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-RESEARCH PAPER-

INTEGRATING ORGANIZATIONAL REPUTATION MECHANISM TO DECISION-MAKING PROCESSES: THE FACEBOOK CASE

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Abstract

Facebook, one of the most widespread social media networks across the world, suffered from a serious decline in the share value of the company in the wake of the unauthorized data sharing scandal that occurred in 2018.This survey conducted in the wake of the news of the scandal attempts to determine whether the people would continue to use their social media accounts or not by utilizing the perceived reputation scale. Facebook is an international platform, but the sample of this study consists only of the users in Turkey. The fact that social media is a dynamic agenda-setting tool by nature has revealed the need to respond quickly to the problem. For this reason, the number of the sample was limited to 663, and 72 participants were excluded from the study as they were found to be invalid within the model. The analysis was done through Decision Trees Technique and the rules that affect the perception of the participants and their preferences are revealed. Participants' reputation perceptions are mapped and the probability value of each decision is calculated by the Naive Bayes algorithm. In the decision tree diagram, thirteen rules were obtained. Then, the probability values of each decision made by the Bayesian classifier were calculated and the output of the decision tree diagram was tested. In the research, when the model which is composed of the answers given to the decision variable was tested with the ROC curve, an average of %97, 9 model classification success was achieved. In the decision tree diagram 13 rules were obtained. Then, the probability values of each decision made by the Bayesian classifier were calculated and the output of the decision tree diagram was tested. As a result, each rule obtained from the Decision Tree Diagram has the same result as the Bayes probability values.

Keywords: *Reputation Management, Organizational Reputation, Naive Bayes, Decision Trees, Reputation Risk, Data Mining.*

JEL Codes*: D81, M10, M15*

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ÖRGÜTSEL İTİBAR MEKANİZMASININ KARAR ALMA SÜREÇLERİNE ENTEGRASYONU: FACEBOOK ÖRNEĞİ

Öz

Dünyanın en yaygın sosyal medya ağlarından biri olan Facebook, 2018 yılında gerçekleşen yetkisiz veri paylaşım skandalının ardından, şirketin pay değerinde ciddi bir düşüş yaşamıştır. Bu skandalla ilgili haberler sonrasında yapılan araştırmada, algılanan itibar ölçeği kullanılmıştır. Araştırma, hali hazırdaki kullanıcıların Facebook hesaplarını kullanmaya devam edip etmeyeceklerini belirlemeyi amaçlamaktadır. Facebook uluslararası bir platformdur, ancak bu çalışmanın örneklemini sadece Türkiye'deki kullanıcılar oluşturmaktadır. Sosyal medyanın doğası gereği dinamik bir gündem belirleme aracı olması, soruna hızla cevap verilmesi gerekliliğini ortaya koymuştur. Bu nedenle, örneklem sayısı 663 ile sınırlı tutulmuş ve modelde geçersiz olduğu tespit edilen 72 katılımcının yanıtları çalışmadan çıkarılmıştır. Analiz karar ağaçları tekniği ile yapılmış, katılımcıların itibar algılarını etkileyen kurallar ve katılımcı tercihleri açıklanmıştır. Katılımcıların itibar algıları haritalanmış, alınan her kararın olasılık değeri Naive Bayes algoritması ile hesaplanmıştır. Karar ağacı şemasında on üç kural elde edilmiştir. Daha sonra, Bayesian sınıflandırıcı tarafından verilen her kararın olasılık değerleri hesaplanmış ve karar ağacı diyagramının çıktısı test edilmiştir. Yapılan araştırmada karar değişkenine verilen cevaplardan oluşan model ROC eğrisi ile test edildiğinde, ortalama %97, 9 model sınıflandırma başarısı elde edildiği gözlemlenmiştir. Karar ağacı şemasında 13 kural elde edilmiştir. Daha sonra, Bayesian sınıflandırıcı tarafından verilen her kararın olasılık değerleri hesaplanmış ve karar ağacı diyagramının çıktısı test edilmiştir. Sonuç olarak, karar ağacı diyagramından elde edilen her kuralın Bayes olasılık değerleri ile aynı sonuca sahip olduğu görülmüştür.

Anahtar Kelimeler: *İtibar Yönetimi, Örgütsel Itibar, Naive Bayes, Karar Ağaçları, Itibar Riski, Veri Madenciliği.*

JEL Kodu*: D81, M10, M15*

**Makalemizin değerlendirilmesi sürecinde emeği geçen değerli hakemlere harcadıkları zaman ve iyileştirilmesi gereken önemli alanları tespit eden içgörülü yorumlar için teşekkür ederiz. Hakemlerin önerileri dikkate alınmış, makalenin iyileştirilmesi ve netleştirilmesi için uygulanmıştır.*

1. INTRODUCTION

In recent years, the concept of corporate reputation has become a hot academic topic (Brown et al., 2006) addressed by both the academia and the business world, especially in relation to some similar concepts such as corporate identity, corporate image and corporate character under the heading of corporate reputation management. It is increasingly recognized for its influence in creating stakeholder support and engagement with companies (Fombrun et al., 2015). One of the most prominent and important features of the concept in the literature is that a considerable number of paradigms in the social sciences are interested in this concept and that it is somehow regarded as point of intersection between these distinct views of reputation such as economic, strategic (management), marketing, organizational, sociological and accounting (Fombrun and van Riel, 1997). Within this research, however, we have adopted the strategic management perspective which is mainly driven by three important approaches. According to the first approach, corporate reputation is regarded as a strategic resource which is a pivotal tool and could help organizations gain competitive advantage in their current environment (Roberts and Dowling, 2002) or as a valuable and intangible asset that provides organizations with a unique position to reach better resources on more favourable terms (Chen and Otubanjo, 2013; de Quevedo et al. 2007). Scholars that embrace this perspective also center upon the resource allocations that firms must make over time to resolve reputational barriers to the mobility of rivals (Barney, 1986) and emphasise the competitive benefits of gaining a good reputation (Fombrun and van Riel,1997; Rindova and Fombrun, 1997). The second approach sets the sight more on attracting consumers and purchase decision making processes. Within the context of this approach, it is asserted that a favorable corporate reputation with positive connotations in the minds of customers pave the way for organizations to attracting new consumers as well as keeping the existing ones (Shkolnikov et al., 2004). Some researches like Ponzi et al. (2011) done later on confirms this view that reputation is an important intangible value because it affects consumers' preferences for products and services, or investors about whom to lend money or job seekers' decisions about where they will work. The third approach embraces the notion of corporate reputation as a value -based on the feedback from stakeholders- creator and also a performance driver through which organizations fulfill needs and improve performance competitively (Chen and Otubanjo, 2013; McGuire et al., 1990). Herein, the emphasis on the notion of value is of great impartance as organizations develop their reputation by focusing on their vision and mission and shaping the behavior that reflects their values. This develops organization the culture and reputation is the product of this culture (Davies, 2006:47). Indeed, this third perspective has a theoretical base in common with the first one which asserts that the concept of reputation help organizations achieve a certain level of competitive advantage in their institutional environment. With respect to the allegement that a favorable organizational reputation helps to generate values that firms in the competitive environment find hard to imitate (Roberts and Dowling, 2002).

1.1. Conceptualizating Organizational Reputation

Reputation management literature has grown to maturity in terms of dimensions of reputations as there have been quite many attempts to conceptualize the notion of reputation and measure reputations of organizations over the last decade. To start with the first corner stone attempt to conceptualize reputation, Pruzan (2011) asserts that there are two basic and mutually complementary perspectives that illustrate how the corporate reputation concept is viewed by organizations and what policies and strategies are developed based on it. These two main perspectives are the pragmatic approach and reflective approach. The difference between these two approaches is basically related to the place where the firms position themselves at the point of profit maximization. Within the pragmatic perspective, profit maximization is the ultimate goal of organizations, and manager performance is assessed in terms of profitability. The reflective approach, however, emphasizes the responsibility of the organization to its environment and the actions to be taken in its context. Accordingly, organizations need to take steps to improve social welfare and ethical values instead of profit maximization (Carroll, 2013:363).

Secondly, in his comprehensive literature review, Barnett (2006) found that corporate reputation is embraced by organizations from three central points. According to him, the first point defines reputation as a state of awareness. In this case, consumers or other stakeholders have a general awareness of the business but do not make a definite judgment. According to Barnett (2006), the second point views the concept as an assessment and takes reputation as a mechanism that operates on some preliminary estimates, evaluations, and judgments. From this point of view, reputation is defined as a value attributed to organizations, organizational characateristics and consistency and reputation can be defined as the shared assessment through which the expectations and norms that arise in the corporate context can be compared to the business performance (Sümer and Pernsteiner, 2014:6). The third point, which complies with strategic management perspective on reputation, basically positions the concept as an asset. With this point of view, reputation is a valuable but fragile economic asset hence this group includes references to the term as a resource or as an intangible, financial or economic asset (Barnett 2006).

Thirdly, Lange et al. (2011) conducted a literature review from which they identified three major reputation conceptualizations: being known, being known for something and generalized favorability (Fombrun et al., 2015). According to Lange et al. (2011), from the view ofbeing known conceptualization, “organizational reputation is stronger if awareness of the firm is broader and if perceivers have a more distinctive perceptual representation of the firm”. The conceptualization of being known for something, on the other hand, means that an “organization has a reputation for something, such as having high-quality products or being an aggressive price predator” (Lange et al., 2011). Lastly, the generalized favorability conceptualization entails perceiver judgments about the firm that are based on aggregated multiple organizational attributes rather than being dependent on a given audience’s expectations for specific organizational outcomes” (Lange et al., 2011; Fischer and Reuber, 2007). However, as Lange et al. (2011) remarks, there is a prominent distinction between the dimensions ofbeing known for something and the generalized favorability as being known for something reflects perceiver expectations for particular desired or undesired organizational attributes or outcomes whereas generalized favorability dimension represents the perceiver’s approach– avoidance reactions to the generalized global perceptions of the firm (Fombrun et al., 2015).

1.2. Dimensional Profusion on Reputation Meausrement Scales

Reputation is increasingly recognized for its influence in creating stakeholder support and engagement with companies (Fombrun et al., 2015). Since the notion of organizational reputation has gone through decades of improvement, the literature has shown a certain level of progress by virtue of the numerous theoretical and empirical surveys not only to conceptualize but also to measure reputation. The growing interest in organizational reputation has led to the development of a variety of different construct measures (Helm, 2005). However, though researchers have shown considerable interest in measuring the corporate reputation construct, this process resulted in a lack of consensus on a valid measurement approache. When researchs made on organizational reputations are examined in the literature, it is observed that in the studies conducted by emphasizing the intercultural validity of the scales formed, generally the quotients of the reputation of the organizations are calculated and reputation-oriented rankings are made in this direction. Indeed, especially the publications based on the United States and business-oriented publications such as Fortune, which are measuring the reputation of organizations in the society through different dimensions of reputation, have started to pay more attention to reputation over the last decade. The literature offers us wide variety of surveys each of which has a unique contribution to organizational reputation measurement. As a cornerstone of reputation literature, Fombrun et. al. (1997) suggested a new instrument called the reputation quotient (RQ) which as they claimed is a robust measure of corporate reputations that considerably improves the state of the art in reputation measurement. The dimensions proposed in RQ are; emotional appeal, products and services, vision and leadership, workplace environment, social and environntentalresponsibilityandfinancial performance. However, Fombrun et. al. (2015) developed TheRepTrak® which evolved from studies conducted by Reputation Institute since 2000 to provide a systematic tool for tracking and analyzing stakeholder perceptions. This new scale is composed of seven dimensions; products, innovation, workplace, governance, citizenship, leadership and performance.

Davies et al. (2001), for instance, proposed The Personified Metaphor as a measurement Approach for Corporate Reputation in which they used the dimensions of sincerity, competence, sophistication, excitement and ruggedness. Another example is The Reputation Index suggested by Cravens et. al. (2003) who defined reputation as the most critical, strategic, and an enduring asset that a corporation possesses. In their scale, they laid the foundations of measurement on the dimensions of products and services, employees, external relationships, innovation, value creation, financial strength, strategy, culture and intangible liabilities. Later on, Helm (2005), used the dimension ssuch as quality of products, commitment to protecting the environment, corporate success, treatment of employees, customer orientation, commitment to charitable and social issues, value for money of products, financial performance, qualification of management and credibility of advertising claims. In their customer-based reputation scale assessing an abbreviated version of the CBR scale, Walsh and Beatty (2007), proposed five dimensions; customer orientation, good employer, reliable and financially strong company, product and service quality, social and environmental responsibility. And finally, Sarstedt et. al. (2013) discussed commonly used reputation measures from a conceptual as well as theoretical perspective, and empirically compared them in terms of convergent validity and criterion validity emphasizing the dimensions of satisfaction, loyalty, trust, commitment. In our survey, we aimed at taking advantage of this multi-dimensional nature of the organizational reputation concept and based on the research problem, satisfaction, loyalty, trust, commitment dimensions asserted by Sarstedt et. al. (2013) and the governance dimension of Fombrun et. al. (2015) were utulized.

2. METHODOLOGY

Facebook, one of the most widespread social media networks across the world, suffered from a serious decline in the share value of the company in the wake of the unauthorized data sharing scandal that occurred in 2018. The economic impact of this scandal can be easily observed on stocks. However, the sense of organizational reputation that emanates from people does not emerge only from investor preferences or from the company's economic appraisal. By 2018, the number of Facebook users has surpassed two billion. This number accounts for the sum of the population of China and India, which has the largest population. In this direction, Facebook is an important tool to create a mass perception. This survey conducted in the wake of the news of the scandal attempts to determine whether the people would continue to use their social media accounts or not. Aside from these questions, participants were asked whether they would continue to use their facebook accounts despite the news as a dependent variable undertaking the purpose of the research as well a few demographic questions. In the study, the analysis was done through decision trees which is a classification-based data mining technique and the rules that affect the perception of the participants and their preferences are revealed. In the survey, data were collected through face-to-face or online questionnaire surveys of 591 people. From the survey data, participants' decision-making processes were modeled by data mining. First, the data passed through the preprocessing process and after databinding, databurging and incomplete data completion, the raw data were made compatible with data mining. The J48 decision tree algorithm was applied to the data acquired from 6 independent variables in order to obtain rules about whether the participants would continue using facebook accounts or not. With reference to the dimensional redundancy in measuring corporate reputation mentioned previously, a wide range of scales and items which indicated reasonable performance in terms of reliability and validity were utilized. In this direction, the survey is fundamentally based on the scales suggested by Sarstedt et al. (2013) who made a stride towards harmonizing the measurement of corporate reputation by empirically comparing these scales in terms of convergent validity and criterion validity and The RepTrak scale of Fombrun et al. (2015). Accordingly, in this study, the reputation perception was measured with a total of 14 questions measuring through the dimensions of Overall Reputation (Walsh and Beatty, 2007), Satisfaction (Sarstedt et. al. 2013), Loyalty (Sarstedt et. al. 2013), Trust (Morgan and Hunt, 1994), Commitment (Henning et al., 2002), and Governance (Fombrun et. al. 2015). Each item to be applied in the survey were meticulously translated into Turkish language upon consulting the experts within the field and the questions were posed in Turkish. However, online questionnaire application could have some validity and reliability constraints compared to face-to-face questionnaire application. Hence, three main measures have been taken to minimize the constraints mentioned. These are duplicate user identification, gradual reliability analysis and preliminary question control respectively.

2.1. Duplicate User Identification

In questionnaire studies, identification information should not be taken to ensure that participants give accurate answers and there is no hesitation from any authority. In addition, if there is no consecutive study such as pre-post test, it should also be ensured that each participant participates only once in the research according to the ethical rules. However, it is very difficult to understand whether there is a repeated participation in the online survey studies without the participant's identification. Hence, the IP addresses were checked via an online tool used to minimize the impact of this restriction and the questionnaires with the same IP address were excluded from the study.

2.2. Gradual Reliability Analysis

Although validity and reliability studies of the scales used in the questionnaire were previously conducted, an additional reliability study of the data collected online will allow us to confirm the reliability of the method used. In order to show that the online questionnaire is correctly perceived by the participants and that consistent data is given, an additional reliability analysis was performed and an acceptable reliability ratio was obtained.

Table 1. Reliability analysis for face to face and online questionnaire data

Method	Valid Cases (n)	Cronbach's Alpha	Items (n)
Face to face	213	0,817	14
Online	378	0,833	14
Total	591	0,843	14

2.3. Preliminary Question Control

In this research, the preliminary questions required for the study are utilized. With these questions, it is aimed to determine whether the participants have prior knowledge about the research topic. In this study, respondents who gave negative responses in any of the two premise problems were restricted by the fact that their responses to the questions would not be meaningful.

3. RESULTS

3.1. Preprocesses Applied to The Data

Among the data gathered, firstly, the answers to the questions, which are the precondition of the main problem of the research, below examined.

• Do you have a personal social media account on Facebook? (Yes/No),

• Have you recently read news about Facebook's data sharing in the media? (Yes/No)

Of the respondents, 43 gave the answer "No" to the first question and 72 answered "No" to the second question. All of those who gave the "No" answer to the first question gave the answer "No" to the second question at the same time. Therefore, the questionnaire of the 72 participants was terminated here, and other questions were not asked. When the responses of the 591 respondents who gave the "Yes" answer to both quesions were examined, it was seen that some of the questions (very few) offered via likert scale were not answered. Binningmethod and linear regression method were applied to these items and the missing data were completed. Because some factors in the obtained data were measured with more than one item, the new factor values were obtained by taking the averages of the items belonging to each factor. As a result of the preprocessing, original data features were preserved and demographic questions, pre-condition questions, and scale items were resized from 591 participants' responses.

3.2. Correlation Analysis

The correlation coefficient in the equation (Andrew and Valerie 2003**)** given below is used to determine the magnitude and direction of the relationship between the variables. Correlation analysis has been applied to determine whether there is a relationship between the independent variable and the dependent variable, and if so, whether the direction is correct. The correlation value is considered to be low unless it is less then -0.50 and greater than 0.50 (Asuero et al., 2006).

$$r = \frac{\sum_{k=1}^{N}[\left(x_{i,k} - \langle x_i \rangle\right)\left(x_{j,k} - \langle x_j \rangle\right)]}{\sqrt{\sum_{k=1}^{N}\left(x_{i,k} - \langle x_i \rangle\right)^2 \sum_{k=1}^{N}\left(x_{j,k} - \langle x_j \rangle\right)^2}}$$

Table 2. Correlation between target variable and Independent variables

Overall Reputation (R)	R1	0.657	0.657	**Trust (T)**	T1 T2	0.787 0.759	0.819
Satisfaction (S)	S1 S2	0.656 0.691	0.765	**Commitment (C)**	C1 C2	0.610 0.619	0.686
Loyalty (L)	L1 L2 L3 L4	0.810 0.797 0.775 0.827	0.862	**Governance (G)**	G1 G2 G3	0.736 0.728 0.733	0.797
Gender		0.046		**Education**		0.138	

At the 0.05 significance level of the gender variable, the correlation value obtained through the target variable was not statistically significant. While the educational status is statistically significant, the correlation value is very low. This may result in the fact that neither of the two variables will have an effect on the decision or it will be very low. For this reason, these two variables are not included as independent variables in Decision Tree and Naive Bayes algorithms. Many methods are used to understand and summarize the distributions of the data. In data mining studies, five number summary is generally preferred. There are multiple items for each factor in the data collected from questionnaires. Factor values were determined by taking the average of the items included in each factor. The 5 digits summary of these calculated values includes the minimum value in this data set, 1. Cartil (Q1), 2. Cartil (median), 3. Cartil (Q3) and maximum value. With the summary information given in Table 2, it is possible to obtain information about the outliers in the data set and the distribution of the data set.

Table 3. Five Number Summary

SUMMARY	Reputation	Satisfaction	Loyalty	Trust	Commitment	Governance	Decision
Minimum	1,000	1,000	1,000	1,000	1,000	1,000	1,000
Q1	2,000	2,000	1,500	2,000	2,000	2,333	1,000
Median	3,000	2,500	3,750	3,000	3,000	3,000	2,000
Q3	4,000	4,000	4,000	3,500	4,000	4,000	3,000
Maximum	5,000	5,000	5,000	5,000	5,000	5,000	3,000

3.3. Classification by Decision Algorithm

Decision trees algorithm is one of the most utilized methods in classifying and obtaining rules partly because the comprehension and interpretation of decision trees is easier when compared with other rule acquisition methods. Primarily, for the Decision Trees algorithm the input data composed of independent variables is required. This data consists of categorical or numerical variables. Depending on the algorithm to be used, pre-processing can be performed on the data. The target (dependent) variable must be of the structure that can be used for the classification.

Decision trees algorithm seeks for the best ranking to guess target variables. In this phase, information gain theory is used for the most part. First, a root node is created. If all the instances belong to the same class, then the node becomes a leaf, otherwise a division is carried out and a branch will be created (Bounsaythip and Runsala, 2001). Using the same algorithms for each number of classes, categorical variables are used, if the data is continuous, it is transformed into categorical. For the finalization of the algorithm, it is necessary that all the samples in a node belong to the same class, the samples do not have the qualities to be separated or there should be no other samples. The most important algorithms developed for this classification case are ID3 (Quinlan, 1986), C4.5 and C5.0 (Quinlan, 1993), C & RT (Breinman et al.,1984), CHAID and QUEST (Kass,1980) algorithms. In the study, the J48 version of the C4.5 algorithm was preferred.C4.5 (J48) Decision Tree algorithm was applied to the data obtained from the questionnaires. The most important step in decision tree implementation is to decide the starting node of the tree. The most common application in the literature is determining the information gain values of each Wang et al., 2017). The information gain values are given in the table 4.

Table 4. Information Gain Value of Factors

FACTORS		ENTROPY INFORMATION GAIN VALUE
Overall Reputation	**R**	0.039
Satisfaction	**S**	0.114
Loyalty	**L**	0.077
Trust	**T**	0.079
Commitment	**C**	0.073
Governance	**G**	0.069

The decision tree algorithm calculates the information gain values by measuring the uncertainty of the entropy values while forming each node, and determines the nodes to be formed in each step of this treegiven in Figure 1.

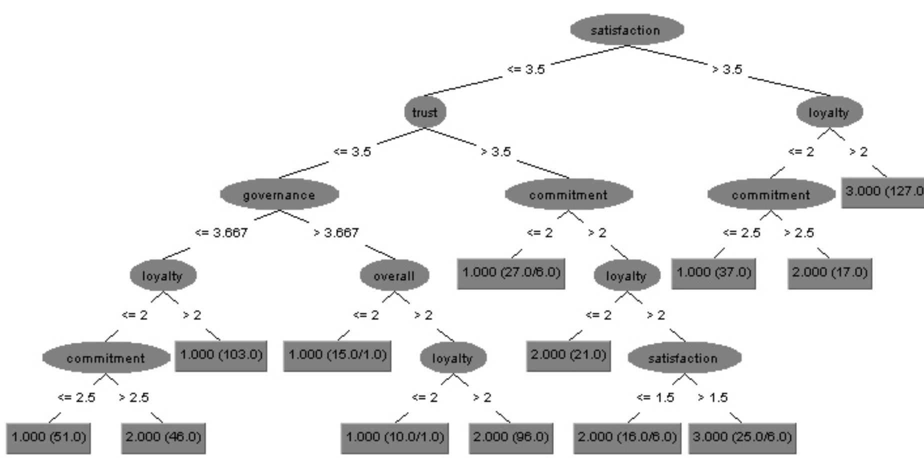

Figure 1. Decision Tree Results

The statistical values of the accuracy ratiosfor the obtained Decision Tree are given in the table. In this study, some parameter values of J48 algorithm were changed and experiments were performed and the mostsimple decision tree diagram was obtained by applying a pruning process. An optimal tree diagram is given. After the necessary pruning and other parameters were determined optimally in the decision tree, the algorithm was run for confidence value 0.50 and the correct classification values were compared at different training /test ratios and the results were tabulated. In table 4, the successful classification scores obtained when the training and test set rates change are given.

Table 5. Various Training - Test Set Accuracy Rate

Train Set - Test Set Confidence 0.5	**Accuracy**	**Under ROC Area**
% 50 - % 50	% 89.1525	% 96.5
% 60 - % 40	% 89.8305	% 97.0
% 70 - % 30	% 90.9605	% 97.6
% 80 - % 20	% 91.5254	% 98.3
% 90 - % 10	% 91.5254	% 99.4

In Decision Tree applications, attempts have been made to make meaningful results without distorting the data integrity and to determine the effects of the participants in decision-making process. The results obtained should be the most basic and the ones that can best represent the sample. The conclusions of the study were obtained as a result of pre-pruning and final pruning. Rule 2, Rule 5, Rule 7 and Rule 9 contain two rules as a final leaf, resulting in two decisions.

3.4. Naive Bayes Classification

The statistical classifier, Naive Bayes Classifier, is used to determine certain events and to make decisions about other events related to these eventsthrough observation. Naive Bayes Classifiers can be used as a decision system on their own. When used together with decision trees, both results are comparable and the probability values of rules derived from decision trees can be calculated.

Scientific discovery, often used as a method of acquiring knowledge, is based on sampling the sub-space of phenomena where hypotheses can be tested and theories are built. In these events, probabilities can be measured and rules can be drawn about relations between different events. However, there is nothing that can be done directly to measure the probabilities. The notation given below (Orre, 2003), which is the most common formulation for bayes classifier, is utilized for the understanding of the process that constitutes the probabilities that we are assuming.

$$P(A|B) = \frac{P(A,B)}{P(B)} = \frac{P(A \cap B)}{P(B)}$$

The probability values of the decision variable are listed In the Table 5.

Table 6. Target Variable Probability Distributions

The case of Continuation	*Frequency Values*	*Probability Values*
Negative	235	0.398
Indecisive	199	0.337
Positive	157	0.266
Total	591	

With Decision Trees C4.5 (J48) algorithm, nodes, branches and leaves on the diagram were obtained. Here, each rule starts with the first node and ends with the leaf. Based on each rule generated by the Naive Bayes algorithm, probability values are calculated and given in the Table 6. Also, the probability values for the Naive Bayes algorithm for each decision made in the decision tree are given in the Table 7.

Table 7. Probability Values for Each Factor

R		**R <= 2.0**	**R > 2.0**	
	Negative	0.5404	0.4596	
	Indecisive	0.2060	0.7940	
	Positive	0.3631	0.6369	
S		**S <= 1.5**	**1,5 < S <= 3.5**	**3.5 < S**
	Negative	0.2255	0.5362	0.0468
	Indecisive	0.3065	0.3769	0.0201
	Positive	0.0510	0.5478	0.3439
L		**L <= 2.0**	**L > 2.0**	
	Negative	0.5254	0.4788	
	Indecisive	0.4350	0.5700	
	Positive	0.0063	0.9927	
T		**T <= 3.5**	**T > 3.5**	
	Negative	0.4128	0.5872	
	Indecisive	0.3970	0.6030	
	Positive	0.1592	0.8408	
C		**C <= 2.0**	**2.0 < C <= 2.5**	**2.5 < C**
	Negative	0.5957	0.0809	0.3234
	Indecisive	0.1106	0.0905	0.7990
	Positive	0.2357	0.1656	0.5987
G		**G <= 3.67**	**G > 3.67**	
	Negative	0.2809	0.7191	
	Indecisive	0.0905	0.9095	
	Positive	0.1975	0.8025	

Table 8. Naive BayesResult For Each Rule

Rule 1	**Negative**	**0.0224**
	Indecisive	**0.0114**
	Positive	**0.3413**
Rule2.1	**Negative**	**0.0079**
	Indecisive	**0.0069**
	Positive	**0.0012**
Rule2.2	**Negative**	**0.0007**
	Indecisive	**0.0019**
	Positive	**0.0003**
Rule3	**Negative**	**0.1875**
	Indecisive	**0.0010**
	Positive	**0.0006**
Rule4	**Negative**	**0.0133**
	Indecisive	**0.1140**
	Positive	**0.0059**
Rule5.1	**Negative**	**0.0024**
	Indecisive	**0.0007**
	Positive	**0.0164**
Rule5.2	**Negative**	**0.0065**
	Indecisive	**0.0115**
	Positive	**0.0070**

Rule 6	**Negative**	**0.0075**
	Indecisive	**0.0065**
	Positive	**0.0004**
Rule 7.1	**Negative**	**0.0045**
	Indecisive	**0.0615**
	Positive	**0.0001**
Rule 7.2	**Negative**	**0.2261**
	Indecisive	**0.0065**
	Positive	**0.0007**
Rule 8	**Negative**	**0.1145**
	Indecisive	**0.0042**
	Positive	**0.0001**
Rule 9.1	**Negative**	**0.0065**
	Indecisive	**0.1547**
	Positive	**0.0123**
Rule 9.2	**Negative**	**0.1606**
	Indecisive	**0.0001**
	Positive	**0.0078**

3.5. Overall Rules

Rule 1:
When Satisfaction > 3.5 and Loyalty> 2,
the case of continuation: positive

Rule 2.1:
When Satisfaction > 3.5, Loyalty<= 2 and Commitment<= 2.5,
the case of continuation: negative

Rule 2.2:
When Satisfaction > 3.5, Loyalty<= 2 and Commitment>2.5,
the case of continuation: indecisive

Rule 3:
When Satisfaction<= 3.5, Trust> 3.5 and Commitment<= 2.0
the case of continuation: negative

Rule 4:
When Satisfaction<= 3.5, Trust> 3.5, Commitment> 2.0 and Loyalty<= 2.0,
the case of continuation: indecisive

Rule 5.1:
When Satisfaction<= 3.5, Trust> 3.5, Commitment > 2.0, Loyalty> 2.0 and Satisfaction> 1.5,
the case of continuation: positive

Rule 5.2:
When Satisfaction<= 3.5, Trust > 3.5, Commitment> 2.0, L > 2.0 and Satisfaction<=1.5,
the case of continuation: indecisive

Rule 6:
When Satisfaction<= 3.5, Trust<= 3.5, Governance> 3.667 and Overall Reputation<=2.0,
the case of continuation: negative

Rule 7.1:
When Satisfaction<= 3.5, Trust <= 3.5, Governance > 3.667, Overall Reputation> 2.0 and Loyalty>2,
the case of continuation: indecisive

Rule 7.2:
When Satisfaction<= 3.5, Trust<= 3.5, Governance > 3.667, Overall Reputation> 2.0 and Loyalty<= 2
the case of continuation: negative

Rule 8:
When Satisfaction <= 3.5, Trust<= 3.5, Governance<= 3.667 and Loyalty>2.0,
the case of continuation: negative

Rule 9.1:
When Satisfaction<= 3.5, Trust<= 3.5, Governance<= 3.667, Loyalty<= 2.0 and Commitment>2.5,
the case of continuation: indecisive

Rule 9.2:
When Satisfaction<= 3.5, Trust<= 3.5, Governance<= 3.667, Loyalty<= 2.0 and C<= 2.5,
the case of continuation: negative

The accuracy values of these rules were obtained by different approaches and were also given in the Table 8 below.

Table 8. Different Approaches for Accuracy Values

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	PRC Area	Class
	0.933	0.024	0.959	0.933	0.946	0.985	0.961	Positive
	0.947	0.096	0.857	0.947	0.900	0.963	0.928	Negative
	0.840	0.013	0.955	0.840	0.894	0.995	0.981	Indecisive
Avarage	0.915	0.048	0.919	0.915	0.916	0.979	0.953	

3.6. Generational Effects on Reputation Factors

Additionally, analysis of variance (ANOVA) was applied to each factor in the scale according to generations X, Y and Z age ranges (Çetin and Karalar, 2016). As a result of the analysis, no significant difference between generations was observed except for the *satisfaction* and *trust* factors.

Table 9. Analysis of Varience (ANOVA)

	Generation X 1965-1980 n = 288	Generation Y 1981-1999 n = 299	Generation Z 2000 - n = 4	Test value F Statistics	p
Overall Reputation (R)	3,0382 ± 0,1655	3,0569 ± 0,1647	3,2500 ± 2,7175	0,052	0,950
Satisfaction (S)	3,1597 ± 0,1382	2,7241 ± 0,1330	2,1250 ± 0,7617	10,986	0,000*
Loyalty (L)	3,0408 ± 0,1456	3,1906 ± 0,1393	2,9375 ± 2,4388	1,111	0,330
Trust (T)	2,9427 ± 0,1179	2,7140 ± 0,1236	4,3750 ± 1,1934	7,782	0,000*
Commitment (C)	2,7118 ± 0,1332	2,8545 ± 0,1268	3,8750 ± 1,3588	3,020	0,051
Governance (G)	3,0660 ± 0,1158	3,2196 ± 0,1109	3,5000 ± 0,5304	2,049	0,130
Decision	2,8438 ± 0,1585	2,7057 ± 0,1345	4,0000 ± 1,8374	2,698	0,068

The values given in the table were calculated within confidence intervals of 0.05 significance level

Hence, The Post Hoc test was utilized to determine the differences between the generations X and Y for *Satisfaction* and *Trust* factors at a significance level of 0.05.

Table 10. Multiple comparisons of the differences between the generations for *Satisfaction* and *Trust* factors.
Tamhane

Dependent Variable	(I) Age_XYZ	(J) Age_XYZ	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Satisfaction (S)	Generation_Z	Generation_Y	-,59908	,24872	,229	-1,6665	,4684
		Generation_X	-1,03472	,24945	,054	-2,0967	,0273
	Generation_Y	Generation_Z	,59908	,24872	,229	-,4684	1,6665
		Generation_X	-,43564*	,09747	,000	-,6690	-,2022
	Generation_X	Generation_Z	1,03472	,24945	,054	-,0273	2,0967
		Generation_Y	,43564*	,09747	,000	,2022	,6690
Trust (T)	Generation_Z	Generation_Y	1,66095	,38022	,058	-,0933	3,4152
		Generation_X	1,43229	,37976	,087	-,3266	3,1912
	Generation_Y	Generation_Z	-1,66095	,38022	,058	-3,4152	,0933
		Generation_X	-,22866*	,08680	,026	-,4365	-,0208
	Generation_X	Generation_Z	-1,43229	,37976	,087	-3,1912	,3266
		Generation_Y	,22866*	,08680	,026	,0208	,4365

*. The mean difference is significant at the 0.05 level.

4. DISCUSSION

In this study, the impact of the reputation perceptions of the participants' on the course of decision-making was examined and 13 different decision rules were determined. Of these rules, the three rules -*Rule 1 (127), Rule 8 (103), Rule 7.1 (96)*- which can map the decisions of 426 participants are sufficient to explain the 72.08 % (426/591) of the sample. However, with the evaluation of the average correct classification rate in terms of transaction cost, 13 rules for optimal classification could be increased up to an average of 97.9% with the Roc Curve method. In addition, this decision tree structure was supported by Naive Bayes method. The study has played an integral role for the perception mapping and data mining techniques. Increasing the sample size by including different socio-cultural structures in future studies will reduce the limitations and will differentiate and improve the decision maps.

5. CONCLUSION

It is widely preferred that the data used in decision trees be mostly quantitative and categorical. Many studies have focused on how a decision tree can be produced efficiently from data sets. In the pre-processes applied to decision trees, the results were obtained by converting some abstract and difficult-to-measure concepts to the numerical data. In this study, we aimed at mapping the effect of perceived reputation in decision processes of facebook users via data-mining as data-mining techniques support macroscopic research by defining hidden associations and patterns inductive approaches. By this means, the effect of reputation perceptions on the path that the participants are following in decision making process is investigated. In the decision tree diagram 13 rules were obtained. Then, the probability values of each decision made by the Bayesian classifier were calculated and the output of the decision tree diagram was tested. As a result, each rule obtained from the Decision Tree diagram has the same result as the Bayes probability values. The plausibility of these rules may be preferred as another test method. But since Decision Tree is a data-mining technique, it should not be forgotten that unexpected results may also occur in some cases and each of the rules must be interpreted carefully. According to rule 2.1, one of the rules obtained in this study, participants stated that they would not continue to use facebook while $S > 3.5$, $L <= 2$ and $C <= 2.5$. Hence, it can be observed how the responses of the participants to the Commitment related items are determinative for the target variable decision. Regarding Rule 9.1, the participants also stated that they are indecisive about to Facebook use, while $S <= 3.5$, $T <= 3.5$, $G <= 3.667$, $L <= 2.0$ and $C > 2.5$. In this rule, we also observed that the answers given to the Commitment items are remarkably important. Particularly in this rule, the responses to all the factors pointed to a negative result, while the Commitment factor had a strong effect to turn the result from negative to indecisive. All the same, in the decision tree obtained, that a factor (here it is satisfaction) settles in the first node is not related to the importance of this factor. Indeed, when the answers given by the participants are examined, the highest factor of information gain is the first node. Therefore, if the decision on the target variable gains weight in any direction, this factor will be pushed down to the lower nodes. When the resulting tree is examined, it is observed that the nodes formed draw near the leaves as the uncertainty decreases.

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ÖRGÜTSEL İTİBAR MEKANİZMASININ KARAR ALMA SÜREÇLERİNE ENTEGRASYONU: FACEBOOK ÖRNEĞİ

1. GİRİŞ

Örgütsel itibar kavramı son yıllarda hem akademi hem de iş dünyası tarafından, özellikle kurumsal kimlik, kurumsal imaj ve kurumsal karakter gibi benzer kavramlarla birlikte ele alınan önemli bir akademik konu haline gelmiştir. Örgütsel itibarın paydaşların örgüte bağlılığını ve desteğini sağlama konusundaki etkisi giderek daha fazla tanınmaktadır (Fombrun, vd.,2015) ve sosyal bilimler çatısı altında pek çok disiplinin ilgi alanına girdiği görülmektedir. Bu araştırma temel olarak örgütsel itibar kavramına kendi içinde üç farklı yaklaşımın gözlemlendiği stratejik yönetim perspektifinden gerçekleştirilmiştir. Bu bağlamda ilk yaklaşıma göre örgütsel itibar, örgütlerin mevcut çevrelerinde rekabet üstünlüğü kazanmalarına yardımcı olabilecek stratejik bir kaynak olarak (Roberts vd., 2002), veya örgütlere daha uygun koşullarda daha iyi kaynaklara ulaşmak için benzersiz bir konum sağlayan değerli bir soyut varlık olarak kabul edilmektedir (Chen vd., 2013). İkinci yaklaşım daha çok tüketicilerin ilgisini çekmek ve satın alma kararını etkileme süreçlerine odaklanmaktadır. Bu yaklaşım çerçevesinde, olumlu bir ötgütsel itibarın, örgütlerin mevcut müşterileri elde tutmanın yanı sıra yeni tüketicileri çekmesinin de önünü açtığı iddia edilmektedir (Shkolnikov vd.,2004). Son olarak, üçüncü yaklaşım, ötgütsel itibar kavramını paydaşlardan gelen geri bildirimlere dayanan bir değer olarak ve aynı zamanda örgütlerin ortaya koyduğu bir performans faktörü olarak ele almaktadır (Chen vd., 2013). Bu yaklaşımda itibar örgütsel kültürün bir ürünüdür. Örgütler itibarlarını vizyon ve misyonlarına odaklanarak ve kendi değerlerini yansıtan davranışları şekillendirerek geliştirdikleri için bu yaklaşımda değer kavramına yapılan vurgunun önemi büyüktür (Davies, 2006).

1.1. Literatür Özeti

Örgütsel itibarı kavramsallaştırma girişimi olarak öne çıkan üç çalışmadan ilki Pruzan (2001), itibar kavramının örgütler tarafından nasıl değerlendirildiğini ve buna göre hangi politika ve stratejilerin geliştirildiğini gösteren iki temel bakış açısının var olduğunu ileri sürmektedir. Bu iki ana bakış açısı, pratik yaklaşım ve yansıtıcı yaklaşımdır. Bu iki yaklaşım arasındaki fark temel olarak firmaların kendilerini kar maksimizasyonu noktasında konumlandırdıkları yerle ilgilidir. Pragmatik bakış açısında, kar maksimizasyonu kuruluşların nihai hedefidir ve yöneticiler performansı karlılık açısından değerlendirilir. Ancak yansıtıcı yaklaşım, örgütlerin karı maksimize etmek yerine sosyal refahı ve etik değerleri geliştirmek için adımlar atması gerektiğini vurgular. Diğer bir kavramsallaştırma girişimi olarak Barnett vd. (2006) örgütsel itibarın, üç merkezi noktadan ele alındığını ileri sürmektedir. Buna göre, ilk bölüm örgütsel itibarı bir farkındalık hali olarak tanımlar. ikinci bölüm ise kavramı bir değerlendirme olarak görür ve örgütsel itibarı bazı ön tahminler, değerlendirmeler ve yargılamalar üzerinde çalışan bir mekanizma olarak görür. Stratejik yönetim perspektifiyle uyumlu üçüncü nokta ise konsepti temelde bir varlık olarak konumlandırır. Bu bakış açısına göre itibar soyut, değerli ve kırılgan bir ekonomik varlıktır. Kavramsallaştırma çabalarında öne çıkan üçüncü çalışmada Lange vd., (2011) ise mevcut literatürün incelenmesinin ardından bilinirlik, bir şeyiyle ünlü olma ve genelleşmiş uygunluk olmak üzere üç önemli itibar kavramsallaştırması olduğunu ileri sürmüştür.

2. YÖNTEM

Facebook ile ilgili skandal olarak ifade edilen haberler sonrasında yapılan bu çalışma, insanların facebook hesaplarını kullanmaya devam edip etmeyeceklerini belirlemeye çalışmaktadır. Katılımcılara bazı demografik sorularla birlikte, araştırmanın amacını üstlenen bağımlı değişken olarak, facebook hesaplarını kullanmaya devam edip etmeyecekleri sorulmuştur. Analizler bir sınıflandırma tabanlı veri madenciliği tekniği olarak karar ağaçları ile yapılmış ve katılımcıların algılarını etkileyen kurallar ve katılımcı tercihleri açıklanmıştır. 591 kişiden yüz yüze ya da çevrimiçi anket yoluyla veri toplanmıştır. Katılımcıların karar alma süreçleri veri madenciliği ile modellenmiştir. İlk olarak, veriler ön işleme sürecinden geçirilmiş ve veri birleştirme, very temzileme eksik veri tamamlama işleminden sonra ham veriler veri madenciliği ile uyumlu hale getirilmiştir. Katılımcıların facebook hesaplarını kullanmaya devam edip etmeyeceği konusunda kuralları elde etmek için 6 bağımsız değişkenden elde edilen verilere J48 karar ağacı algoritması uygulanmıştır. Araştırmada, çalışmada bahsedilen kurumsal itibarın ölçülmesinde boyutsal zenginliğe atıfta bulunarak, güvenilirlik ve geçerlilik açısından makul performans gösteren çok çeşitli ölçekler ve maddeler kullanılmıştır. Buna göre, bu çalışmada, itibar algısı Genel İtibar, Memnuniyet, Sadakat, Güven, bağlılık ve yönetim boyutlarından oluşan toplam 14 soru ile ölçülmüştür.

3. BULGULAR

Bu çalışmada, facebook kullanıcılarının karar süreçlerinde algılanan itibarın etkisini veri madenciliği teknikleriyle haritalamak amaçlanmıştır. Bu sebeple, itibar algılarının, katılımcıların karar alma sürecinde izledikleri yol üzerindeki etkisi araştırılmıştır. Karar ağacı şemasında 13 kural elde edilmiştir. Daha sonra, Bayesian sınıflandırıcı tarafından verilen her kararın olasılık değerleri hesaplanmış ve karar ağacı diyagramının çıktısı test edilmiştir. Sonuç olarak, Karar Ağacı diyagramından elde edilen her kural Bayes olasılık değerleri ile aynı sonuca sahiptir. Kural 2.1'e göre, bu çalışmada elde edilen kurallardan biri olan katılımcılar, $S > 3.5$, $L <= 2$ ve $C <= 2.5$ iken facebook kullanmaya devam etmeyeceklerini belirtmişlerdir. Burada katılımcıların bağlılık ile ilgili maddelere verdikleri yanıtların hedef değişken kararında belirleyici olduğu görülmektedir. Kural 9.1 ile ilgili olarak, $S <= 3.5$, $T <= 3.5$, $G <= 3.667$, $L <= 2.0$ ve $C > 2.5$ iken katılımcılar Facebook kullanımı konusunda kararsız olduklarını, olduğunu belirtmişlerdir. Bu kuralda da bağlılık maddelerine verilen cevapların da oldukça önemli olduğunu gözlemlenmiştir. Özellikle bu kuralda, tüm faktörlere verilen yanıtlar olumsuz bir sonuca işaret ederken, bağlılık faktörünün sonucu olumsuzdan kararsız durmuna getirme noktasında güçlü bir etkiye sahip olduğu gözlemlenmiştir.

4. TARTIŞMA ve SONUÇ

Bu çalışmada, katılımcıların itibar algılarının karar verme süreci üzerindeki etkisi incelenmiş ve 13 farklı karar kuralı belirlenmiştir. Araştırmada elde edilen kuralların uygunluğu başka bir test yöntemi olarak tercih edilebilir. Ancak Karar Ağacı bir veri madenciliği tekniği olduğundan, bazı durumlarda beklenmeyen sonuçların ortaya çıkabileceği ve kuralların her birinin dikkatli bir şekilde yorumlanması gerektiği unutulmamalıdır. Elde edilen karar ağacında, memnuniyet faktörünün ilk düğümde yerleşmiş olması bu faktörün önemi ile ilgili değildir. Katılımcıların verdiği cevaplar incelendiğinde bilgi kazanımının en yüksek faktörü ilk düğümdür. Bu nedenle, hedef değişkene ilişkin karar herhangi bir yönde ağırlık kazanırsa, bu faktör alt düğümlere doğru itilecektir. Ortaya çıkan ağaç incelendiğinde, oluşan düğümlerin belirsizlik azaldıkça yaprakların yanına çizdiği gözlemlenebilir. Bu kurallardan, 426 katılımcının kararlarını haritalandırabilen - Kural 1 (127), Kural 8 (103), Kural 7.1 (96) – örneklemin % 72.08'ini (426/591) açıklamak için yeterlidir. Bununla birlikte, ortalama doğru sınıflandırma oranının işlem maliyeti açısından değerlendirilmesiyle, Roc Curve yöntemiyle optimal sınıflandırma için 13 kural ortalama olarak% 97,9'a yükseltilebilir. Ayrıca, ortaya çıkan karar ağacı yapısı Naive Bayes yöntemi ile desteklenmiştir ve algı haritalaması ve veri madenciliği tekniklerinin birlikte ele alınması sebebiyle ayrı bir öneme sahiptir. Gelecekteki çalışmalara farklı sosyo-kültürel yapıları dahil ederek örneklem büyüklüğünün arttırılması sınırlılıkları azaltacak ve karar haritalarını farklılaştıracak ve geliştirecektir.