (Breiman, et al., 1993: 21).

The error rate is calculated by dividing the number of events classified incorrectly by the number of events, and the accuracy rate is calculated by dividing the number of events classified correctly by the number of events. So the accuracy rate is equal to subtracting the error rate in one digit (Accuracy rate = 1- error rate) (Küçüköğlu, 2010: 6).

The classification tree is created in three stages. Accordingly, the first step is to create a tree of maximum size. For this, each observation is assigned to a class until the initial data set is divided into the last observation. After creating this maximum-sized tree, the second step is to decide whether the size of the tree is optimal. For this purpose, pruning is carried out. Even though the high-size tree gives a low misclassification rate, when it is applied to a new dataset, it will produce false results and be difficult to interpret. When the size of the tree is too small, it does not contain the information in the initial dataset and results in a high misclassification rate. In the third and last step, after the optimum size tree is created, the tree is used to classify new observations (Saitoğlu, 2015: 56, 57).

The main weakness of this method is that the results are not based on a probabilistic model. That is, in a new data set, there is no probability level or confidence interval for the predictions obtained using the decision tree. The accuracy of the results depends only on historical data (Yohannes and Hoddinott, 1999: 11).

3.4.2. Regression Trees

On the other hand, regression trees have a structure similar to classification trees despite some differences. Dependent variable must be continuous in regression trees (Loh, 2011: 9). Regression tree is preferred due to its advantages such as not requiring any assumptions about the distribution of independent variables and not being affected by events such as multicollinearity, outliers, missing observation. Regression tree method is a nonparametric analysis method that detects the relationship and interaction between dependent and independent variables and separates the population into homogeneous subclasses (Yücel, 2017: 19).

Developing regression trees is simpler than classification trees, and the impurity criteria used for tree growth are also used in tree pruning. In addition, there is no restriction for the regression tree during the creating process. Each observation has equal weight and the impurity criterion used is based on the least squared deviation calculation (Saitoğlu, 2015: 68).

The process of creating regression trees can be summarized in four steps (Küçüköğlu, 2010: 9);

Step 1 starts the analysis with root node, which includes all observations

Step 2 separation is continued until the S value expressed as

$$S = \sum \sum (y_i - m_c)^2 \quad (3.1)$$

is minimum. This expression can also be written as

$$S = \sum n_c V_c \quad (3.2)$$

m_c is also

$$m_c = \sum c Y_i / n_c \quad (3.3)$$

where m_c predictive value for any c branch; V_c , separation variance of c branch; n_c , number of observations in this branch.

If all individuals in *step 3* node get the same values for all the arguments considered, the splitting of the tree is terminated. Otherwise S is lowered to the very last point that can be minimized. If the biggest decrease in S is less than the specified threshold value, the split will be stopped

Step 4 returns to step one for each new node and the continues with identified process.

The regression tree algorithm is based on an aggregation of similar variables into the same tree node, and all of these sub-branches end up connecting to the root node, which is the dependent variable (Breiman et al. 1984). The algorithm of the regression tree basically consists of three processes; tree creation, pruning and selection of the most suitable tree structure. Regression tree algorithms, which are aimed at creating the highest level of homogeneous subtrees, determine the highest number of subtrees that can be created during the tree creation. However, since it is need to select trees that show significant relationships with the dependent variable between subtrees, the pruning function of the algorithm works (Yücel, 2017: 19).

In the regression trees algorithm, induction is performed with a recursive partitioning. The test choice in each node is usually determined by the least-squares error criterion. Preferred split in each node t is the split s that maximizes (Torgo, 1997: 2)

$$\Delta Err(s, t) = Err(t) - P_L \times Err(t_L) - P_R \times Err(t_R) \quad (3.4)$$

In the equation, P_L and P_R denote the proportion of samples falling on the left and right branches of the t node, respectively; $Err(t_L)$ and $Err(t_R)$ are the margins of error of the left and right branches, and $Err(t)$ is the mean square error in the node given by

$$\frac{1}{N_t} = \sum_i^{N_t} (y_i - y_t)^2 \quad (3.5)$$

In tree formation, observations in the child node continue until the same as the independent variable. After getting the same value, the tree formation is completed

and the tree model is interpreted by writing how each data group is distributed (Breiman et al., 1984).

3.4.3. Learning Algorithms in Classification and Regression Trees

Today, new methods and algorithms emerge almost every day, as well as many methods used in data mining. These methods are mostly statistical methods and some of them have been used for many years. Other methods are the new generation methods, which are generally based on statistics, but mostly supported by machine learning and artificial intelligence (Savaş et al., 2012: 9).

The first classification tree algorithm in history is THAID (THeta Automatic Interaction Detection) (Messenger and Mandell, 1972). The THAID algorithm was introduced by Morgon and Messenger in the 1970s for classification purposes. However, before THAID, AID (Automatic Interaction Detection) (Morgan and Sonquist, 1963) algorithm has emerged as the first regression tree (Loh, 2014: 329; Loh, 2011: 9). A decade later after the introduction of the THAID algorithm, Breiman et al. (1984) had introduced a new, sophisticated tree-based algorithm called CART (Classification and Regression Trees) (Gepp and Kumar, 2015: 339) and highly accepted by scientific literature.

There are many other algorithms (eg C4.5, C5.0, CHAID and QUEST) used in decision trees (Çalış et al., 2014: 6). All of these algorithms achieve basically the same; they divide the data into subgroups and examine all areas of the data set to find the best classification or prediction. The process continues recursively and splits the subgroups into smaller units until the tree is finished. Depending on the algorithm used, the target and input fields used in tree construction can be continuous (numerical range) or categorical (IBM Knowledge Center, ____f). Table 10 summarizes the most popular decision tree algorithms in the literature.

Table 10: Decision Tree Algorithms

C&RT	There is a binary split (only two subgroups) operation based on Gini. Target and input fields can be numeric or categoric (ordered, nominal or flags). The method uses recursive partitioning at each step by minimizing the impurity.
CHAID	This algorithm uses chi-square statistics to determine optimal splits. Unlike the CHAID, CART and QUEST creates non-binary trees. So some splits can have more than two branches. In the CHAID algorithm, the target and input fields can be a numerical range (continuous) or categorical. There is also a modification called Exhaustive-CHAID. The Exhaustive CHAID algorithm follows a more comprehensive process to examine all possible splits and takes longer to calculate.
QUEST	QUEST is a scalable classifier used to decrease the processing time required for C&RT analysis. QUEST is faster than other algorithms, but it may not be suitable to run on large data sets due to memory requirement. Input fields can be numerical ranges (continuous), but the target field must be categorical. All splits in this algorithm are binary.
C 4.5 and C 5.0	C5.0 is an improved version of C4.5. They are created by multiple branches emerging from the node. Results can be a decision tree or a set of rules. Use split info or gian info in formula. The data is divided so as to provide maximum information gain at all levels. Pruning is based on the error rate on each leaf. The target variable must be categorical.
SPRINT	SPLIT is more ideal for large datasets. The process of splitting is based on the value of a single attribute. It processes all memory limitations using the attribute list data structure.

Source: Çalış et al., 2014: 7; Sharma and Kumar, 2016: 2095; IBM Knowledge Center, ____f; Statsoft, ____.

The target variable of this study is the engagement rate with continuous data features. Therefore, C&RT and CHAID algorithms which are the subject of continuous variables are used in the learning model of the study. The next section summarizes the operation of the C&RT and CHAID algorithms.

3.4.3.1. The Classification and Regression Algorithm

C&RT (also called CART) was introduced by Breiman et al. (1984) and is a continuation of Morgan and Sonquist's tree algorithm named AID (Automatic Interaction Detection). CART algorithm, which can accept both numeric or categoric (nominal, ordered, or flags) data types as the target variable, can be used as a solution algorithm in classification and regression problems (Çalış et al., 2014: 6).

The C&RT model is a tree-based classification and regression model to predict continuous dependent variable. C&R Tree analysis apply the recursive binary partitioning method to divide training data into segments with similar outputs. It begins by examining the input fields to identify the best distinction with a decrease in the pollution index caused by splits in the C&RT node. The split creates two subgroups (which are then divided into two subgroups) (see Figure 24) and continues this way until the results criteria are triggered. C&RT analysis also offers the option of growing the tree first and then pruning it. The model performs this process using a cost complexity algorithm that adjusts risk estimation based on the number of terminal nodes. This method produces a smaller tree output with better cross-validation capabilities (IBM Knowledge Center, ____d).

While branching occurs in decision trees, various variables play a role. It is very important with which variable to start branching during this formation. Therefore, when creating a decision tree, algorithms must initially calculate some values and continue according to these values (Tapkan et al., 2011: 249). Accordingly, it is one of the first problems that must be solved according to which criteria to branch out in decision trees. For C&RT models, there are four different heterogeneity measures used to find divisions; Gini measure for categorical target variables, Twoing measure for ordinal target variables and The least squared deviation (LSD) for continuous target variables (Oğuzlar, 2010: 84). Since the target variable is continuous in this study, the formula for the least squared deviation (LSD) heterogeneity measure for the continuous target variables is presented below

$$R(t) = \frac{1}{N_w(t)} \sum_{i \in t} w_n \int_n (y_t - y(t))^2 \quad (3.6)$$

The LSD measure $R(t)$ is the simple (weighted) intra-node variance for node t and is equal to the risk estimate for the node. According to formula, $N_w(t)$ shows the number of weighted states in node t , the weighted variable value if w_n is present for state i , the value of the frequency variable if f_n is present, y_1 is the value of the target variable, and $y(t)$ is the weighted average for node t (Oğuzlar, 2010: 84).

C&RT algorithms are quite powerful for missing data and a large number of datasets. Prediction times do not usually require long training time. Moreover, C&RT models are easier to understand than other ones and rules derived from the model can be easily interpreted. Unlike C5.0, C&RT, continuous and categorical target variables can be used (IBM Knowledge Center, ____g). One of the advantages of C&RT analysis is that it features a relatively automated “machine learning” method. In other words, relatively less input is required compared to the complexity of the analysis. This presents a clear contrast to other multivariate modeling methods analysis of intermediate results (Lewis, 2000: 6).

3.4.3.2. Chi-Square Automatic Interaction Detection Algorithm

CHAID was first introduced as a tree classification method by Kass (1980). CHAID is based on the THAID algorithm developed by Morgan and Messenger in 1973 (Kass, 1980: 120).

CHAID is a classification method that creates decision trees using chi-square statistics for optimal splits. The CHAID algorithm splits the file through the first variable and then creates contingency tables for each node to select the second best variable (Haughton and Oulabi, 1997: 44). In the CHAID prediction model, an essential step is to select the relevant features for classification (Ramaswami and Bhaskaran, 2010: 15). Therefore, CHAID algorithm first examines crosstabs between each input and output and tests its importance through the chi-square independence test. If there is more than one statistical significance, CHAID will choose the most significant (smallest p -value which can specify by the user). If there are more than two categories entered, the categories that do not differ are narrowed. Category merging stops when it differs at the test level. Any category can be merged for nominal inputs,

but only contiguous can be merged for an ordered set (IBM Knowledge Center, ____e; Haughton and Oulabi, 1997: 44).

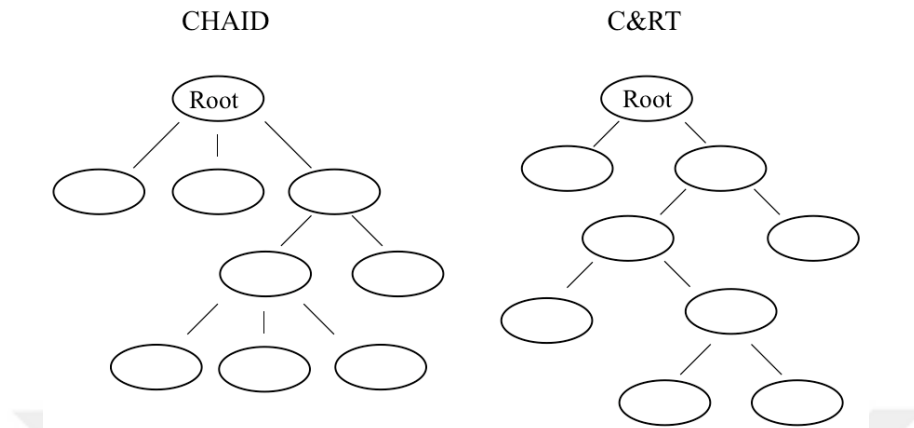


Figure 24: Branching of CHAID and C&R Trees

In CHAID flow, target and input variables can be continuous or categorical, and unlike the C&RT nodes, CHAID generate nonbinary trees that means some splits can be divided into two or more sub-branches (see Figure 24) at each level. In this way, a larger tree is usually generated. Both continuous and categorical arguments can be analyzed but for ordinal variables used in the model must be numeric (not a string) and, if necessary, can be converted with the "Reclassify" node. (IBM Knowledge Center, ____e; Naftulin, and Rebrova, 2010: 652).

In the logistic regression technique used in cases where the dependent variable is categorical (0-1; binary), risk factors (odds ratio) related to the model can also be estimated. In CHAID analysis, this has a higher ability to do, because, in CHAID analysis, independent variables are included in the model according to their most important features, characters with similar features are included in the same homogeneous nodes. Thus, the parameters of the regression equation obtained give more reliable results (Kayri and Boysan, 2007: 140). Furthermore, CHAID analysis is not concerned with lost and extream data but tends to form a separate group from these data. It can be said that the CHAID algorithm, which can divide all data into sub-nodes, has a strong translational algorithm (Sezer, 2019: 12).

CHAPTER FOUR

A MACHINE LEARNING APPLICATION FOR SOCIAL MEDIA COMMUNICATION IN CONTAINER SHIPPING

In this part of the study, the focus is on social media engagement. The researcher primarily aimed to reveal which social media channels container shipping companies use the most. For this purpose, container shipping companies listed in Alphaliner top 30 are included in the research sample. The research continued on the LinkedIn platform, as the review of all social media channels would produce superficial analysis that was unrelated to the research question. However, the biggest challenge encountered at this point has been the data privacy policy of the LinkedIn platform. To collect the dataset, a REST API (Representational State Transfer Application Programming Interface) was developed in LinkedIn on the developer page. At the same time, writing the Python code to be used for extracting the research data has started. The API prepared by the researcher has failed due to the LinkedIn data restriction. When the reason for this was investigated, it was seen that platforms such as Facebook and LinkedIn made dramatic data access restrictions to protect user-information after the Cambridge Analytica scandal (Schroepfer, 2018; Bastos and Walker, 2018). As per the terms of the use of the LinkedIn API (LinkedIn, 2019), it has been seen that the required amount of data cannot be obtained even if permission is obtained from the platform. In this process, although the LinkedIn team was contacted, no results were obtained and alternative methods were evaluated.

In the data collection process, an alternative method was followed by taking into consideration the platform's data privacy policies. For this purpose, only public data of companies on LinkedIn platforms have been used. At this point, the use of data scrapping programs has come to the agenda. However, although the use of such programs is legal (Woollacott, 2019), LinkedIn does not want such third-party software to be used. In such cases, there may be a blocking of the user profile by LinkedIn. In this study, where ethical and legal issues are prioritized, public LinkedIn data was collected manually by the researcher without using any software. Due to LinkedIn's other data restriction policy, only one year of data could be included in the research. In addition to companies' LinkedIn public information, a total of 4067

messages and comments published between November 12, 2018, and November 12, 2019, were recorded by the researcher.

After interpreting the descriptive statistics, engagement rates were calculated to understand the social media success of companies. However, in this section, as determined in the preliminary study of this research, Bitiktas and Tuna (2020), it has been determined that the engagement calculation formula in the literature can no longer work correctly due to the changing algorithms of the platforms. For this purpose, it was aimed to develop a new engagement calculation approach in the study. Accordingly, the current formula assumes a linear relationship between the number of followers of the company and the number of engagement. However, as a result of the analyses, it was determined that this relationship is an exponential relationship. For this, the relationship between the two variables was first determined by curve estimation analysis and a non-linear regression function was developed. Thus, a new calculation method has been proposed to the literature in the research. In this part of the study, an exploratory qualitative research process was carried out by consulting to the experts, who are academicians and practitioners, as well as by conducting the literature review.

In the continuation of the study, a machine learning model was developed to predict high-engaged LinkedIn messages. Regression trees under classification and regression models were the subject of these analyses. The process has continued with the specified steps of the machine learning and data mining literature. The analyzes were carried out using IBM Watson machine learning services. Finally, the research findings are discussed and contributions to theoretical and practical reports are reported.

4.1. METHODOLOGY

4.1.1. Population and Sampling of the Study

Alphaliner ranks the 100 largest container operators worldwide according to their capacities. Alphaliner is one of the most preferred databases of many parties in the maritime sector and its contents are constantly updated (Alphaliner, 2019). For

these reasons, the research was conducted on the social media accounts of the Alphaliner top 30 companies listed on 01.11.2019, which account for 91.7 % of world liner capacity on a TEU basis. The social media accounts were accessed primarily through the container liners' official websites. However, because many companies do not link to their social media accounts with their websites, some official social media accounts were found using the search engines of related platforms and Google search engine.

At this stage, it was determined that companies follow different strategies on their social media accounts regarding brand names. These strategies include using the corporate brand (eg CMA CGM Group), the sub-brand (eg COSCO Shipping Line), or using both the corporate and sub-brand (e.g. ARKAS and ARKAS Line). Priority was given to the social media accounts for the shipping companies' liner services. Accounts that were not verified or created for a particular region or country were excluded. In addition, companies with a social media account that had not shared any content in the year preceding the research date were also excluded.

The sampled container shipping companies were active on many platforms, such as Facebook, Twitter, Instagram, LinkedIn, Youtube, Vimeo, and Google+. In this study, the five most preferred social media channels in B2B markets were highlighted (Statistica, 2019e). As can be seen in Table 11, the most preferred platform for the container shipping companies was LinkedIn. Previous research has also found that LinkedIn is the favorite platform for B2B businesses to reach potential customers, employees, and suppliers (Quinton and Wilson 2016; Andersson and Wikström, 2017; Gruner and Power, 2018). Other preferred social media channels for container shipping companies were Facebook, YouTube, Instagram, and Twitter. Some companies preferred to use channels like Blog, WeChat (especially in Asia), Xing, and Vimeo. However, these channels are not included in the table as they were not prevalent. The most active companies on social media were Maersk, MSC, CMA CGM, Hapag-Lloyd, ONE, Zim, Arkas, SPIL, and Grimaldi liners. Conversely, although some companies had social media accounts, they were not using them actively (e.g. Simatech, RCL). Table 11 also shows the geographical variation in social media usage. For example, Asian companies tend not to use social media.

Table 11: Social Media Accounts of the Top 30 Businesses Listed in Alphaliner (Nov, 2019)

Company	Headquarter	Facebook	Twitter	LinkedIn	Instagram	YouTube
APM-Maersk	Denmark	✓	✓	✓	✓	✓
Mediterranean Shg Co (MSC)	Switzerland	✓	✓	✓	✓	✓
COSCO Group	China	✓	✓	*	-	-
CMA CGM Group	France	✓	✓	✓	✓	✓
Hapag-Lloyd	Germany	✓	✓	✓	✓	✓
Ocean Network Express (ONE)	Singapore	✓	✓	✓	✓	✓
Evergreen Line	Taiwan	*	-	*	-	-
Yang Ming Maritime Trans. Corp.	Taiwan	-	-	*	-	-
Pacific Int. Line	Singapore	✓	-	✓	-	-
Hyundai M.M.	South Korea	✓	✓	✓	-	-
Zim	Israel	✓	✓	✓	✓	✓
Wan Hai Lines	Taiwan	-	-	*	-	-
Zhonggu Logistics Corp.	China	-	-	-	-	-
IRISL Group	Iranian	-	-	*	✓	-
Antong Holdings (QASC)	China	-	-	-	-	-
KMTC	South Korea	-	-	*	-	-
SITC	China	-	-	*	-	-
X-Press Feeders Group	Singapore	-	-	✓	-	-
TS Line	China	-	-	*	-	-
SM Line Corp.	South Korea	-	-	*	-	-
Arkas Line/Emes	Turkey	✓	*	✓	✓	✓
Sinotrans	China	✓	-	*	-	-
Sinokor	South Korea	-	-	*	-	-
RCL (Regional Container L.)	Thailand	*	-	*	-	-
UniFeeder	Denmark	-	-	✓	-	✓
Salam Pacific Indonesia Lines (SPIL)	Indonesia	✓	-	✓	✓	✓
Swire Shipping	Singapore	-	-	✓	-	-
Matson	USA	✓	-	✓	-	*
Grimaldi (Napoli)	Italy	✓	✓	✓	✓	✓
Emirates Shipping Line	United Arab Emirates	-	-	✓	-	-

* No message has been published on the account in the past year.

These container shipping companies were continuously updating their social media usage strategies. For example, Maersk announced a significant change in their social media usage on 14.08.2018 to stop sharing from the social media accounts of its subsidiary companies (e.g. "Maersk Line" and "Maersk Oil"). Instead, it now continues with the main brand name, which is called "Maersk" across all social media channels (Maersk Line, 2018). Understanding the reasons behind Maersk's strategic decision could be another research topic. MSC, which had previously distanced itself from

social media except for LinkedIn, first started to share on its official social media accounts on 27.08.2018 by making a radical decision (MSC, 2018). It announced that it would adopt an innovative method in digital marketing for the shipping sector (MSC, 2015).

As Table 11 shows, the social media usage of container shipping companies have unique features. Given this variety, sampling all these social media channels would be unfeasible and produce superficial analyses irrelevant to the research question. Therefore, LinkedIn was selected for analyzing shipping companies' social media shares. The reasons why LinkedIn was selected as the social media channel in this research are listed as follows;

- Within the scope of the sample, the social media accounts of container shipping companies are mostly on LinkedIn (see Table 11).
- LinkedIn is the most effective platform for B2B markets and shipping companies operate in the B2B market (Bodnar and Cohen, 2011; Schaffer, 2011; LinkedIn, 2020a).
- LinkedIn's leads are almost three times higher than Facebook or Twitter and have the highest visitor-to-lead conversion rate compared to them (Koufopoulos, 2015).
- According to the preliminary study (Bitiktas and Tuna, 2020), LinkedIn is the platform where container shipping service buyers interact the most on social media.

Table 12 presents the companies' market share, total posts, follower numbers, ads status, company size, headquarters and year of foundation.

Table 12: Selected Companies' Market Share and LinkedIn Status

Company Name	TEU Share	LinkedIn Status			Company Specifications			
		Follower	Total Posts	Language	Ads From This Page	Comp. Size	Headquarters	Year of Foundation
A.P. Moller- Maersk	17.8	626,093	219	English	20+	10,001+	Copenhagen	1904
MSC	15.9	279,137	143	English	2	10,001+	Geneva	1970
CMA CGM Group	11.3	322,289	288	English	0	10,001+	Marseille	1978
Hapag-Lloyd	7.3	149,894	215	English	20+	10,001+	Hamburg	1847
ONE	6.7	29,222	183	English	0	10,001+	Singapore	2017
Pacific Int. Line	1.7	5,182	7	English	0	10,001+	Singapore	1967
Hyundai M.M.	1.6	17,716	72	English	0	1,001-5,000	South Korea	1976
Zim	1.2	26,434	142	English	16	5,001-10,000	Israel	1945
X-Press Feeders Group	0.4	5,297	72	English	0	201-500	Singapore	1972
Arkas Line/Emes	0.3	1,056	92	Turkish / English	0	1,001-5,000	Istanbul	1996
UniFeeder	0.2	7,395	83	English	1	201-500	Aarhus	1977
SPIL	0.2	29,648	53	English	6	1,001-5,000	Surabaya	1970
Swire Shipping	0.2	5,599	68	English	0	201-500	Singapore	1883
Matson	0.2	4,795	16	English	16	1,001-5,000	Honolulu	1882
ESL	0.2	6,967	23	English	0	201-500	Hong Kong	2006
Total	65	1,511,125	1,608	-	-	-	-	-

* Based on existing TEU capacity available on board operated ships listed in Alphaliner (November 2019).

** Last one year

In addition to the above reasons, one of the motivations to study the LinkedIn platform in this study is; although there are various publications in the literature on social media, especially Twitter and Facebook, the number of studies using the LinkedIn platform is very rare. The main reason for this is that LinkedIn is the strictest platform for data sharing. This study is the first study conducted on the LinkedIn platform for container shipping companies.

4.1.2. LinkedIn Overview

LinkedIn was founded in 2002 by Reid Hoffman and officially launched for use in 2003 (LinkedIn Newsroom, 2020). The LinkedIn platform, which was acquired by Microsoft in 2016, is seen today as the most known and largest professional social networking with over 660 million users from more than 200 countries (Davis et al., 2020). The most important feature that sets LinkedIn apart from other social media channels is that it offers the world's leading professional cloud solution and professional business network (LinkedIn, 2020b). According to LinkedIn statistics, over 30 million businesses are listed on LinkedIn (LinkedIn Newsroom, 2020).

LinkedIn is seen as the most effective social media channel for B2B marketers to reach their current and potential customers. Twitter and Facebook take the second and third places respectively (Demandwave 2017, Green Hat, 2019). By creating a LinkedIn group, B2B marketers can lead people to discuss a topic under the business brand, thereby strengthening the business's LinkedIn presence. In addition, it is possible to expand the customer portfolio by creating various networks. Moreover, it is a fact that LinkedIn is a platform that creates high value for activities such as recruitment and posting jobs (Kelsey, 2017: 86, 87).

Professionals use the LinkedIn platform for services such as managing their careers, creating their profiles, organizing connections, getting new trainings (courses), reading articles, browsing job postings, and calling other people (Yan et al., 2019: 2943). LinkedIn is also an important platform that offers financial planners and marketers the opportunity to connect with new business professionals. Providing businesses and professionals with the opportunity to expand their networks, the LinkedIn platform also provides its users with up-to-date information. Especially

through joining different LinkedIn groups, professionals can communicate with new connections outside their network. In this way, various discussions and engagements such as information sharing take place in front of the group members (Luke, 2009: 19). Creating a LinkedIn page is one of the most important issues regarding the use of LinkedIn for B2B companies. Creating a LinkedIn page is the first step for companies to interact with their existing and potential customers and build their brand presence on LinkedIn. Today, more than 50 million organizations worldwide tend to build strong relationships with their customers and employees via LinkedIn pages, according to LinkedIn data (Jobanputra, 2020a). LinkedIn pages provide businesses with the opportunity to interact with their interested customers and the ability to tell brand stories (Jobanputra, 2020b).

LinkedIn platform, which is considered as a career development tool for individuals, has an effective "network of professionals" feature for businesses. It is seen as a great way to communicate, especially for a particular niche. However, it can also be used as a resource to observe the competitive strategies of businesses (McCabe, 2017: 90). The use of LinkedIn is technically free, but there are also advertising options to reach more audiences (Serafin, 2018: 38).

In the literature, the number of academic studies using LinkedIn is very low compared to other platforms. According to the research of Zhang and Leung (2015), most of the social media studies conducted between 2006-2011 used Facebook (44%). The second most studied social media channel is MySpace (13%). On the other hand, LinkedIn has been the least used platform (10%), including the remaining platforms. Today, it is observed that the studies for Instagram and YouTube platforms, especially Twitter, have increased.

4.1.2.1. LinkedIn Privacy Policy and Data Restriction

The biggest barrier encountered in collecting research data in this study was the privacy policy and data restriction procedure of the LinkedIn platform. In the study, legal contracts and privacy agreements of the platforms were prioritized during the data collection phase. When signing up for LinkedIn, users must accept the "User

Agreement”, “Privacy Policy”, and “Cookie Policy”. These terms are also additional contracts for using the LinkedIn API (LinkedIn, 2019).

At the beginning of the study, LinkedIn data was collected through the Python programming language and the API (Application Programming Interface) services offered by LinkedIn for developers. In this process, secondary data sources, LinkedIn Developer platform, educational visual content, and expert software developers were used as information sources. At this point, LinkedIn API usage agreements were prioritized in addition to the user agreement, privacy policy and cookie policies that LinkedIn implements for its users.

To collect the research data, a new API named “*Bitiktas*” was created on the LinkedIn Developer page and this API was verified by LinkedIn on September 19, 2019 (See Figure 25). Later, LinkedIn requested a Callback URL information for OAuth 2.0, giving a Client Id and Client Secret. When the application is ready, Authorization Code and Access Token information are obtained from LinkedIn, respectively. This information is required to use the API service.

The screenshot displays the LinkedIn Developer application interface for 'Bitiktas'. On the left, the company profile shows a verified status on September 19, 2019, with a green 'Verified' badge. Below this, the app name 'Bitiktas' is listed, along with a privacy policy URL (not specified) and an app logo. On the right, the 'Application credentials' section provides the Client ID (78xxwne9zkhleu) and a masked Client Secret. The 'Permissions' section lists three permissions: 'r_emailaddress' (3-legged member permission), 'r_liteprofile' (3-legged member permission), and 'w_member_social' (3-legged member permission).

Figure 25: Installation and Authorization Information of the API Created on LinkedIn

However, there was a restriction in this process; the LinkedIn platform may not always make its data available. For this, it is necessary to choose the appropriate one among LinkedIn's services in different categories and contact LinkedIn. At this point, within the scope of the purpose of the research, a request was made to use the “Marketing Developer Platform” service of LinkedIn and LinkedIn managers were contacted for the data to be used in the research. LinkedIn privacy and intellectual property managers responded negatively to this request and stated that it is not allowed

to collect any personal information on LinkedIn's developer platform without the consent of users. Later, although it was stated that the data request was for academic use in the ongoing mailing process, LinkedIn privacy administrators did not step back and as a result, it was seen that the use of API could not provide the data needed. Although the LinkedIn API Terms of Use (LinkedIn, 2019) has been studied in detail, a starting point for retrieving data via the API has not been identified.

In the ongoing process, studies on this subject in the literature have been examined. Although it has been seen in previous studies that similar data can be retrieved by legal methods, it was seen that the social media platform increased data security measures and made various restrictions on data sharing (Facebook, 2018c), especially after the Cambridge Analytica scandal in early 2018 (Bastos and Walker, 2018; Ellen, 2019).

The best social media sites with advanced APIs that can provide data through authorized partners are listed in the Table 13 with their strengths and weaknesses (Krishnan and Rogers, 2014: 28). However, this situation has witnessed some updates on the platforms with new data restriction policies. Furthermore data restriction policies of social media channels since 2018 have also negatively and profoundly affected academic studies. Many academic researchers have criticized the restriction of APIs usage, which facilitates the acquisition of large-scale data (Bastos and Walker, 2018). Considering that the LinkedIn platform has much more limitations on data access than other platforms (see Table 13), these new restrictions made it more difficult to reach the desired data in this study.

Due to these barriers of social media channels to receive data through APIs, the research has focused on third-party scrapping applications. However, applications such as Netvizz, NodeXL and SocialMediaLab have also been observed to be out of service due to the platform's data restrictions (Bastos and Walker, 2018). For example, Netvizz application has been used in many academic studies before (Rieder et al., 2015; Marres, 2015; Larsson, 2016; Burgess and Matamoros-Fernández, 2016). But the developer of Netvizz has announced in his blog that the Netvizz application will lose access to Facebook pages as of September 4, 2019, and will not work from that date (Bernhard, 2019).

Table 13: Social Media Channels and Their Relationship with APIs

Site	Strengths	Weaknesses
Facebook	Largest user base. Strong API allows understanding of user sentiment and demographic information.	Users do not come here with a buying mindset.
Twitter	Contains short messages and allows a large number of data points. Has an active community and provide many third-party applications.	Although it is easy to read, it contains less data.
YouTube	The largest video site to date. Powerful API can show user trends.	It is used as a less communication channel than Twitter and Facebook. Comments on a video tend to be less interactive.
LinkedIn	Professional network. Ideal for understanding industry trends.	There are too many limitations in data access.

Source: Krishnan and Rogers (2014: 28, 29).

Although, still, a number of third-party apps provide data from LinkedIn (like browser plug-ins), such apps are breaking LinkedIn's privacy policies and user agreements. LinkedIn explicitly stated that such applications should not be used under the heading “Prohibited Software and Extensions” (LinkedIn, 2018).

Upon these restrictions, a detailed literature research was conducted on what content can be obtained on the LinkedIn platform with what kind of methods. Although the LinkedIn platform is reluctant to share user data, the law states that it is legal to retrieve public data (Woollacott, 2019). On the other hand, according to the EU General Data Protection Regulation (GDPR), which came into force in 2018, platforms must act in accordance with the law on protecting user data. However, GDPR is only valid for personal data. Personal data here refers to “data that can be used to directly or indirectly identify a particular individual”. For example, e-mail address, date of birth, IP or physical address are included in this type of data. If personal data will not be collected from the platforms, GDPR cannot be applied (Ellen, 2019). Therefore, this study focuses on the public data of LinkedIn users.

Table 14 presents a list of public data on LinkedIn. Accordingly, it is possible to analyze public LinkedIn data in two categories, namely business pages and messages, within the scope of the research subject.

Table 14: Public Data on the LinkedIn Platform

Page	Content
Language	Message (last one year)
Location(s)	Number of reactions
Headquarters	Number of comments
Foundation	Comment
Ads usage	Company replies
Number of follower	Other media and messaging
Company size	features
Number of company employees on LinkedIn	

As a result, it is seen that if public data for business pages on LinkedIn is received without using third party applications, there will be no legal and technical problems. In this context, the data required in the research process was decided to be taken manually on the LinkedIn platform, provided that it is open to the public. In the next section, the data that are publicly available on LinkedIn and which can be used in this research are discussed in more detail.

4.1.3. Data Collection

After the sample determination, the researcher started to collect data for the messages shared by the related companies on the LinkedIn platform. To facilitate data collection, it was necessary to select and appropriate program. However, none of the tools used previously for academic research were appropriate or reliable for the present study. The researcher prepared a REST API to collect data from LinkedIn, but this technology could not be used due to the platform's data restriction policies. API development process is detailed under the heading “LinkedIn Privacy Policy and Data Restriction”. Researcher manually transferred companies’ LinkedIn data to the Excel sheet. At this point, care has been taken to ensure that the data collected is public data that will not be in violation of the LinkedIn data privacy policy. The list of publicly available LinkedIn data of the companies that are planned to be used in the research is presented in Table 15.

Table 15: Public Data on LinkedIn Pages of Companies

Public Data	Description	Purpose of Usage
Company Name	Corresponds to the company's username on LinkedIn. For example, A.P. Moller- Maersk or Arkas Line.	Descriptive statistics and all processes in machine learning model.
Number of Followers	The total num. of followers on the company's LinkedIn page.	Descriptive statistics and Engagement rate calculation
Total Post	Total num. of messages posted on the LinkedIn page in the past year.	Descriptive statistics
Language	Language used in LinkedIn messages	LinkedIn status
Headquarters	Company head office	LinkedIn status
Primary Country	The region / country where those who manage the LinkedIn page are located.	LinkedIn status
Location of People Who Manage the Page		
Ads From This Page	Advertisement usage status in LinkedIn messages	LinkedIn status
Company Size	Number of employees of the company	LinkedIn status
Foundation Year	Establishment year of the company	LinkedIn status
Message Link	Link of the message in the browser	Easy access to messages
Media Type	Media type used; link, text, photo and video	Selected Feature in Machine Learning Model
Link Usage Status	Link usage status with message (https://)	Selected Feature in Machine Learning Model
Hashtag Usage Count	How many hashtags (#) are used with the message.	Selected Feature in Machine Learning Model
Word Usage Count	How many words are used in the message	Selected Feature in Machine Learning Model
Reshare Status	Whether the message is the original message of the company	Selected Feature in Machine Learning Model
Message	The message itself. Then the purposes were coded with a theoretical categorization.	Selected Feature in Machine Learning Model (as purpose)
Number of Reaction	How many user reacted to the message via the Like button	Engagement rate calculation
Number of Comment	How many users commented on the message	Engagement rate calculation
Interactivity Level	The level of interaction of the message; no-active (no user response), reactive (user response) and interactive (company response)	Selected Feature in Machine Learning Model
Top Comment (X2)	The top two comments on the post.	To understand interactivity level and reply purpose
Company Reply (X2)	Company response to the top two comments	To understand interactivity level and response purpose

Source: Prepared by author.

In the research, only messages shared in the past year have been used because of another restriction LinkedIn made on public data. LinkedIn only displays messages that have been shared in the past year, previous posts are not allowed. Due to this limitation, only messages between November 12, 2018, and November 12, 2019, were included in the research. Then, all these data are transferred to the excel sheet and prepared for content analysis. As a result of the data collection process, except for the data used in descriptive statistics, a total of 1679 posts and 2388 replies were reached. Another important point to be mentioned here is; in order to make this process more reliable and prevent mistakes and confusion, a screenshot of each message was recorded. These images were deleted after dissertation defense in accordance with the LinkedIn user agreement. A sample screenshot is presented in Figure 26.



Figure 26: A share of MSC Business on LinkedIn Page
Note: Used with the permission of LinkedIn.

4.1.4. Content Analysis

The content analysis is a widely used research method (Ettredge et al., 2001) in cases where companies provide information (Bonsón, and Ratkai, 2013). In this study, a theoretical approach was preferred for the categorization of social media

messages. This approach is a feature that differentiates this study from other social media studies. Accordingly, the literature-based message strategies, which were detailed in the previous sections, have been revealed. This theory-based categorization was created in accordance with the nature of the shipping market, taking into account the distinctions of Swani (2014) and North (2015).

In this study, companies' LinkedIn posts were categorized according to content types by researcher and specifically-trained independent coder. The researcher and a specially trained independent coder have similar coding experience in the study of Bitiktas and Tuna (2020). After completing the coding processes, the coders compared their results and re-analyzed disputed messages to reach a consensus when there was a dispute about the coded messages. The reliability of this process is detailed in the next section.

In some uncertainty situations encountered during content analysis, the author of the most influential social media engagement studies (Swani et al., 2013; Swani, et al., 2014; Swani et al., 2017) was contacted and received his opinion. In accordance with this, companies' LinkedIn messages were classified in terms of brand strategy (corporate or product), message appeal (functional or emotional), selling strategy and external information. Then messages are examined under video, photo and other (link, status, etc.) categories to understand the media types of the messages.

The product of maritime transport is usually a service, specifically a line or logistics service. For instance, Maersk line, Maersk Drill, and Maersk Oil are services offered by Maersk Group so content shares using any of these companies were categorized as a product brand. However, in contrast to the Swani et al. (2017) categorization, corporate and product brand name were considered together because container shipping companies are often mentioned along with the product and company brand (e.g., ZIM, Hapag-Lloyd, CMA CGM, Maersk).

Bendixen et al. (2004) define emotional values as positive values regarding a brand or product that motivate purchases. In some cases, however, emotional appeals can provoke negative feelings, although they are mostly stimulated by humor, romance, fear, guilt, games/contests, etc. (Swani et al., 2017). Special day celebrations and commemoration days can also be grouped under this category. Functional appeals provide information about the product (specification, features, performance, etc.) and

usually show the product's technical characteristics (Swani et al., 2017). This representation can be achieved by physical or other visual methods (Mudambi et al., 1997), such as shares related to a ship's TEU capacity or speed.

Sales-related shares are aimed at selling a product. B2B companies can produce such shares for users to experience, especially when introducing a new product. Information cues and links provide information to the public about the company's own product or company.

This analysis revealed that some shares corresponded to more than one content type, so the priority of the relevant content was taken into consideration. For example, special day greeting messages using the brand of the company were placed in the emotional category. Examples of coding are presented in Table 16.

Table 16: LinkedIn Message Coding Examples

Post	Coding
<i>"Yesterday, we were honored that this is the 5th year Maersk Portugal won awards for Best Global Carrier and Best Shipping Carrier to Asia by the readers of Transporte & Negócios Magazine, within the Prémios Carga 2018 Edition. Thank you to all our customers, our partners and the entire Maersk Portugal Team!"</i>	Brand strategy (company)
<i>"Operating result for 2018 considerably improved – Hapag-Lloyd achieved a higher operating result in the 2018 financial year than in the prior year. http://bit.ly/2IAR2ca"</i>	Functional appeal
<i>"#ONE wishes all our customers, friends and colleagues, a happy Deepavali! #OceanNetworkExpress #containershipping #deepavali"</i>	Emotional appeal
<i>"With Instant Booking, what you see is what you get! Get booking confirmation on the original vessel you requested. Book with us today: https://bddy.me/2T94LLx"</i>	Direct sales
<i>"A boom in fresh produce! Read what the Chinese New Year means for the global fruit market – and for those shipping the fruit. 🍎🍌🍊"</i>	External information

4.1.5. Validity and Reliability

In this study, reliability and validity components were prioritized in every stage of the research to ensure objectivity. Kirk and Miller (1986) define reliability as "the extent to which a measurement procedure yields the same answer however and

whenever it is carried out” and validity as “the extent to which it gives the correct answer” (Kirk and Miller, 1986:19).

In this study, both field experiments and content analysis are used. The use of field research design maximizes the validity of the study. For an accurate and valid study, the studied behavior should be restricted as little as possible by the researcher or the design of the research. As events occur naturally, the most accurate and valid results are obtained (Wrench et al., 2008: 451, 452). In field experiments, researchers examine how at least one independent variable leads to a change in a dependent variable in the natural environment. This influence is known as causality. Researchers do not have control over the independent variable because they cannot manipulate or influence it (Allen, 2017). This study is a real field experiment because the data used were collected in the natural environment of the companies and they were not intervened. This means that each company shares and interacts without the pressure of observation by researchers.

Reliability is often a problem with field experiments because if the environment is completely natural, it is difficult to repeat the exact conditions (North, 2015: 51). In this study, it was tried to collect as much data as possible from the LinkedIn platform to avoid seasonal effects (such as financial crisis or oil prices). If several months of data had been collected, the research result would have been at risk of being affected by seasonal conditions. Therefore, one year of data was collected. The reason that no data has been collected for more than one year is that only one year of data is available due to LinkedIn's data restriction policy.

The fact that only one year of data is displayed on the LinkedIn platform means that messages from a year ago are being deleted over time. At this point, screenshots of LinkedIn messages were taken to ensure reliability for the data collection process. In the data collection process, a screenshot of 1679 content shared by 15 LinkedIn accounts between November 12, 2018 and November 12, 2019 was recorded and filed. This data will not be published in this study, as required by the LinkedIn platform's data privacy policy.

Reliability issue was also brought up during the content analysis. Inter-coder reliability was calculated to ensure the reliability of the agreement level between the coders. Inter-coder reliability defined as “the extent to which independent coders

evaluate a characteristic of a message or artifact and reach the same conclusion” (Lombard et al., 2002). The inter-coder reliability of the coding of the qualitative data will be calculated using the Perreault and Leigh (1989) *Ir* formula.

$$Ir = \sqrt{\{[(F_o/N) - (1/k)] [k / (k-1)]\}} \quad (4.1)$$

F_o shows the number of coder agreements, *N* stands for the total number of coder decisions, and *k* represents the number of categories (Perreault and Leigh, 1989). According to this formula, the threshold for acceptable inter-coder reliability is higher than 0.8 (Sürücü and Dektaş-Şakar, 2018). The inter-coder reliability value for this study was 0.83.

Finally, face validity was another issue of this study. Face validity is based on expert opinion, similar to content validity in qualitative research (Karakoç and Dönmez, 2014: 42). However, the way of evaluation is quite different. In face validity, the expert is asked whether the research related to the research is well constructed and useful, and his personal opinion is learned. Content validity reaches the same answers, but it has a statistical approach (Shuttleworth, 2009). The development process of this study is a good example of the face validity approach. After it was determined that the engagement calculation methods in the literature were wrong, it was taken to the opinions of the most influential academics and social media experts who closely follow the social media algorithms to develop a new approach. Both academic and practitioner views strengthened the rationale for the error in the literature and the new approach.

4.2. FINDINGS AND RESULTS OF THE STUDY

4.2.1. Descriptive Statistics

The data set contains 1676 messages obtained from the LinkedIn page of 15 companies and 12 variables, one of which is the dependent variable for these messages. Three variables in the dataset are nominal (interactivity, media type, message type), two variables are binary (link and reshare status), and three variables are continuous

(hashtag, word and engagement). As can be seen in Figure 27, the most content belongs to CMA CGM, Maersk and Hapag-Lloyd. The companies with the lowest number of messages were Pacific, Matson and Emirates.

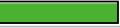
Value /	Proportion	%	Count
Arkas		5,49	92
CMA		17,18	288
Emirates		1,37	23
Hapag		12,83	215
Hyundai		4,3	72
Maersk		13,01	218
Matson		0,95	16
MSC		8,53	143
ONE		10,92	183
Pacific		0,42	7
SPIL		3,16	53
Swire		4,06	68
Unifeeder		4,95	83
X-Press		4,36	73
ZIM		8,47	142

Figure 27: Distribution of the Number of Messages by Companies

As Figure 28 shows, the most preferred content types for these shipping companies were functional (35.62%; n= 597) and branding purpose (37.05%; n= 621) whereas direct selling contents (3.7%; n= 62) were avoided. Emotional (12.11%; n= 203) and external informational (9.96%; n= 167) content was similarly preferred.

Value /	Proportion	%	Count
Branding		37,05	621
Direct Sale		3,7	62
Emotional		12,11	203
External		9,96	167
Functional		35,62	597
None		1,55	26

Figure 28: Distribution of Company Shares by Message Purpose Category

In terms of media type, photo (66.65 %; n= 1,117) was the most used content. It has been determined that the link (14.32%; n= 240) and video type (16.77%; n= 281) contents are used in similar proportions. The least preferred content type by companies has been text (2.27; n= 38). In Figure 29, media types preferred by companies are visualized in the size of companies.

Value /	Proportion	%	Count
Link		14,32	240
Photo		66,65	1117
Text		2,27	38
Video		16,77	281

Figure 29: Distribution of Company Shares by Media Type Category

It was determined that the number of messages without a link (66.05%; n= 1,107) is twice the number of messages link used (33.95%, n= 569). In Figure 30, link usage status of companies are visualized in the size of companies.

Value /	Proportion	%	Count
No		66,05	1107
Yes		33,95	569

Figure 30: Link Usage Status in LinkedIn Messages

It has been observed that reshare-type shares (4.71%; n= 79) are used very rarely. At this point, it is explained that companies share their own messages (95.29%; n= 1,597). In Figure 31, reshare status of messages are visualized.

Value /	Proportion	%	Count
No		95,29	1597
Yes		4,71	79

Figure 31: Reshare Status of LinkedIn Messages

In terms of interactivity, the ratio of interactive messages (11.22%; n= 188) was found to be very low compared to reactive (62.89%; n= 1,054) and no-active messages (25.89; n= 434). Interactivity status of LinkedIn messages is visualized in Figure 32.

Value /	Proportion	%	Count
Interactive		11,22	188
No Active		25,89	434
Reactive		62,89	1054

Figure 32: Interactivity Status of LinkedIn Messages

The mean number of hashtag usage was 2.848 (SD= 4.10) for all messages. Number of hashtag usage of companies, on average, from the highest to the lowest; Arkas (M= 9.52), X-Press (M = 5.63), Swire (M = 4.72), SPIL (M = 4.70), ONE (M = 4.44), Hyundai (M = 3.47), CMA CGM (M = 3.45), Emirates (M = 2.83), Pacific (M = 2.29), Maersk (M = 1.69), Unifeeder (M = 1.30) ZIM (M = 1.22), MSC (M = 1.09), Matson (M = 0.38) and Hapag-Lloyd (M= 0.191).

In terms of the average number of words used in the messages, from the highest to the lowest; Swire (M = 92.01), Emirates (M= 72.83), X-Press (M= 66.55), CMA CGM (M= 62.28), Unifeeder (M= 59.70), Hyundai (M= 58.00), Arkas (M= 53.15), Hapag-Lloyd (M= 45.00), SPIL (M= 40.15), MSC (M= 40.01), Maersk (M= 38.00), ZIM (M= 34.65), ONE (M= 32.90), Pacific (M= 32.57), Matson (M= 26.88).

The values of the engagement variable, which is the focus of the study, could not be calculated due to the error in the current calculation method in the literature. At this point in the study, an additional study is required to define the engagement rates of the messages. In the next part, a calculation method for the value of the engagement variable will be presented.

4.2.2. Engagement Rate

As mentioned earlier, the focus of this study is the engagement of social media messages. This engagement is used as an important indicator in understanding the success of social media content. In this section, the engagement rates of container shipping companies' LinkedIn pages with the current formula in the literature. However, as a result of the fact that the current formula ranks the business pages quite incorrectly, a new approach to engagement calculation has been developed.

In this section, an exploratory qualitative research process was carried out by consulting experts who are academicians and practitioners, as well as using the systematic literature review that was conducted previously. Exploratory research is used in cases where the knowledge that has reached a certain level of maturity previously needs to be explored anew because of changed so much (Stebbins, 2001: 7). Exploratory research can be carried out by detailed literature review and consultation with experts (Altunışık et al., 2005: 61).

4.2.2.1. Current Engagement Rate Formula

Engagement on LinkedIn is described as “how many times LinkedIn members clicked, liked, commented on, and shared the post in both organic and paid ways, as well as the number of followers acquired through paid ways” (Browning, 2013: 39). Therefore, the engagement rate is calculated by the number of interactions, clicks, and the number of followers gained, divided by impressions (LinkedIn Help, 2019). This calculation method is made similarly in other platforms. For instance, Twitter engagement rate can be calculated by dividing the number of engagement (total number of retweet, comment and like) by the number of impression (Wadhwa et al., 2017: 1866).

However, it is not possible to reach the number of impressions in practice. Because data regarding impression numbers on LinkedIn pages can only be viewed by page administrators and making the calculation of the engagement rate impossible because companies do not share such data. Therefore, various formulas have been derived for calculating the engagement rates between academics and practitioners. Following is the basic logic of generally accepted engagement rate formulas (Harode-Rosario et al., 2018; Sürücü and Dektaş-Şakar, 2018; Escobar-Rodríguez and Bonsón-Fernández 2017; Bonsón and Ratkai, 2013);

$$eR = tE / nF * 1000 \quad (4.2)$$

The value of eR in the formula represents the rate of engagement, tE stands for the total engagement of the messages, nF shows the number of follower and 1000 is the constant of the equation.

On the other hand, recent changes in news feed algorithms of social media channels have raised doubts about the validity of such formulas for this study. For example, in January 2018, Facebook, which is the pioneer of these changes, announced that they had made some important changes to the News Feed algorithm. To encourage more meaningful interaction among users, News Feed demonstrations would be linked to a standard, and publications from businesses, brands, and the media would be shown less (Facebook, 2018a). This algorithmic change means that company messages have

less organic reach than before. In addition, the number of a company's Facebook followers no longer directly affects this organic access. Thus, it is expected that the classical engagement rate calculation formulas developed by academic researchers to calculate engagement based on the number of fans/followers, as mentioned above, may no longer give meaningful or reliable results regarding social media usage.

In this part of the study, the engagement rate formula is customized for the LinkedIn platform and the engagement rates of the companies are calculated within the scope of the research sample. The classic engagement rate formula for the LinkedIn platform is as follows;

$$eR = (tR + tC) / nF * 1000 \quad (4.3)$$

The value of eR in the formula represents the rate of engagement, tR stands for the total reaction of the messages, tC shows the total comment of the messages, nF shows the number of followers and 1000 is the constant of the equation. The engagement rates of the companies were calculated using the formula and presented in table x.

As can be seen from Table 17, the engagement formula assumes a linear relationship between the number of followers of companies and the total number of reactions and comments. In other words, as an example, if the average engagement rate of a page with 1.000 followers is 10, the average engagement of a page with 10.000 followers is expected to be 100. However, as stated earlier, due to the change in the LinkedIn news flow algorithm, the rate of increase in the number of followers does not increase at the same rate as the engagement rate. The main reason for this is that the messages posted in business pages are not shown to all followers.

As can be clearly seen in Table 17, the rate of engagement decreases significantly as the number of followers increases compared to the current formula. Companies such as MSC, CMA CGM, and Maersk, which have high followers, perform very poorly under the current formula compared to companies such as ARKAS and Matson with few followers. However, it is a fact that MSC, CMA CGM, and Maersk use social media quite actively and at an advanced level. In the light of

these results, it is clear that the current formula makes an erroneous measurement. All of these are suggest that there may be an exponential relationship between the number of followers and the number of engagement.

Table 17: Engagement Rates According to the Current Formulas in the Literature

Company Name	Avarage Sum of Reaction and Comment	Number of Follower	Page Engagement Rate
Pacific Int. Line	64,71	5182	12,49
UniFeeder	78,19	7395	10,57
Matson	49,50	4795	10,32
X-Press Feeders Group	54,22	5297	10,24
Arkas Line/Emes	9,73	1056	9,21
ESL	56,65	6967	8,13
Swire	31,94	5599	5,70
Hyundai M.M.	100,86	17716	5,69
ONE	161,28	29222	5,52
SPIL	129,30	29648	4,36
Zim	106,07	26434	4,01
MSC	895,27	279137	3,21
Hapag-Lloyd	362,16	149894	2,42
CMA CGM Group	589,79	322289	1,83
A.P. Moller- Maersk	802,30	626093	1,28

4.2.2.2. Development and Implementation of a New Calculation Method for Engagement Rate

In the previous part of the study, it has been revealed that the formulas for calculating the engagement rate of the companies are not working correctly. The existing formulas assume that there is a linear relationship between the number of followers of companies and the average number of reactions and comments. However, due to the changing algorithms of many social media platforms including LinkedIn, the linear relationship assumption between the number of followers and the number of engagement has disappeared. In order to make such calculations more accurate, a new

method should be developed. In this section, a function will be developed to perform such calculations.

When the average number of reactions and comments presented in Table 17 and the number of followers were visualized with the help of Excel in the X and Y dimensions, it was explained that the relation in question was not linear. So there is a nonlinear relationship between these two variables. Curve estimation was done using SPSS program to create the function of this relationship. The engagement rates of the companies were recalculated by means of the best regression model explaining the relationship.

4.2.2.2.1. Curve Estimation Analysis

In this section, the most appropriate type of mathematical function between the number of followers and average engagement variables will be estimated. Engagement (dependent variable) and the number of followers (independent variable) data were estimated using curve estimation using the SPSS tool. Accordingly, analyses were carried out taking into account the average number of engagement and followers of each companies. The results of the analysis are as follows.

Table 18: Model Summary and Parameter Estimates

Dependent Variable: Average Engagement of Company							
	Model Summary					Parameter Estimates	
Equation	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.814	56.875	1	13	.000	83.420	.001
Logarithmic	.804	53.214	1	13	.000	-1169.483	140.242
Inverse	.182	2.885	1	13	.113	309.367	-528825.668
Power	.955	276.195	1	13	.000	.160	.658
Exponential	.617	20.974	1	13	.001	65.737	5.535E-6

The independent variable is Follower

In Table 18, the function with the highest determination coefficient is the power function ($R^2 = 0.955$). For this reason, the model that best describes the relationship between average engagement and follower variables has been the power

function. Below Figure 33 is the graphical representation of the power function and other functions that occur during curve estimation analysis.

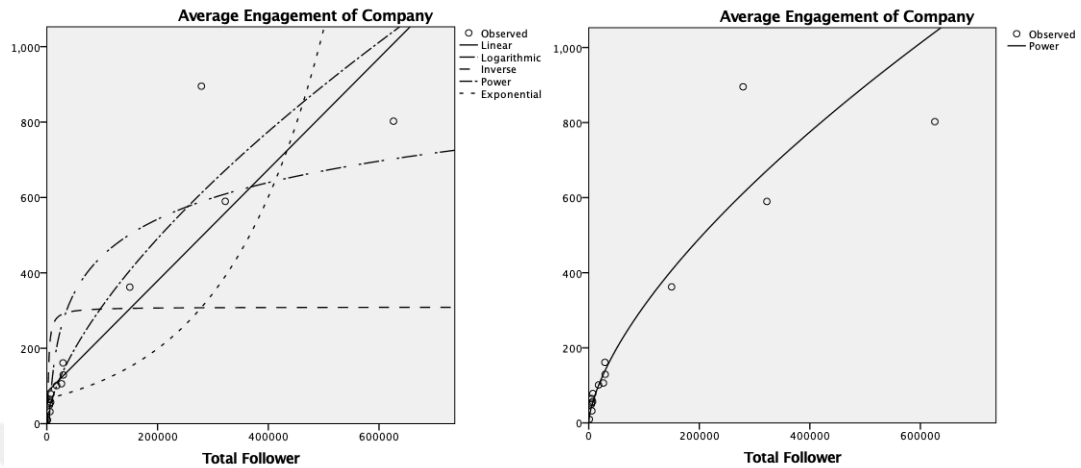


Figure 33: All Functions and Power Function Curves

4.2.2.2.2. Non-Linear Regression Analysis

The power function is a formulation that defines the relationship between average engagement and the total number of followers. Before specifying this function, it would be a correct approach to detail the degree of fit of the regression model. Table 19 contains a summary of the regression model R^2 and the adjusted R^2 values.

Table 19: Model Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate
.977	.955	.952	.277

The independent variable is Total Follower

Accordingly, the level of relationship between the variables is $R^2 = 0.955$. The corrected determination coefficient is $R^2 = 0.952$. Therefore, 95.2% of the Average Engagement variable is determined by the follower argument. The reason for the 4.8%

change is unknown. Also, $R^2 = 0.952$ indicates that the goodness of fit of the model is very high. ANOVA summary of the regression model is also presented in Table 20.

Table 20: ANOVA Results of Regression Model

	Sum of Squares	df	Mean Square	F	Sig.
Regression	21.129	1	21.129	276.195	.000
Residual	.995	13	.077		
Total	22.124	14			

The independent variable is Total Follower.

As can be seen in the Anova summary, the regression model is also important since the significance value of the F test is less than 0.05 ($0.000 < 0.005$).

Table 21: Coefficients Results of Regression Model

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
ln(CompFollow)	.658	.040	.977	16.619	.000
(Constant)	.160	.064		2.487	.027

The dependent variable is ln(Avarage Engagement).

In the Table 21 above, when the model parameters of the variables (significant) with a significance value less than 0.05 are written in the equation, the power function that define the regression model is formed as follows;

$$y = 0,16x^{0,658} \quad (4.4.)$$

In this formula "y" dependent variable corresponds to the engagement value, "x" independent variable corresponds to the number of followers, and 0.16 is the constant of the equation. This function will be used to reveal the predicted number of engagements by the number of followers of companies. Thus, the predicted engagement number and actual engagement number will be compared, and the real engagement performance of the companies will be revealed.

In the power function, when the number of followers of each company is replaced by the x independent variable, the predicted engagement values for the y dependent variable are presented in Table 22. Table 22 also contains the difference between the actual engagement values and the predicted values and the square of this difference. These difference values will be used for the optimization of the regression model in the following sections.

Table 22: Actual and Predicted Engagement of Companies

Company	Follower	Actual Avg. Engagement	Predicted Value	Difference	Square Difference
Maersk	626093	802,30	1043,06	240,76	57965,17
MSC	279137	895,27	613,01	-282,26	79672,03
CMA CGM	322289	589,79	673,82	84,03	7061,18
Hapag-Lloyd	149894	362,16	407,18	45,02	2026,93
ONE	29222	161,28	138,85	-22,43	503,13
Pacific Int. Line	5182	64,71	44,49	-20,22	409,03
Hyundai M.M.	17716	100,86	99,90	-0,97	0,93
ZIM	26434	106,07	129,99	23,92	572,05
X-Press	5297	54,22	45,14	-9,08	82,49
Arkas	1056	9,73	15,62	5,89	34,72
UniFeeder	7395	78,19	56,22	-21,97	482,86
SPIL	29648	129,30	140,18	10,88	118,38
Swire	5599	31,94	46,81	14,87	221,20
Matson	4795	49,50	42,27	-7,23	52,21
ESL	6967	56,65	54,06	-2,60	6,74

The correlation between the predicted engagement values calculated using the power function and the actual engagement values is summarized in the Table 23.

According to Table 23, a very high and significant ($r = 0.942$, $p < 0.05$) correlation was achieved between actual engagement and predicted engagement values. On the other hand, total square difference was calculated as "149209.04" in Table 22.

Table 23: Correlations between Actual Engagement and Predicted Engagement

		Actual Avg. Engagement	Predicted Value
Actual Avg. Engagement	Pearson Correlation	1	.942**
	Sig. (2-tailed)		.000
	N	15	15
Predicted Value	Pearson Correlation	.942**	1
	Sig. (2-tailed)	.000	
	N	15	15

** . Correlation is significant at the 0.01 level (2-tailed).

In order to improve the regression model, optimization was made by using the Solver tool in Excel. The final form of the function created by Excel solver by minimizing Total Square Difference (Least Square Method) is as follows;

$$y = 0,586x^{0,551} \quad (4.5)$$

Table 24: Optimized Actual and Predicted Engagement of Companies

Company	Follower	Total Reaction and Comment	Predicted Value	Difference	Square Difference
Maersk	626093	802,30	915,15	112,86	12736,40
MSC	279137	895,27	586,41	-308,87	95398,79
CMA CGM	322289	589,79	634,74	44,95	2020,22
Hapag-Lloyd	149894	362,16	416,31	54,15	2932,25
ONE	29222	161,28	169,11	7,83	61,30
Pacific Int. Line	5182	64,71	65,20	0,49	0,24
Hyundai M.M.	17716	100,86	128,36	27,50	756,12
ZIM	26434	106,07	160,02	53,95	2910,96
X-Press	5297	54,22	66,00	11,78	138,73
Arkas Line	1056	9,73	27,14	17,41	303,23
UniFeeder	7395	78,19	79,32	1,12	1,26
SPIL	29648	129,30	170,47	41,17	1694,59
Swire	5599	31,94	68,04	36,10	1303,47
Matson	4795	49,50	62,47	12,97	168,33
ESL	6967	56,65	76,75	20,10	404,09

In this function, y (dependent variable) corresponds to "engagement rate", x (independent variable) corresponds to "number of followers" and 0.586 corresponds to the constant of the equation. When the relevant variables in the power function are substituted for each company, the predicted engagement values are presented in Table 24. Additionally, Total Square Difference obtained as a result of the new model has been minimized as "120829.98".

The correlation between the predicted engagement values calculated using the optimized power function and the actual engagement values is summarized in Table 25. Accordingly, the correlation coefficient was higher than the previous function. A very high and significant ($r = 0.949$, $p < 0.05$) correlation was obtained between the actual engagement and predicted engagement values.

Table 25: Optimized Correlations between Actual Engagement and Predicted Engagement

		Total Reaction and Comment	Predicted Value
Total Reaction and Comment	Pearson Correlation	1	.949**
	Sig. (2-tailed)		.000
	N	15	15
Predicted Value	Pearson Correlation	.949**	1
	Sig. (2-tailed)	.000	
	N	15	15

**. Correlation is significant at the 0.01 level (2-tailed).

The average engagement rate of LinkedIn pages of companies calculated using the optimized power function is presented in Table 26. Accordingly, it was determined that the MSC has the highest engagement rate with a value of 1,5267 on the LinkedIn platform. Arkas Line has the lowest engagement rate with a value of 0.3584.

Table 26: Engagement Rates of Companies' LinkedIn Accounts

Company	Avarage Engagement Rates
MSC	1,5267
Pacific Int. Line	0,9925
UniFeeder	0,9858
ONE	0,9537
CMA CGM Group	0,9292
A.P. Moller- Maersk	0,8767
Hapag-Lloyd	0,8699
X-Press	0,8215
Matson	0,7923
Hyundai M.M.	0,7858
SPIL	0,7585
ESL	0,7381
Zim	0,6628
Swire	0,4694
Arkas Line/Emes	0,3584

4.2.3. Tools and Resources Used for Machine Learning Modeling

Machine Learning services of IBM Watson Studio were used for modeling machine learning. IBM Watson Studio is a data science and machine learning platform. Watson Machine Learning (WML) serves as an IBM Cloud product within Watson Studio for developers and data scientists to prepare forecasting models. WML service is a set of REST APIs that make smarter decisions and solve difficult problems and can be called from programming languages (IBM, ____ a).

Besides, under IBM's compute services, the "Cognos Dashboard Embedded" service was used to visualize the analysis outputs of the research data. IBM Cognos Dashboard Embedded is an API-based solution that gives developers' end-to-end data visualization capability (IBM, ____ b). At this point, in order to obtain a richer visual graphic experience, SPSS Modeler desktop program was also used. IBM SPSS Modeler desktop program was used to obtain the visuals in the descriptive analysis part of the study. Another service used in IBM Watson Studio was "Cloud Object

Storage” under data service. Cloud Object Storage is a cloud storage service for research data. After the necessary installation and adjustments, these services become available with WML.

On the other hand, IBM Knowledge Center and analytical help and tutorials were primarily used in the development and interpretation of the flow model. In addition, academic studies related to the subject and educational video contents were used. These sources are presented in the relevant sections of the study.

4.2.4. Development of Machine Learning Flow Models

Figure 34 summarizes the process of data mining and machine learning, starting with the selection of variables. The target variable of the study was engagement. Initially, the model was given 18 input variables. In the data processing step, the data to be added to the model were determined with the feature selection node. As a result of feature selection criteria, a total of 7 input variables are included in the model.

After determining the data to be included in the model, the rate of training and test data was decided to apply machine learning. Three different scenarios have been implemented for this decision. Accordingly, 50:50, 67:33 and 80:20 ratios were applied for training and testing data, and the partition with the highest coefficient of prediction was preferred.

Then, as detailed in the previous sections, C&RT and CHAID algorithms, which are appropriate for the purpose of this study and the characteristics of the data, were applied. In following section, estimation performances of models prepared with C&RT and CHAID algorithms are evaluated. This evaluation was carried out with analysis and evaluation nodes. As a result of the evaluations, the best model was chosen and the related rules and results were interpreted. In the following sections, the machine learning model is created by following the steps of this process.

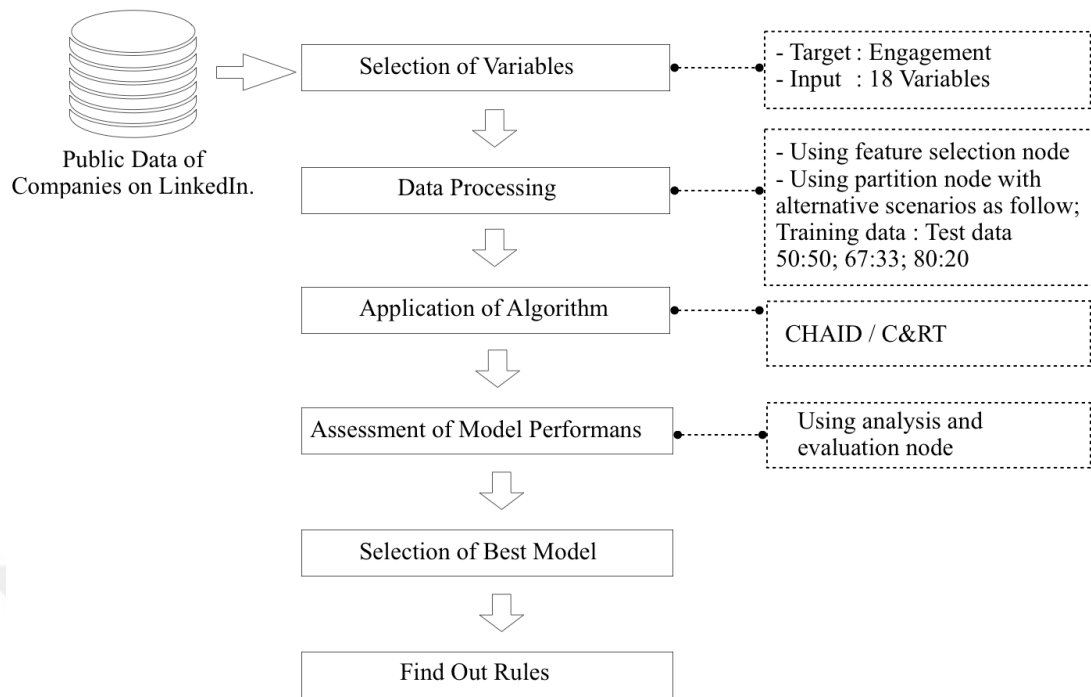


Figure 34: Process of Machine Learning Flow Model

4.2.4.1. Selection of Variables

As mentioned before the target variable of this study was engagement. Engagement rates were calculated by the method developed in this study. Accordingly, the engagement rate of each message is defined as the target variable for the machine learning model.

The number of initial input variables defined in the model was 18 under 3 categories. The feature categories are as follows; company specifications, message characteristics and reply status. The input variables listed under these three categories are as follows; company name, year of foundation, headquarters, number of employees, TEU capacity, Alphaliner rank, ownership type, message purpose, media type, link usage, hashtag usage, word count, reshare status, interactivity level, reply purpose (x2) and company reply (x2) (indicated by x2 as the first two comments to messages are taken into account). The screenshot of the sample dataset for the initial target and input variables is presented in Figure 35.

Company	Foundation	Headquarters	Employees	TEU	Rank	Ownership	Follower	Message	Media	Link	Hashtag	Word	Reshare	Interactivity	ReplyPurp	CompRep	ReplyPurp2	CompRep2	Engagem
Maersk	1904	Copenhagen	10000 +	4191829	1	Public	626093	Direct Sale	Video	Yes	0	24	No	Reactive	1	0	0	0	0.200
Maersk	1904	Copenhagen	10000 +	4191829	1	Public	626093	Functional	Video	Yes	1	37	No	Reactive	3	0	1	0	1.730
Maersk	1904	Copenhagen	10000 +	4191829	1	Public	626093	Branding	Photo	No	0	52	No	Reactive	1	0	1	0	0.500
Maersk	1904	Copenhagen	10000 +	4191829	1	Public	626093	Branding	Link	Yes	2	26	No	Reactive	1	0	1	0	0.940
Maersk	1904	Copenhagen	10000 +	4191829	1	Public	626093	Branding	Link	Yes	5	46	No	Reactive	6	0	1	0	0.970
Maersk	1904	Copenhagen	10000 +	4191829	1	Public	626093	Branding	Photo	Yes	0	38	No	Interactive	1	0	4	2	0.980
Maersk	1904	Copenhagen	10000 +	4191829	1	Public	626093	Functional	Photo	Yes	5	30	No	Interactive	4	0	3	3	1.390
Maersk	1904	Copenhagen	10000 +	4191829	1	Public	626093	Direct Sale	Video	Yes	0	21	No	Reactive	6	0	1	0	0.570
Maersk	1904	Copenhagen	10000 +	4191829	1	Public	626093	Branding	Photo	Yes	4	32	No	Reactive	1	0	1	0	1.180
Maersk	1904	Copenhagen	10000 +	4191829	1	Public	626093	Branding	Photo	No	4	52	No	Reactive	1	0	1	0	2.930
Maersk	1904	Copenhagen	10000 +	4191829	1	Public	626093	External	Video	Yes	4	13	No	Reactive	6	0	1	0	0.640
Maersk	1904	Copenhagen	10000 +	4191829	1	Public	626093	External	Video	No	2	44	No	Reactive	6	0	6	0	1.410
Maersk	1904	Copenhagen	10000 +	4191829	1	Public	626093	Branding	Video	No	1	34	No	Reactive	6	0	6	0	1.350
Maersk	1904	Copenhagen	10000 +	4191829	1	Public	626093	External	Photo	Yes	0	34	No	Reactive	5	0	3	0	0.430

Figure 35: A Screenshot From the Dataset of the Initial Target and Input Variables

To summarize, at the beginning of the machine learning model, one target variable and 18 input variables were defined with the data asset node (named as “LinkedIn” in figure C&RT and CHAID). In the next section, these variables will be processed with the feature selection node.

4.2.4.2. Data Processing

The perspective of this study is the subjects that affect message-oriented engagement. In other words, the characteristics of the company or the type of follower/company replies made are excluded from this study. For the purpose of the study, only the messages-related features are included in the model in order to understand what types of messages affect the engagement rate. Therefore, the feature selection node (named as “*type*” in the models) was applied to the initial input variables presented in Figure 36.

Then, as a result of feature selection criteria, total of 7 input variables were included in the model. These are; message purpose, media type, link usage, hashtag usage, word count, reshare status and interactivity level. The list of initial input variables and final input variables after feature selection criteria is presented in Figure

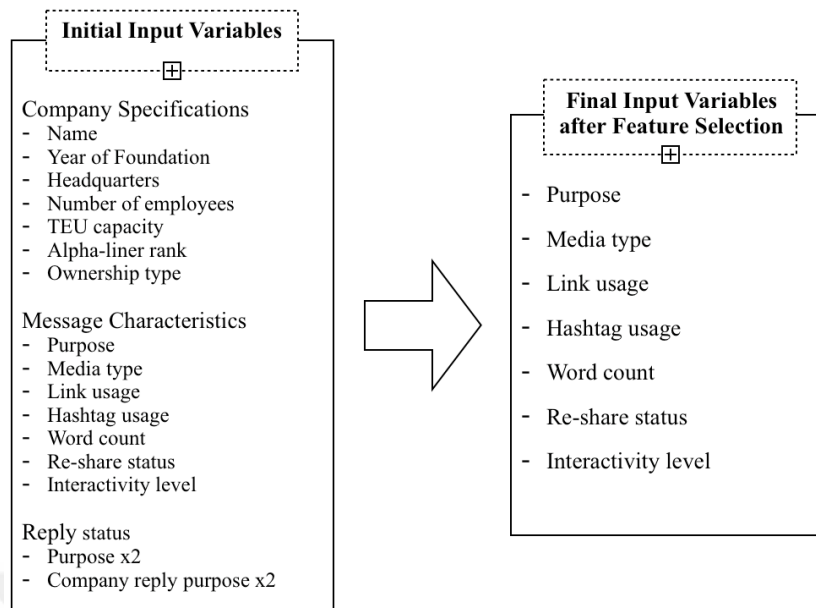


Figure 36: Initial and Final Input Variables

36. Descriptive information of the target and input variables is presented with the data audit node (named as “8 fields” in the models) in Figure 37.

In the next step of the data processing, the partitioning node was used to identify training and testing data. Three different scenarios were applied to determine the most efficient training and testing partition and the most efficient partitions were applied to the relevant algorithms. The partitions applied in these scenarios were 50:50, 67:33 and 80:20, respectively. Accordingly, the most consistent prediction rate for the C&RT algorithm was 80% for training data and 20% for testing data. For the CHAID algorithm, 50% training and 50% testing partition provided the highest prediction consistency. As a result, 80:20 ratio was applied for the partition node (named as “80:20” in the model) of the C&RT algorithm and 50:50 ratio (named as “50:50” in the model) for the CHAID.

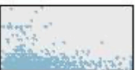
	Field	Graph	Measurement	Min	Max	Mean	Correlation	Correlation T	Correlation T df.	Correlation T sig.	Covariance	Std. Dev	Skewness	Unique	Valid
1	Message		Nominal	--	--	--	--	--	--	--	--	--	--	6	1676
2	Media		Nominal	--	--	--	--	--	--	--	--	--	--	4	1676
3	Link		Flag	--	--	--	--	--	--	--	--	--	--	2	1676
4	Hashtag		Continuous	0	33	2,848	-0,059	-2,412	1674,000	0,016	-0,146	4,100	3,084	--	1676
5	Word		Continuous	0	226	49,019	0,049	2,001	1674,000	0,046	1,039	35,170	2,157	--	1676
6	Reshare		Flag	--	--	--	--	--	--	--	--	--	--	2	1676
7	Interactivity		Nominal	--	--	--	--	--	--	--	--	--	--	3	1676
8	Engagement		Continuous	0,020	3,186	0,853	--	--	--	--	--	0,605	1,736	--	1676

Figure 37: Descriptive Information of the Target and Input Variables

On the other hand, in cases where the dependent variable is continuous, F tests are used for partitioning algorithms. On the other hand, if the dependent variable is nominal, Pearson chi-square statistics should be used. Finally, if the dependent variable is in order, the likelihood–ratio test is used (Maimon and Rokach, 2005: 164). In this study, F tests were used because the dependent variable is continuous. Also, based on the rules, the level of significance for splitting and merging nodes is set as 0.05 (p-value of <0.05).

4.2.4.3. Application of the Learning Algorithms

Until this part of the study, the process of selecting variables and processing the data has been carried out. In this section, C&RT and CHAID algorithms that are suitable for the research purpose and data features will be defined to the model. In this context, the machine learning flow model created with the Machine Learning module in IBM Watson Studio is visualized in the Figure 38.

The model contains the same nodes for both algorithms up to the partition node. These are data assets (named as LinkedIn), Outlier and Extreme (named as Outlier), and feature selection node (names as Type). The partition node is organized in two different structures for C&RT and CHAID algorithms. As mentioned earlier, while 80:20 partition is made for the C&RT algorithm, 50:50 partition is made for the CHAID algorithm. The application and evaluation of the C&RT and CHAID algorithms continued in the next section under two headings.

4.2.4.3.1. C&RT Algorithm

The first model established with C&RT algorithm, 80% of the initial dataset was used to create the model and 20% to test the model. The results of the data set are shown in the Table 27.

As can be seen from Table 27, 1329 of 1676 messages were used as training data and 347 messages as test data. The model was created using training data and then verified with test data.

Table 27: Training and Test Data (C&RT)

'Partition'	1_Training	2_Testing	Total
Percent (%)	80	20	100
Occurrences	1329	347	1676

In the C&RT method, the model was created by determining the most important among all variables. Variables without significance coefficients were excluded from the model. Accordingly, the six variables found significant with p -value of <0.05 as a result of the first model are visualized in the Figure 39 below.

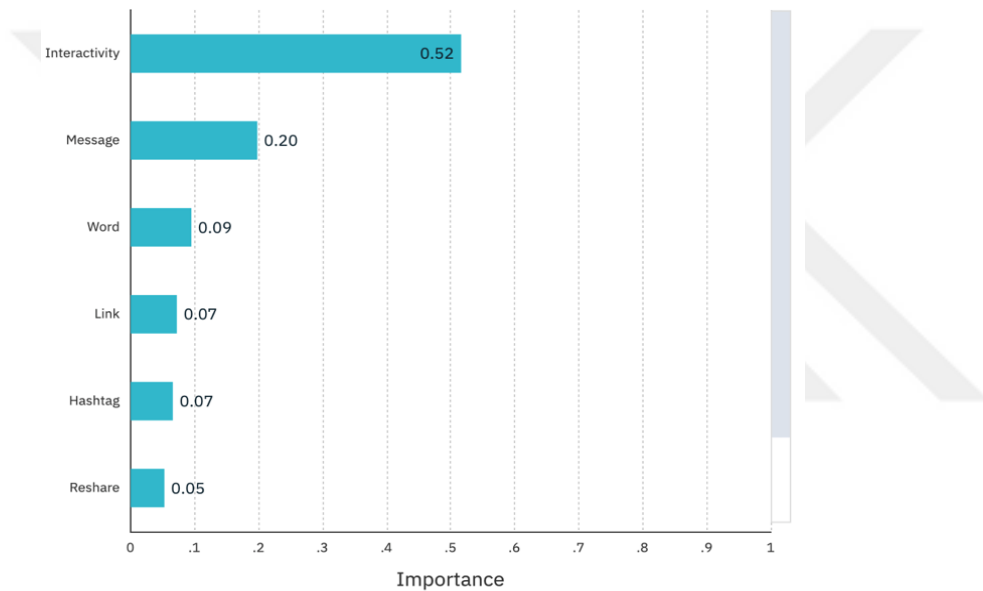


Figure 39: Predictor Importance of Engagement (C&RT)

As can be seen in Figure 39, the number of determinant variables in the C&RT model was six. Interactivity was the most decisive variable with a significance of 0.52. The message variable, on the other hand, took its place as the second most important determiner with its 0.20 significance degree. Word variable was the third most important variable affecting the model with a ratio of 0.09. The variables related to the use of Link and Hashtag took an equal share with an effect of 0.07. The variables with the least effect on the model were the Re-share state. Media type, on the other hand, was removed from the model because it does not have any determination coefficient in the C&RT model.

4.2.4.3.2. CHAID Algorithm

Second model established with CHAID algorithm, 50% of the training dataset was used to create the model and 50% to test the model. The results of the data set are shown in the Table 28 below.

Table 28: Training and Test Data (CHAID)

'Partition'	1_Training	2_Testing	Total
Percent (%)	50	50	100
Occurrences	822	854	1676

As can be seen from Table 28, 822 of 1676 messages in total were used as training data and 854 as test data. The model was created using training data and then validated with test data. The significant variables forming the model and their significance are visualized in Figure 40.

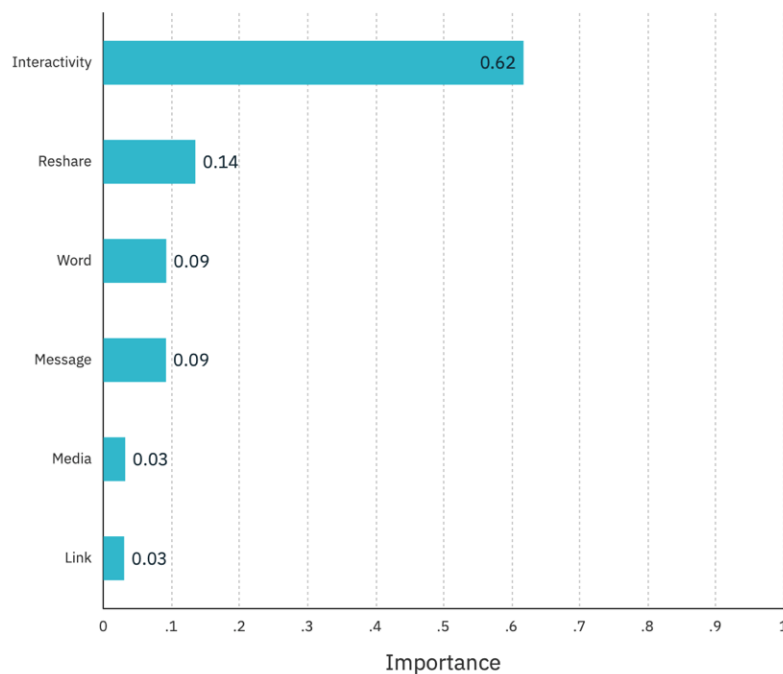


Figure 40: Predictor Importance of Engagement (CHAID)

As can be seen in Figure 40, the number of determinant variables in the CHAID model was six. Interactivity was by far the most decisive variable with a significance of 0.62. Re-share variable took its place as the second most important determiner with its 0.14 significance degree. Word and Message variables affected the model with a ratio of 0.09. The least effective variables on the model were Media and Link. The use of the hashtag was removed from the model since there is no determination coefficient in the CHAID model.

4.2.4.4. Assessment of Model Performance

In this part of the study, performances of decision models using C&RT and CHAID algorithms are evaluated.

4.2.4.4.1. C&RT Model Performance

Table 29 summarizes the relationship between predicted engagement and actual engagement values. In the C&RT model, 1329 data were trained and an engagement rate was predicted for each. A correlation of 0.509 coefficient was determined between the estimated engagement (\$ R-Engagement) values and the actual engagement values. On the test data, this correlation coefficient was found to be 0.437. Linear correlation (also known as Pearson correlation) indicates the strength of the linear relationship. The correlation coefficient is indicated by the letter “ r ” and can take values between -1 and +1. The coefficient of +1 indicates that there is a perfect linear relationship between the variables (Altunışık, et al. 2004: 197). In order for the correlation coefficient to be significant, it is expected to be different from at least 30% (İslamoğlu, 2011: 259). There are different assumptions in the literature regarding the strength of the relationship between the variables according to the absolute value of the correlation coefficient. In this study, the distinction of Gerber and Finn (2005) was used. Accordingly, if the correlation coefficient between the variables is less than 0.3, there is a weak relationship, if it is between 0.30 and 0.60, there is a medium-strength relationship, and if it is greater than 0.6, there is a strong relationship (Gerber and Finn,

2005). In this context, it can be said that the correlation coefficients of 0,512 and 0,441 reached in the model show a medium-strength relationship.

Table 29: Comparing \$R-Engagement with Engagement (C&RT)

■ Results for output field Engagement

■ Comparing \$R-Engagement with Engagement

'Partition'	1_Training	2_Testing
Minimum Error	-1.373	-1.093
Maximum Error	2.316	2.289
Mean Error	-0.002	0.012
Mean Absolute Error	0.367	0.392
Standard Deviation	0.518	0.55
Linear Correlation	0.512	0.441
Occurrences	1,329	347

In Table 29, there are minimum, maximum and mean error and standard deviation results resulting from the prediction of engagement values. These values are calculated for both training and test data. Minimum and maximum errors indicate the min. and max. error of the difference between observed and predicted engagement values. Mean error point out the average of errors across all data and it represents whether there is a systematic bias in the model. Standard deviation indicates the standard deviation of the errors (IBM Knowledge Center, ____a).

The evaluation node was used to compare the accuracy of the C&RT prediction model. The evaluation node is used to evaluate and compare the prediction model prepared. Evaluation charts present how the model performs to predict specific results. They work by sorting the data according to the predicted value and confidence of the prediction, dividing the records into groups of equal size which call as quantiles and then drawing the value of the business criteria from highest to lowest for each quantile. Multiple models are seen as separate lines on the chart. Outcomes are handled by defining a particular value or range of values called “hits”. Hits generally indicate some kind of success (IBM Knowledge Center, ____b). In this study, the hit value was determined based on the average engagement rate. Accordingly, the hit value was determined for the condition equal to or higher than the average value of 0.853 obtained for all messages.

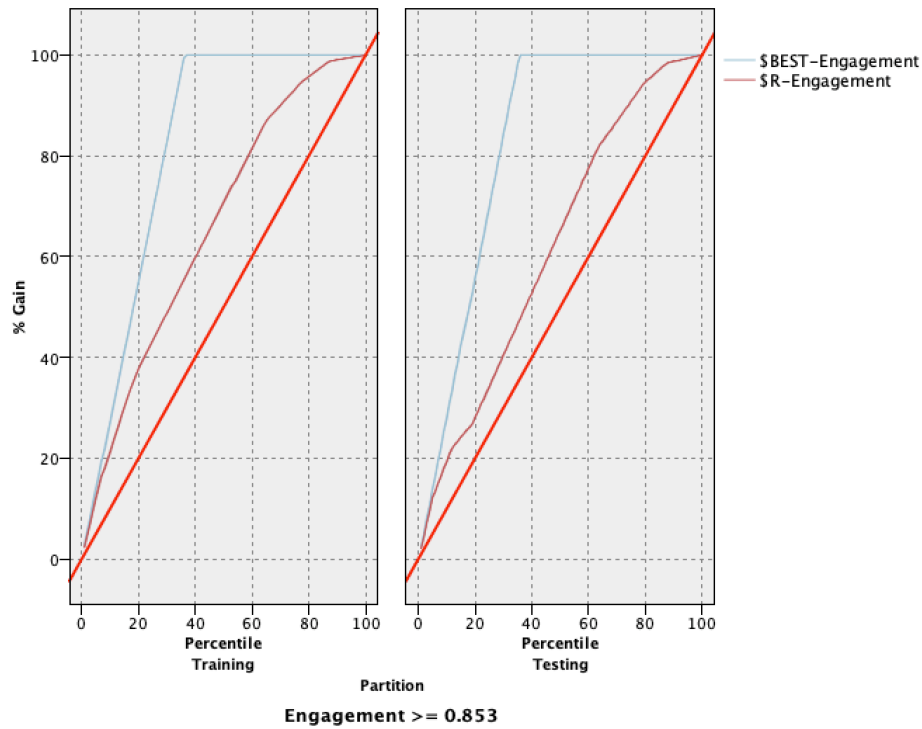


Figure 41: Evaluation Chart of Training and Testing Records (C&RT)

The gain ratio was taken into account while creating the chart. Gains are defined as the “ratio of total hits occurring in each quantile” and they are calculated as $(\text{num. of hits in quantile} / \text{total num. of hits}) \times 100\%$ (IBM Knowledge Center, ____ b). As can be seen in Figure 41, there are three different lines on the chart. These; baseline (red), best line (blue) and business rule (claret red). Baseline visualizes the accuracy rate of the predictions made without any model application. Best Line visualizes the best prediction situation possible. The Business rule curve visualizes the prediction accuracy rate of the model applied in the study. In this context, the fact that the business rule curve is close to the best line curve means that the correct prediction rate is high. For example, according to Figure 41, when 20% of the predictions (percentile training) made within the scope of Training data is selected, 20% of these predictions (% Gain) may be correct if no model is used. However, when the model created in this study is used, the accurate rate rises to 37.8%. If the best model is used, this rate can increase to 55.1%. Accuracy rates for training data can be interpreted similarly.

4.2.4.4.2. CHAID Model Performance

Table 30 summarizes the relationship between predicted engagement and actual engagement values. In the CHAID model, 822 data were trained and an engagement rate was estimated for each. A correlation of 0.634 coefficient was determined between the estimated engagement (\$ R-Engagement) values and the actual engagement values. On the test data, this correlation coefficient was found to be 0.472. It can be said that the 0.634 and 0.472 correlation coefficients reached in the model indicates a strong and moderate relationship according to the distinction of Gerber and Finn (2005) mentioned earlier.

Table 30: Comparing \$R-Engagement with Engagement (CHAID)

■ Results for output field Engagement

■ Comparing \$R-Engagement with Engagement

'Partition'	1_Training	2_Testing
Minimum Error	-1.403	-1.693
Maximum Error	1.492	2.418
Mean Error	-0.091	-0.086
Mean Absolute Error	0.361	0.401
Standard Deviation	0.466	0.547
Linear Correlation	0.634	0.472
Occurrences	822	854

Table 30 also represent the minimum, maximum and mean error and standard deviation results of the prediction of engagement values of training and test data. On the other hand, as mentioned before the hit value was determined based on the average engagement rate in this study. Accordingly, the hit value was determined for the condition equal to or higher than the average value of 0.853 obtained for all messages. This value was used in the flowing section to evaluate the model.

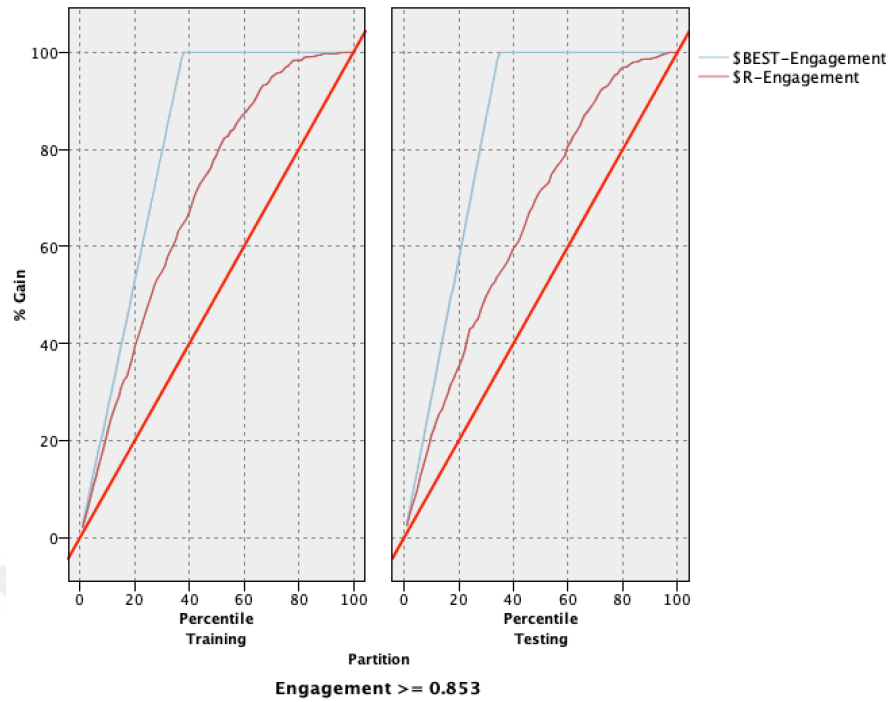


Figure 42: Evaluation Chart of Training and Testing Records

As in C&RT model, the gain ratio was taken into account while creating the chart. According to Figure 42, when 20% of the predictions (percentile training) made within the scope of Training data is selected, 20% of these predictions (% gain) may be correct if no model is used. However, when the model created in this study is used, the accurate rate rises to 39.4%. If the best model is used, this rate can increase to 53.1 %. Accuracy rates for training data can be interpreted similarly.

4.2.4.5. Selection of Best Model

In this section, the results of C&RT and CHAID flow models are compared. Table 31 shows the correlation coefficients (r), which are the indicators of the predictive performance of C&RT and CHAID models. According to the results obtained with the C&RT algorithm, r value for training and test data was 0.512 and 0.441, respectively. The r value obtained as a result of the CHAID algorithm was 0.634 and 0.472 for the training and test data, respectively. Accordingly, the highest r value

for both training and test data was provided by the CHAID algorithm. This also reports that the most accurate prediction percentage for training and test data is the model built with the CHAID algorithm.

Table 31: Linear Correlations of C&RT and CHAID Algorithm Results

Training /Testing	C&RT	CHAID
Training	0.512	0.634
Testing	0.441	0.472

In this context, the final decision support model was designed using the CHAID algorithm. In the next section, the creation of the decision tree and top decision rules are reported.

4.2.4.6. Interpretation of Rules

The next stage of the analysis is for the creation of the decision tree. Informations about the model resulting from the application of IBM Watson Studio modeler is presented in Table 32. Accordingly, as stated earlier, six determinant variables were included in the model. Within the framework of these variables, a decision tree with a depth of six was created. Depth refers to the longest path from the root of the decision tree to the leaf. The number of nodes that determined the size of the decision tree was 25. Nodes represent groups and subgroups that occur in the regression tree and are shown in boxes.

According to the terminology, the group at the very beginning of the tree is called “Root Node” and the whole analysis starts with this node. CHAID Tree is then divided into sections into different branches. Partitioning here refers to the division of data into smaller groups. The new nodes resulting from partitioning are called “Child Node”, while the nodes divided into sections are called “Parent Node”. If a node is not further subdivided, this indicates the end of its growth in that part of the tree, and it is

Table 32: Model Information (CHAID)

Target Field	Engagement
Number of Features	6
Tree Depth	6
Number of Nodes	25

further subdivided, this indicates the end of its growth in that part of the tree, and it is called the “Terminal Node”. If a root node or parent node partitioned into new subgroups (child node), the tree grows a level or gains depth. (Ma, 2018: 19). The terminology for nodes is visualized in Figure 43.

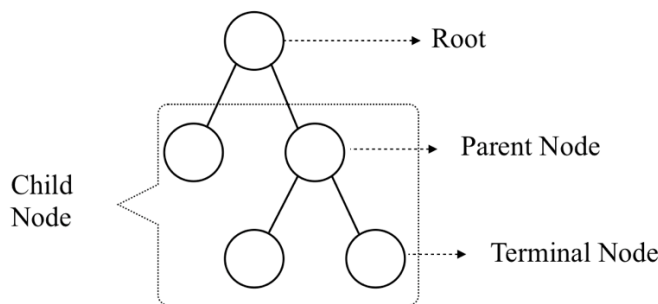


Figure 43: Nodes in Tree Data Structure

The visualization of the regression tree, which shows the mentioned nodes and branch statistics, is presented in Figure 43. As can be seen in Figure 44, there are 25 nodes numbered 0-25. One of these nodes is root node, 10 nodes are parent and 14 nodes are terminal (or leaf node). The size of the nodes in Figure 44 varies according to the number of messages it contains. For example, node 0, called root node, is the most populated node with 822 messages. On the other hand the biggest parent node (Node 3) has 523 message while the smallest parent node (Node 12) has 28 posts. The largest terminal node (Node 21) has 199 message while the smallest terminal node (Node 19) has 10 members.

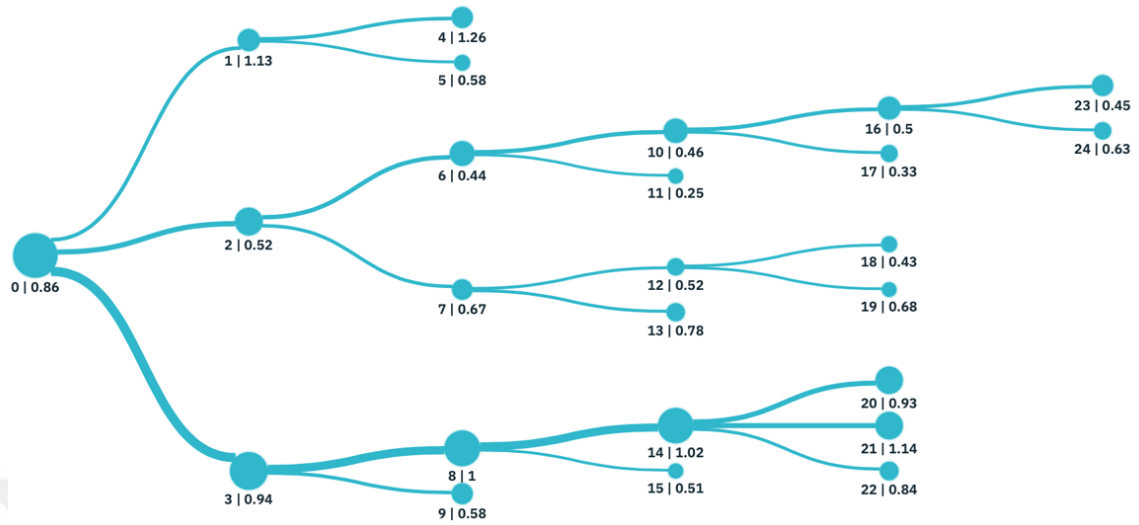


Figure 44: Tree Diagram of CHAID Algorithm

As can be seen from Node 0, the mean value of engagement ratio is 0.86 for the entire 822 messages (mean=0.86, n=822). The CHAID results show that the first significant predictor is the level of interactivity. Therefore, root node is divided into branches according to the interactivity level of the message. As shown in Figure 44, messages that are interactive, Node 1, have considerably higher engagement rate (mean = 1.13) compared to Reactive, Node 3 (mean = 0.94) and No-active, Node 2 (mean 0.52). Interactive messages are separated into two by message type. Accordingly, the messages categorized as Branding, Emotional and Functional, Node 4, generate a higher engagement ratio (mean = 1.26) than the messages categorized as Direct sale and External, Node 5 (mean= 0.58).

No-active messages, Node 2, are split into two by message type. The messages categorized as Functional, Node 7, generate a higher engagement (mean= 0.67) than the messages categorized as Branding, Direct-Sale, Emotional, External and None, Node 6 (mean= 0.44). Reactive messages, Node 3, are divided into two by message type. The messages categorized as Branding, Emotional and Functional, Node 8, lead to greater engagement (mean= 1.00) than the messages categorized as Direct Sale, External and None, Node 9 (mean= 0.58).

Re-share status also divide the Node 6 and Node 8 into two branch; non-resshared (Node 10 and Node 14 respectively) and re-shared (Node 11 and Node 15). Messages created by the company, Node 10 and Node 14, have significantly higher engagement level (mean= 0.46 and 1.02) than the reshared messages, Node 11 and Node 15 (mean= 0.25 and 0.51). Node 7 is partitioned into two by word count. Accordingly, the messages containing more than 36 words, Node 13, cause a greater engagement rate (mean= 0.78) than the messages containing 36 words or less, Node 12 (mean= 0.52).

On the other hand, Node 10 is partitioned into two by media type. Link and photo type media, Node 16, generates higher engagement (mean= 0.5) than text and video type media, Node 17 (mean= 0.33). Node 12 is also splitted into two by link usage status. Accrodingly, the messages using a link, Node 19, gets higher engagement score (mean= 0.68) than the messages not using a link, Node 18 (mean= 0.43). Node 14 is splitted into three by word count; the messages containing more than 40 words and less than or equal to 90 words (word> 40 & word<=97), Node 21, generates higher engagement level (mean= 1.14) than the messages containing 40 words or less, Node 20 (mean= 0.93) and the messages containing higher than 97 words, Node 22 (mean= 0.84). Similarly, Node 16 is splitted into two by word count. The messages containing more than 51 words, Node 24, causes bigger engagement value (mean= 0.63) than the messages containing equal or less than 51 words, Node 23 (mean= 0.45).

Table 33 summarizes the most important decision rules and results. In this study, a total of 14 rules were identified to be associated with engagement rate of companies' LinkedIn messages. The rules here are defined by a list of conditions defining the partitioning of the data discovered by the algorithm. These rules can also be used to assign individual records to sub-nodes (child nodes) based on the values of different predictors (IBM Knowledge Center, ____ c).

Table 33: Top Decision Rules of Learning Outputs

Rule ID	Rule	Mean of Prediction	Record count	Record percentage
21	((Interactivity = Reactive)) and ((Message = Branding or Message = Emotional or Message	1.139	199	24.209

	= Functional)) and ((Reshare = No)) and ((Word>40.0 and Word <= 97.0))			
20	((Interactivity = Reactive)) and ((Message = Branding or Message = Emotional or Message = Functional)) and ((Reshare = No)) and ((Word <= 40.0))	0.929	195	23.723
4	((Interactivity = Interactive)) and ((Message = Branding or Message = Emotional or Message = Functional))	1.260	75	9.124
23	((Interactivity = No Active)) and ((Message = Branding or Message = Direct Sale or Message = Emotional or Message = External or Message = None)) and ((Reshare = No)) and ((Media = Link or Media = Photo)) and ((Word <= 51.0))	0.446	75	9.124
9	((Interactivity = Reactive)) and ((Message = Direct Sale or Message = External or Message = None))	0.582	74	9.002
22	((Interactivity = Reactive)) and ((Message = Branding or Message = Emotional or Message = Functional)) and ((Reshare = No)) and ((Word> 97.0))	0.837	43	5.231
13	((Interactivity = No Active)) and ((Message = Functional)) and ((Word> 36.0))	0.778	38	4.623
24	((Interactivity = No Active)) and ((Message = Branding or Message = Direct Sale or Message = Emotional or Message = External or Message = None)) and ((Reshare = No)) and ((Media = Link or Media = Photo)) and ((Word> 51.0))	0.629	28	3.406
17	((Interactivity = No Active)) and ((Message = Branding or Message = Direct Sale or Message = Emotional or Message = External or Message = None)) and ((Reshare = No)) and ((Media = Text or Media = Video))	0.328	26	3.163
18	((Interactivity = No Active)) and ((Message = Functional)) and ((Word <= 36.0)) and ((Link = No))	0.433	18	2.190
5	((Interactivity = Interactive)) and ((Message = Direct Sale or Message = External))	0.580	17	2.068
11	((Interactivity = No Active)) and ((Message = Branding or Message = Direct Sale or Message = Emotional or Message = External or Message = None)) and ((Reshare = Yes))	0.254	12	1.460
15	((Interactivity = Reactive)) and ((Message = Branding or Message = Emotional or Message = Functional)) and ((Reshare = Yes))	0.505	12	1.460
19	((Interactivity = No Active)) and ((Message = Functional)) and ((Word <= 36.0)) and ((Link = Yes))	0.675	10	1.217

The top decision rules in Table 33 correspond to the terminal nodes of the decision tree in Figure 44. It is possible to evaluate these rules into four categories according to their record rates. Rules 21 and 20 are the most populated IDs. Rules 4, 23, and 9 correspond to high-population IDs. Rules 22, 13, 24, and 17 are IDs with a medium number of populations. Finally, rules 18, 5, 11, 15, and 19 were considered IDs with a small number of populations.

From the first category, rule ID 21 has the highest number of records ($n = 199$) and record rate (24,209%). According to this rule, the mean of prediction rate of messages that are more than 40 words and equal to or less than 97 words, non-reshared, branding, emotional or functional purposed, reactive messages corresponds to 1.139. The rule with 20 IDs is the second-largest population ($n = 195$; 23.723%) rule. This rule states that the mean prediction rate of messages that are equal to 40 words and less than 40 words, non-reshared, branding, emotional or functional purposed, reactive messages is 0.929.

In the second category, according to rule 4 ($n=75$; 9.124%), the mean of prediction rate of messages that are branding, emotional or functional purposed, interactive messages is 1.260. This rate is also the highest mean engagement rate prediction within 14 rules. Rule ID 23 with the same record percentage and number of records ($n= 75$; 9.124) indicates that the mean of prediction rate of messages that are equal to or less than 51 words, link or photo media type, non-reshared, branding, direct-sale, emotional or none-purposed and inactive messages is 0.446. Rule ID 9 ($n= 74$, 9.002%) shows that the mean prediction rate of messages that are direct sale, external information or none-purposed, reactive messages is 0.582.

Rule 22 ($n= 43$, 5.231%) in the third category represents that the mean prediction rate of messages that are higher than 97 words, non-reshared, branding, emotional or functional purposed and reactive messages is 0.837. According to rule 13 ($n= 38$, 4.623%), the mean of prediction rate of messages that are higher than 36 word, functional purposed and inactive messages is 0.778. Rule ID 24's ($n= 28$, 3.406%) mean of prediction rate of messages that are higher than 51 words, link or photo type, non-reshared, branding, direct sale, emotional, external or none-purposed and inactive messages is 0.629. Rule 17 ($n= 26$, 3.163%), which has the least population of the third category, shows that the mean prediction rate of messages that are text or video type,

non-reshared, branding, direct sale, emotional, external or none purposed, inactive messages is 0.328.

On the other hand, Rule 18 (n= 18, 2.190%), which is in the category with the lowest population, represents that the mean prediction rate of messages that not link used, equal to or less than 36 words, functional purposed and inactive messages is 0.433. Rule 5 (n= 17, 2.068%) in this category, indicates that the mean of prediction rate of messages that are direct sale or external information purposed and interactive messages is 0.580. According to rule 11 (n=12; 1.460%), the mean of prediction rate of messages that are reshared, branding, direct sale, emotional, external information or none-purposed and inactive messages is 0.254. This rate is also the lowest mean engagement rate prediction within 14 rules. For rule 15 (n= 12, 1.460%), the mean of prediction rate of messages that are reshared, branding, emotional or functional and reactive messages is 0.505. And finally, rule 19 (n= 10, 1.217%) shows that the mean prediction rate of messages that are link used, equal to or less than 36 words, functional purposed, inactive messages is 0.675.

4.3. GENERAL DISCUSSION AND CONCLUSIONS

Digitalization has been the most important agenda issue of recent times. Digitalization, which is the subject of various technologies and strategies, has a direct impact on the existence and daily activities of both individuals and businesses. One of the areas where this effect is most apparent is communication. Communication, in fact, has had a constantly transforming structure throughout history to transmit information faster and easier. With the impact of digitalization, social media has emerged as the newest communication channel of the 21st century.

Social media, which is seen as one of the basic technologies of digitalization (Probst et al., 2018: 7), has also brought an innovative dimension to marketing communication, especially with a two-way interaction feature (Lacka and Chong, 2016). Social media technologies are increasingly used in B2B markets and research (Salo, 2017), and this trend is expected to become more widespread. This study contributes to this rapidly developing area within the scope of the nature of container shipping companies. This study also offers an innovative approach that contributes to

the gap between data science and marketing literature, using digital data collected from a predetermined social media channel.

This study is a unique study that explores and explains the digitalization of marketing communications in container shipping companies using the latest digital technologies and digitally generated data. In the study, qualitative and quantitative methods have been followed together in order to reveal the strategies and features of the current communication in the social media of container shipping companies and to develop a predictive model for the success level of this communication.

In this study, it is explained that, like other B2B markets (Michaelidou et al., 2011: 1153), container shipping companies have not yet fully adopted social media (see Tablo 11). However, although lacking full adoption, container shipping companies have extreme cases in social media compared to other B2B sectors. For example, Maersk, a container shipping company, started using social media technology in 2011 and achieved great success in this field in a short time (Katona and Sarvary, 2014). In fact, according to the findings of this study, contrary to what is stated in the literature, the fact that Pacific Int. Line started using social media (January 2011) before Maersk (April 2011) is actually proof that container shipping companies can be considered as a pioneer in using social media within B2B sectors. In this context, instead of examining the *“acceptance of social media technology”* in container shipping markets, the answer to the question of *“how can shipping companies use social media more successfully”* was sought.

In this context, engagement, which is used as an important indicator in the measurement of social media success, has been the focus of this study. For the purpose of this study, preliminary research (Bitiktas and Tuna, 2020) has been carried out by using the engagement rate calculation methods proposed in the literature (Haro-de-Rosario et al., 2018; Escobar-Rodríguez and Bonsón-Fernández 2017; Bonsón and Ratkai, 2013). However, as a result of the fact that the existing formulas in the literature miscalculated the success of Facebook and LinkedIn business pages, there was a need to develop a new approach to engagement calculation.

In the new method developed in this study to calculate social media engagement rates of companies, it has been determined that there is an exponential, not linear, relationship between the interaction level of content and the number of

followers of the page due to the algorithm change of the platforms. In other words, the increase in the number of organic impressions of the messages does not occur at the same rate as the increase of the number of followers of the page. It is known that platforms apply this for the purpose of providing relevant content to their users (Facebook for Business, 2014) and increasing their ad revenue. That is to say, the new algorithms aim to enable users to increase their average session duration by providing content related to them, on the other hand, to enable content producers to apply for more advertising programs instead of organic reach to reach wider audiences. It is expected that the new method, which was developed instead of the erroneous engagement calculation formula previously identified in the preliminary study of this research (Bitiktas and Tuna, 2020), will have an important contribution to academic studies.

According to the new approach developed in this research, it is explained that the company with the highest engagement rate on the LinkedIn platform is MSC. On the other hand, Arkas Line was the company with the lowest engagement rate. Maersk, known as the pioneer of social media, ranked sixth after Pacific Line, UniFeeder, ONE and CMA CGM. This situation actually reflects the competition of businesses that understand the importance of social media in digitalization. For example, MSC, which previously stayed away from social media channels other than LinkedIn, started to share on many social media channels with a radical decision in the last quarter of 2018 (MSC, 2018). In the digital marketing of the shipping industry, MSC, which promises to do what has never been done before (MSC, 2015), has indeed followed a successful social media strategy, as can be presented from the finding of this study.

On the other hand, in the light of descriptive statistics, it is explained that most of the companies lack the generally accepted social media strategy and do not make effective use of social media platforms. For example, it has been observed that most companies do not have a stable content sharing calendar, despite having a social media identity. This means that companies are devoid of content sharing planning. CMA CGM, Maersk and Hapag Lloyd were the companies that shared the most content in the past year, while those that shared the least content were Pacific Line, Matson, and Emirates. For example, at this point, although the Pacific International Line is one of

the companies with the highest engagement rate, it is surprising to find that they have shared a small amount of content.

In the study, it has been revealed that the social media message strategies of companies differ according to their business objectives. For example, Maersk has taken into consideration four areas in determining its social media strategy; communication, customer service, sales, and internal use (Katona and Sarvary, 2014). The company's first goal was to be closer to its customers through social media (Nunan et al., 2018; Spekman and Dotson, 2010). In this context, they emphasized brand awareness instead of direct sales. In this study, it is observed that the companies mostly share the message about brand awareness and functional features of the product or company. As noted by Dong (2015), direct selling messages are observed to be the least shared content type. It is explained that the shipping companies as an industrial service provider use social media as a communication tool with their existing and potential customers and employees rather than seeing it as a direct sales channel. However, there are also companies that share call-to-action links to a small extent to increase visitor-leading conversion rates. The engagement rate of such content is relatively weak compared to other types of content. This is perfectly normal because the purpose of such content is not increasing the engagement rate, but increasing the visitor-lead conversion rate.

In this study, the distinctive features of social media messages in terms of engagement rates were determined and the characteristics of those with high engagement were identified by the decision tree model. At this point, a machine learning model has also been developed to predict high engaging content. Thus, it was predicted what level of engagement a message could receive, depending on its characteristics. In machine learning modeling, message-oriented seven features (purpose, media type, link usage, hashtag usage, word count, re-share status and interactivity level) were selected and these features were ranked according to their importance by two different algorithms. Accordingly, the interactivity level was the most determining feature for both algorithms. That is, as the level of interactivity increases, the engagement rate of the message increases. The level of interactivity is discussed in three stages in this study. Accordingly, as Rafaeli (1988) stated, communication has one of the non-reactive, reactive and interactive features. In non-

active communication, which also describes mass communication, there is one-way communication between the sender and the receiver. In reactive messages, the receiver of the message also has a reply. In interactive communication, both parties (the sender and the receiver) are exposed to a two-way message flow (Ariel and Avidar, 2015; Rafaeli, 1988: 119). In this study, interactive messages received the highest engagement rate with a significant difference. This finding also supports the literature (Blasco-Arcas et al., 2013; Chu and Kim, 2011; Wu, 2005; Teo et al. 2003; Rafaeli, 1988). In terms of the level of engagement, interactive messages were followed by reactive messages. The least engaging message type was non-active messages. However, in the study, it was observed that the number of interactive messages was quite low (11.2%), while the number of reactive messages was the highest (62.9%) content type.

In this study, social media messages are classified according to their engagement levels and features through the decision tree, which is an output of the machine learning model. At this point, both theoretical and practical implications have been obtained. In the next chapters, these implications are discussed in detail.

Finally, one of the most important discussion topics of this research is that the theoretically based features of the social media messages that are the subject of the research did not perform as well as expected in developing a prediction model. This is thought to be due to the restrictions in the data collection process. In order to better predict the impact of social media messages, it is thought that a large data set should be used. Or it is assumed that different algorithms that may be more successful in predicting such data should be tested, and if possible, a new algorithm should be written.

THEORETICAL IMPLICATIONS

This study contributes to academic literature in many ways. First, this study is one of the few studies in the literature that deals with the digitalization of B2B marketing communications. Despite its increasing importance and interest, and perceived value for B2B companies, the role of social media in industrial markets has not been sufficiently addressed, and research on its usage is still an embryonic stage

(Lacka and Chong, 2016; Siamagka et al., 2015). This study contributed to filling this gap in the role of social media in B2B markets, especially for container shipping companies.

In addition to the research of social media within the scope of B2B, this study provides a platform-based contribution. Many studies in the literature are generally using social media platforms such as Twitter and Facebook, where data collection is relatively easy. However, LinkedIn is seen as the most effective platform for B2B markets (Bodnar and Cohen, 2011; Schaffer, 2011; LinkedIn, 2020a). Moreover, within the sample of this study, the platform most used by shipping companies is LinkedIn. However, the number of academic studies using the LinkedIn platform is quite rare. This study provides a comprehensive resource for future research to reveal platform-based differences.

One of the most important contributions of this study to the literature is that it offers a new approach to calculating social media engagement rates. With the new news feed algorithms adopted by social media channels, existing calculation formulas in the literature have expired. This calculation error in the literature was first detected by Bitiktas and Tuna (2020) and was confirmed again in this study. It is thought that the new approach to calculate the engagement rate proposed in this study is important for future research to give more accurate results.

This study is the first to apply machine learning modeling by considering social media engagement on a message-oriented theoretical foundation (WOM). In the literature, there are studies dealing with social media engagement with different methods (Bhattacharya et al., 2017; Khan, 2017; Smith and Gallicano 2015; Bonsón and Ratkai 2013). However, in this study, an innovative approach that provides more reliable results based on artificial intelligence (AI) has been demonstrated in understanding the characteristics of content types with a high engagement rate. In accordance with the working principle of machine learning modeling, the data was first trained and then tested. As a result of the analysis, the predictive power of both test data and training data was very similar.

The most important contribution of this study to the social media engagement literature is that the features affecting the engagement rate are ranked according to their importance. In this study, the features of social media messages that provide high

engagement through machine learning modeling are listed according to their importance. Accordingly, the most important feature affecting the engagement level of the social media messages of container transportation companies was the level of interactivity.

Finally, in this study, it contributes to the gap in marketing literature regarding data science. In the present day, where digitalization is rapidly spreading, the science of marketing must adopt disciplines such as data science and machine learning in order to benefit from big data (Chintagunta et al., 2016). This study contributes to extend knowledge of data science in marketing literature.

MANAGERIAL IMPLICATIONS

This study followed explanatory and exploratory methods to produce many novel findings regarding the use of social media by container shipping companies. These findings are thought to provide valuable recommendations to practitioners in the container shipping industry regarding successful social media management.

Findings show that the use of social media in the container shipping market is problematic, as in other B2B industries. As this sector is relatively new to social media and this communication environment is changing rapidly, these companies need to urgently develop an effective social media communication strategy to maintain their brand awareness, competitiveness, market shares and strong customer relationships. When determining social media strategy, there are three key steps to be taken in the first stage. The first is to determine the goals of social media use, the second step is to choose the most appropriate social media channels for their target audience and, as the last step, they should decide on the most effective marketing communication activities. This study provides practitioners with critical recommendations for effective social media communication.

In the first stage of the research, it has been determined that the shipping companies are active in many platforms such as Facebook, Twitter, Instagram, LinkedIn, YouTube and Vimeo. In this study, the five most preferred social media channels in B2B markets are highlighted (Statistica, 2019e). Accordingly, the most preferred platforms for container shipping companies are LinkedIn, Facebook,

YouTube, Instagram, and Twitter, respectively. Given this variety, the research continued on LinkedIn, as addressing all these social media channels would produce superficial analyzes that were irrelevant to the research question. However, due to the most popular and highest number of users, preliminary research was carried out on Facebook. In addition to the implications for practitioners in this preliminary study on Facebook (Bitiktas and Tuna, 2020), more comprehensive implications were obtained on the LinkedIn platform in this study.

At this point, it should be noted that the first thing that attracts the attention of the researcher in the data collection process is that users who interact with the messages of the companies' LinkedIn page has more sectoral ties than those on the Facebook platform. In other words, reactions and comments to messages on the LinkedIn platform are made up of people who have somehow connected with the shipping industry. On the other hand, it has been observed that the comments on the messages include topics such as the brand and products of the company as well as the job application. This situation, which is determined outside the scope of the research question, gives practitioners a clue to choose the right platform according to the purpose of social media usage.

In the study, it was determined that the most important feature affecting the engagement level of social media messages of container transportation companies is the level of interactivity. In this context, it is recommended that companies respond to user replies in order to increase the level of engagement. In this research, while the companies with the highest level of interactive are CMA CGM and Hapag-Lloyd, the non-interactive companies are Arkas, Hyundai M.M. and ESL. This finding is in line with the average engagement rates of the business pages. However, it is not sufficient to say that the only determinant of the engagement rate is the level of interactivity. Other message features such as reshare status, word count, and message type also have a dominant effect on engagement.

In this study, the CHAID algorithm in machine learning modeling has higher accuracy in predicting. In the light of the findings from the CHAID decision tree and rule sets, the first recommendation to the practitioners is for message types within the scope of the Word-of-Mouth (WOM) psychological motivation theory. Accordingly, branding, emotional appeal, and functional appeal contents have higher engagement

rates than external information and direct sales content. In particular, the functional appeal has been the most engaged content type in general. According to the descriptive statistics, it was observed that the container shipping companies mostly shared content for branding, functional and emotional appeal purposes. In this context, companies are recommended to increase the number of functional content.

On the other hand, the literature underlines that emotional values have a powerful role in industrial purchasing decisions (Andersson et al., 2013). As the findings of this research suggest, container shipping companies are recommended to share more emotional appeal content. Also, De Vries et al. (2012) as emphasized, companies should continue to care about brand content to strengthen brand awareness. Furthermore, container shipping marketers should abstain from the use of direct selling messages in their communications to their social media followers. It is also recommended to reduce the frequency of messages for external information purposes.

Another of the clearest recommendations based on the findings of this study is about the reshare status of messages. As a result of the analysis, it was explained that the sharing of the content created by other accounts had a negative impact on the engagement rate. In this context, companies are recommended to create their own content.

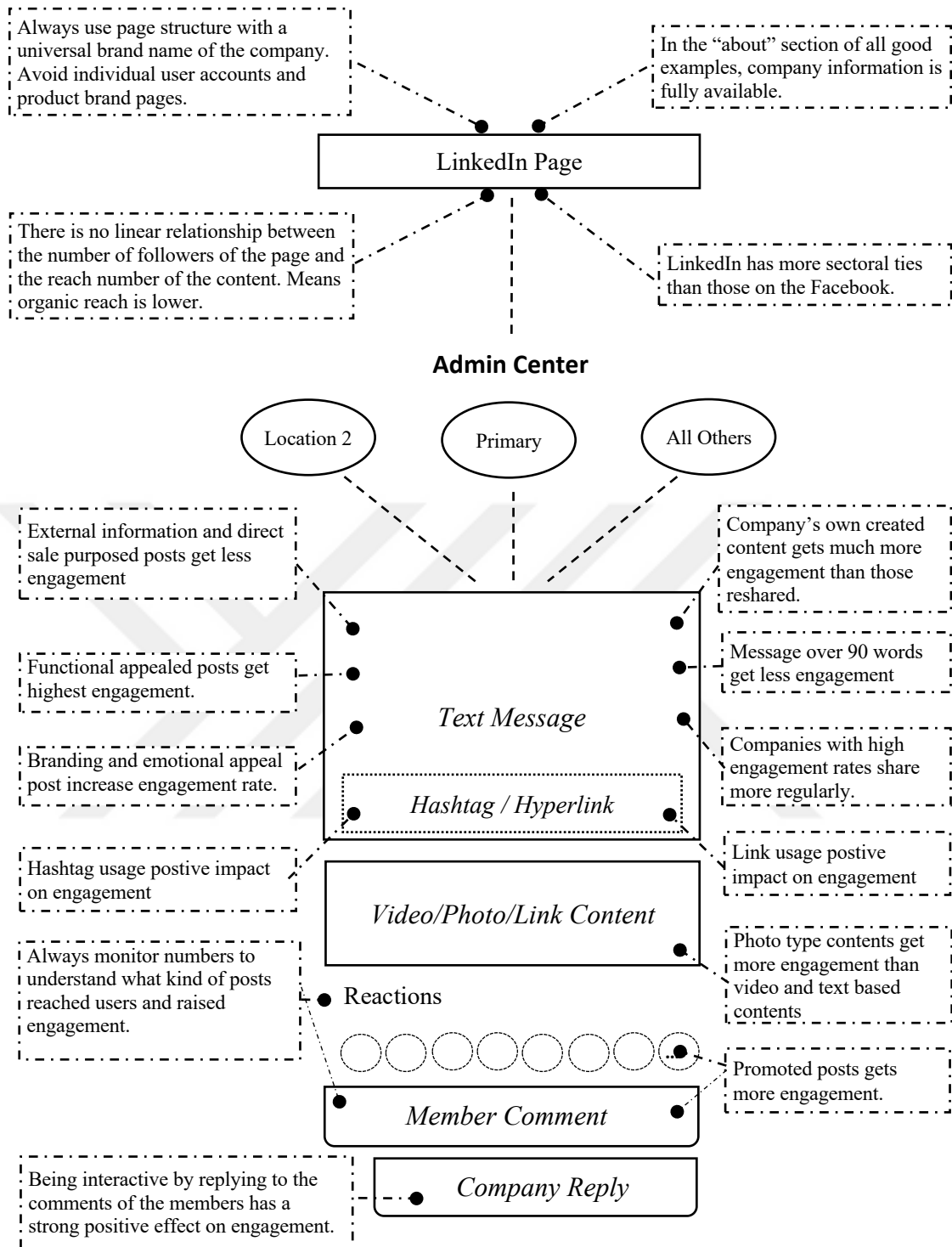
According to this research, other feature that has an effect on obtaining a high engagement rate was the number of words. Given both the decision tree and rule sets, companies are advised to avoid messages that contain too many words. If it is necessary to give a numerical value, it can be said that messages above 90 words on average cause relatively lower engagement.

Another recommendation in terms of message feature is on link usage and media type. In this context, it is recommended that companies share links in their messages. However, Rowe and Alani (2014) stated that the use of a large number of references caused low engagement. Apart from this, as stated in the literature (Saxton et al., 2015; Naveed et al., 2011; Suh et al., 2010), the use of link has been found to have a positive effect on the engagement rate. Furthermore, it is explained that although there is not a very clear difference in line with the literature (Tafesse and Wien, 2018; Denктаş-Şakar and Sürücü, 2018; Kim et al., 2015; Su et al., 2014; Cvijikj and Michahelles, 2013), photo-type content gets more engagement than video and text.

In the literature, there are reports indicating that high vividness (photo and video) encourages enduring attitudes among users (Coyle and Thorson, 2001) for B2B companies. Based on the findings of this study, companies are advised to keep the number of photo-type content shares high.

Finally, in line with LinkedIn business facts and the latest algorithm logic, a blueprint was designed for container shipping companies to share content. Figure 45 visualizes the managerial implications for a successful social media communication strategy.





Note: Technical terms and structures are adapted from the LinkedIn Help Center (<http://bit.ly/2WgvPcG>, <http://bit.ly/2QdYTgX>) and LinkedIn general page view (www.linkedin.com/...).

Figure 45: A Blueprint for Publishing on LinkedIn Business Page for Container Shipping Marketers.

LIMITATIONS AND FURTHER RESEARCH

The first and most important limitation of this study was experienced in the data collection process, as required by LinkedIn's data privacy policy. Accordingly, in the study, a rich database that could increase the predictive power of machine learning modeling could not be created, only public data allowed by the platform could be collected or used. Similarly, due to another data restriction made by the platform, the research has been able to reach the data of the last 12 months for the LinkedIn messages of the companies. In order to overcome such a restriction in future research, a longitudinal (panel) data collection process is recommended.

Another limitation of the study was that container shipping companies tend not to use social media platforms much, which narrowed the available sample. As seen in Table 11, container shipping companies have unique features in social media usage. Given this variety, only LinkedIn data was used in the research, since it would not be possible to sample all these social media channels and would produce superficial analyzes irrelevant to the research question.

This research is dealt with the subject of engagement in social media communication from a message-oriented perspective. Future research can achieve higher accuracy results by including business features (such as ownership type, head office, marketplace, and structure) or page features (such as follower number, degree of advertising, frequency of content sharing) in the machine learning model.

In this study, decision tree algorithms were used to better understand the properties of successful content while creating the machine learning model. Future research can also test different algorithms that will yield higher accuracy by focusing only on prediction. In fact, as a next step, a new algorithm with a higher predictive power specific to social media communication can be developed. Especially with this study that contributes to the in-depth understanding of the problem in social media communication, developing a new algorithm will be a great way for the solution.

In this study, mostly text-based analysis and interpretation were followed. Future research can code and make sense of visual content such as photos and videos with advanced artificial intelligence techniques (such as deep learning). Such a study can make more meaningful contributions today when vividness has become more

popular. Especially, the increasing interest in channels such as Instagram and YouTube, where visuality stands out, makes this kind of research more meaningful.

Finally, as one of the findings of this research study, some companies seem to have chosen to stop posting messages, especially on the LinkedIn platform (see Table 11). It might be worth researching why companies stop posting messages and what benefits they can achieve if they continue.



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APPENDICES

Appendix 1: Message Strategy Coding Scheme

Message Strategy Coding Scheme

Variable	Description
Branding	Social media message that the company or product brand mentioned.
Functional appeal	Social media messages that indicate the features and performances of the company or a specific product.
Emotional appeal	Social media messages that include fear, humor, romance, sensuality, adventure, guilt, game / competition and other emotional themes. Emotional appeals highlight negative or positive emotions.
Direct calls to purchase	Direct calls to purchase messages refer to clear statements that encourage potential buyers to make an immediate purchase. Includes buy commands, also known as a call-to-action.
External information	Refers to any news content messages that do not include the company or product.

Appendix 2: Content Coding Scheme

Coding Scheme

Company and Page Informations

Company name: ____ Total post: ____ Headquarters: ____
Company foundation: ____ Company size: ____ TEU Capacity: ____
Ownership: ____ Page follower: ____

Post Informations:

Post Number: # ____

Q1. Type of Post:

1) Photo	1=Yes	0=No
2) Video	1=Yes	0=No
3) Text	1=Yes	0=No

Q2. Number of reaction ____

Q3. Number of comment ____

Q4. Hashtag status 1= Yes 0= No

Q5. Link status 1= Yes 0= No

Q6. Reshare status 1= Yes 0= No

Q7. Primary Purpose of Post

1) Company/product brand	1=Yes	0=No
3) Emotional Appeal	1=Yes	0=No
4) Functional Appeal	1=Yes	0=No
5) Direct Sales	1=Yes	0=No
6) External Information	1=Yes	0=No

