UTILIZING DECISION TREES ON EMPLOYEE DECISION-MAKING PROCESSES: A MODEL PROPOSAL

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Introduction/background: This paper offers an idiosyncratic relational framework built on the organizational silence theory and the organizational support theory. It exploits the distinct advantages that using decision trees in classification and prediction applications offer to form a unique predictive model.
Aim of the paper: This paper argues that a relational framework built on the organizational silence theory and the organizational support theory can give important clues about how employees make certain decisions in the workplace as well as about factors that have an impact on their decision-making processes.
Materials and methods: The research applies decision trees learning – a data mining technique – to unfold the hidden patterns and unprecedented relationships between the two constructs that until now had not been revealed.
Results and conclusions: The suggested model, which consists of 13 rules, exhibits the effects of perceived organizational support and employee silence behavior on employee decisions with an approximately 79% correct classification rate, showing the success of the model as well as its appropriate relational framework.
The presented findings indicate that a relational framework built on the organizational silence theory and the organizational support theory has a lot to offer in terms of building effective HR strategies and policies. The study also extends the understanding of the antecedents of silence behavior in different social contexts.

Keywords: Perceived Organizational Support, Employee Silence, Decision Trees, HRM.

1. Introduction

Decision making is an inherent characteristic of human life, and therefore an inseparable part of our lives. We make hundreds of decisions and choices every day either consciously or not. What we do and what we feel are ultimately the results of our decisions. By all means, decision making which is an important aspect of the overall cognitive function that determines our life choices (Sahakian & Labuzetta, 2013) is influenced by so many factors including our beliefs regarding personal relevance (Acevedo, & Krueger, 2004) as we have rather divergent personal aspirations, interests, experience (Juliusson et al., 2005) as we make judgments based on our experiences and interpret them accordingly, individual differences (de Bruin et al., 2007) reflecting different psychological characteristics or simply cognitive biases (Stanovich & West, 2008) that root in our way of thinking or the way we perceive the world. In other words, this complex cognitive function that is integral to our everyday lives may well be subject to perceptual, individual, organizational, or environmental issues that are often contextually constructed. In this study, however, we focus on the two pivotal organizational issues that influence this complicated cognitive process: employee silence, and perceived organizational support. As in almost every area of life, we make decisions and arrive at certain judgments in our workplaces and these judgments forming a common framework of attitudes affect the next decisions to be made. Thus, just as successful managers should have good decision-making skills reflecting their ability to correctly recognize and define problems and to then select an appropriate course of action to solve problems, they also need to develop an understanding of the effects of employees' workplace experience and thoughts on their decisions. In this sense, we suggest that a relational framework built on organizational silence theory (Morrison & Milliken, 2000; Milliken, Morrison & Hewlin, 2003; Pinder & Harlos, 2001) and the organizational support theory (Eisenberger et al.1986; Rhoades & Eisenberger, 2002; Shore & Shore, 1995) will give important clues of how employees make certain decisions in the workplace and factors that have an impact on their decision-making processes. Accordingly, the present study extends the prevailing views regarding the relationship between organizational silence and organizational support by applying decision trees learning – a data mining technique – to explore the hidden patterns or relationships that prior studies haven't been able to reveal. Decision trees algorithm is a technique that is utilized in classifying and obtaining rules and the algorithm seeks for the best ranking to guess target variables (Yüncü & Fidan, 2019). Hence, the study primarily offers a novel and idiosyncratic perspective for both theoretical frameworks by utilizing the distinct advantages of using decision trees in classification and prediction applications (Kotu & Deshpande, 2015) to form a unique predictive model. The model exhibits the effects of perceived organizational support and employee silence behavior on employees' decisions with an approximately 79% correct classification rate. Along similar lines, by utilizing a supervised machine learning technique (Tan, 2015), the study also extends the understanding of the antecedents of silence behavior and the impact of perceived organizational support on employees' attitudes towards the organization.

2. Literature Review

Previous studies within the field of organizational behavior have well established the importance of perceived organizational support and employee silence as two fundamental constructs, though within different theoretical frameworks. As literature regarding the relationship between the two constructs is yet far from reaching maturity, the two multi-dimensional constructs still offer a wide range of areas to explore, particularly for those who aim at reaching comprehensive relational models. However, one should also see that building such powerful models require a high level of knowledge and familiarity of two profound and compelling theoretical background.

Employee silence theory which dates back to the 1970s explores hypotheses to determine why some groups remain silent while others are more vocal in forums of public discourse (Beheshtifar et al., 2012). Accordingly, employee silence refers to the intentional withholding of information, opinions, suggestions, or concerns about potentially important organizational issues (Wang & Hsieh, 2013). Today, the literature on employee silence, however, is largely grounded on the studies conducted by Morrison & Milliken (2000), Pinder & Harlos (2001), Milliken et al. (2003), Van Dyne et al. (2003), who indicate that employee silence is a pervasive, multi-dimensional phenomenon and therefore has become an issue particularly for modern organizations. Morrison & Milliken (2000) refers to employee silence (they prefer to use the term organizational silence) as a collective-level phenomenon by arguing that there are powerful forces in many organizations that cause widespread withholding of information about potential problems or issues by employees. For Morrison & Milliken (2000), employee silence is a consequence that roots in managers' fear of negative feedback and a set of implicit beliefs often held by managers. They put forth the concept of climates of silence to explain how norms in organizations influence some victims of abuse to keep quiet (Pinder & Harlos, 2001) on the assumption that there are certain organizational norms that very often prevent employees from speaking up. Accordingly, Morrison & Milliken (2000) suggest a model through which the authors identify contextual variables (rather than individual variables) that create conditions conducive to silence and explore the collective sense making dynamics that can create the shared perception that speaking up is unwise. They also discuss the negative consequences of systemic silence in terms of organizational change and development. Pinder & Harlos (2001), on the other hand, criticize the traditional assumption that employee silence is merely the absence of voice that reflects inaction and endorsement and assert that silence can communicate and that it is accompanied by characteristic thoughts, feelings, and actions.

By reviewing distinct pieces of literature such as anthropology, sociology, and linguistics to unfold further meanings and conceptual challenges related to employee silence behavior, they define employee silence as the withholding of any form of genuine expression about the individual's behavioral, cognitive and/or affective evaluations of his or her organizational circumstances to persons who are perceived to be capable of effecting change or redress. Hereby, Pinder & Harlos (2001) and introduce quiescence and acquiescence silence as the two forms of employee silence along with their behavioral, affective, and cognitive components. Within this integrative model of employee silence in organizations, they also explain why some mistreated employees become silent, how some break their silence, and what organizational contexts produce and reinforce employee silence. Milliken et al. (2003), later, focused on the types of issues that employees are reluctant to raise, and investigated the reasons why employees sometimes prefer to remain silent rather than speak up. Based on an interview with 40 employees, they found that the fear of being viewed or labeled negatively was found to be the most common reason for employees' silence behavior within an organizational setting. In their model through which they primarily aim to develop a better understanding of how and why employees sometimes choose to remain silent about their concerns, they underline two salient insights. First, interviewed employees were quite focused on the potential risks of voicing their concerns, which means that their decisions to remain silent are largely driven by the desire to avoid negative outcomes. Second, in asking the question 'What will happen if I raise this issue?' employees consider information culled from both past experiences and observations of the present context. Another study that contributed to the employee silence literature was made by Van Dyne et al. (2003) and we also utilized these forms of silence throughout this study. By asserting that the traditional conceptualizations of silence urge on relatively passive behavior, Van Dyne et al. (2003) differentiated three forms of silence in their novel conceptual framework based on employee motives (Acquiescent Silence, Defensive Silence, and ProSocial Silence). Accordingly, acquiescent silence refers to withholding relevant ideas, information, or opinions, based on resignation. Hence, it raises disengaged more passive behavior. Defensive Silence, on the other hand, refers to withholding relevant ideas, information, or opinions as a form of self-protection, based on fear and contrary to acquiescent silence it is both an intentional and a proactive behavior the purpose of which is to protect the self from external threats (Van Dyne et al., 2003; Schlenker & Weigold, 1989). The final form of employee silence asserted by the authors is Prosocial silence. Indeed, it is this third form of silence through which Van Dyne et al. (2003) extend existing conceptualizations of silence, thereby contribute to the employee silence literature significantly. With this new form of silence that had not been addressed before, the authors refer to the silence behavior of withholding work-related ideas, information, or opinions to benefit other people or the organization. In this regard, ProSocial Silence is discretionary behavior and based on awareness and consideration of alternatives and the conscious decision to withhold ideas, information, and opinions.

As for the theory of perceived organizational support, the literature on perceived organizational support is largely grounded on the studies conducted by Eisenberger et al., (1986), Shore & Shore, (1995), Rhoades & Eisenberger (2002). Indeed, the theory adopts Levinson's (1965) point of view that employees personify the organization, viewing it as having dispositional characteristics including benevolent or malevolent intentions toward them

(Hayton et al., 2012). With the contributions of Chen et al. (2009), Neves & Eisenberger (2014), Hayton et al. (2012), Eisenberger et al. (2013), Kurtessis et al. (2015), and Shanock et al. (2019), however, the theory has made significant progress in a way that extended the understanding of perceived organizational support significantly. In short, the theory suggests that Perceived Organizational Support (POS) refers to employees' perception concerning the extent to which the organization values their contribution and cares about their well-being. Therefore, the theory discusses the development, nature, and outcomes of such perceived organizational support. In point of fact, POS literature contains plenty of evidence that indicates that employees with high POS levels evaluate their jobs more positively in terms of their mood, stress level, or job satisfaction (Chen et al., 2009; Rhoades & Eisenberger, 2002). Alternatively, if the employees get valued resources such as pay raises, based on the reciprocity norm they will develop their POS positively and therefore, feel obligated to make an effort to repay the organization by helping it to reach its valued objectives (Neves & Eisenberger, 2013). Therefore, the POS theory, which approaches the relationship between organization and employee from the employee's perspective, holds great potential for understanding how and why HR management strategies are built and how they work (Shanock et al., 2019).

Hereby, the importance of perceived organizational support and employee silence as two fundamental constructs is well established within prior literature. However, the literature regarding the relationship between the two constructs is yet far from reaching maturity, there are still prominent gaps to be filled particularly regarding both this relationship and the antecedents of these constructs. The number of studies with such a perspective is very limited. Although these constructs have been investigated in many studies separately, it is clear that the number of studies in which the concepts of employee silence and perceived organizational support are discussed together is relatively few. Some examples of studies with similar perspectives include Khalid & Ahmed (2016), Tucker et al. (2008), Tangirala & Ramanujam (2008), Wang & Hsieh (2013), Singh & Malhotra (2015) and Yu & Liu (2016). However, the two multi-dimensional constructs still offer a wide range of areas to explore, particularly for those who aim at reaching comprehensive relational models. This is mainly because the relationship between perceived organizational support and employee silence must be examined using multidimensional and alternative techniques by re-evaluating the constraints related to the direction of the relationships. In this sense, data mining methods offer a great opportunity to reveal hidden patterns between the two constructs. In this context, this study extends the prevailing views regarding the relationship between organizational silence and organizational support by applying decision trees learning to explore the hidden patterns or relationships that prior studies haven't been able to reveal.

3. Methodology

As we are actually living in the data age in which a large spectrum of data is collected on a daily basis, analyzing this big data has become a pivotal need. Data mining, which can meet this need by providing tools to discover knowledge from data, is a family of methods used to access information by creating systematic rules from data (Han et al., 2011). Compared to statistical models, more successful results are obtained both on the real data and the one created through simulations (Agrawal & Srikant, 2000). Since real-life data often do not have easily noticed rules unlike synthetic data, data mining methods are preferred to reveal hidden patterns (Hand & Adams, 2014; Maimon & Rokach, 2005). Understanding hidden patterns that cannot be easily noticed, especially in decision problems, can be easily achieved under data mining methods inspired by the decision-making construct of the human brain. Instead of obtaining linear relations in the data, the realization of artificial learning, which basically means understanding the internal nature of the data and its effects on the decision process, reveals more effective results in the solution of the decision problem. In simpler terms, artificial learning provides a powerful method to create high-performance systems (Quinlan, 1986). Data mining is handled within the scope of three different scenarios, namely classification, clustering, and prediction (Agrawal & Srikant, 2000). In this research, a classification scenario was created by using decision trees, one of the data mining methods. With this design, 692 blue-collar employees from different sectors were asked 25 questions from two different scales and one decision variable question, apart from demographic questions. In this study, employee silence scale developed by Van Dyne et al. (2003) and perceived organizational scale developed by Shanock et al. (2019) were utilized. The obtained data were analyzed through decision trees, which is a data mining technique.

Decision Trees

Decision trees is a data mining technique used in classification and solution of prediction problems (Han et al., 2011; Silahtaroğlu, 2008; Agrawal & Srikant, 2000; Quinlan, 1986). It is faster and easier to understand and interpret than a large number of methods used in complex decision problems (Silahtaroğlu, 2008). In the decision tree application, part of the data set is used for the training of the decision tree. Then, the model is created by means of the rules obtained from the learning data set. Each branch on the decision tree model from nodes to leaves represents a rule. Thus, the decision tree diagram enables us to understand which of the factors used in the study is effective on the decision variable and to reveal the relationships between these factors (Quinlan, 1986). The decision tree diagram that is formed here is obtained by following two basic steps below (nodes, branches, and leaves, respectively):

I) Entropy values are calculated with the help of equation 1 for each variable (factor) other than the decision variable. The factor with the highest knowledge gain is determined and selected as the starting node, or in other words, the root node.

Since the increase in entropy value shows that the uncertainty in the variable increases, a tree structure is created from a low uncertainty level to high. This process is continued at every step and the decision variable (leaf) is reached.

S_i signifying the factors, for the entropy value:

$$E(S) = -\sum_{i=1}^{n} \frac{S_i}{S} \left(\log \frac{S_i}{S}\right) \qquad (1)$$

For information gain, the conditional entropy value is calculated and subtracted from the total entropy value:

$$E(S_j|S_n) = \frac{S_i}{S} \left(\log \frac{S_i}{S}\right)) \qquad (2)$$

Information gain:

$$E(S) - E(S_j|S_n) \qquad (3)$$

Thus, a tree diagram is created by determining the factor with the highest knowledge gain and placing it in root and successive nodes (Bhargava et al., 2013).

ii) By determining the minimum threshold value for the number of observations per leaf, branches that are deemed unimportant are pruned and more understandable rules are obtained. Pruning also increases the power of generalization by removing the rules with few examples in the resulting decision tree (Quinlan, 1986).

4. Findings

4.1. Decision Trees Demographic Characteristics of the Participants

In addition to questions about their gender, age, education level, marital status, the participants were also asked about their professional life, such as experience, rotation status, working time at the last place of work. Summary tables for this information are given below.

Table 1.
Demographic variables summary

Variable	Category	Frequency	Percentage
Gender	Woman	359	51,9
	Man	333	48.1
Marital Status	Single	367	53.0
	Married	325	47.0
Level of Education	High School	144	20.8
	Associater degree	129	18.6
	Under Graduate	237	34.2
	Graduate	182	26.3

As stated in Table 1, 359 people, 51.9% of 692 participants, are women and 333 people, 48.1% are men.

53% of the participants, that is 367 people, defined themselves as single and the remaining 47%, that is, 325 people, as married (Table 1).

The education levels of the participants are specified in Table 1 as 20.8% and 144 persons, 18.6% and 129 persons, 237 persons with 34.2% and 182 persons with 26.3%, respectively, as high school, associate degree, undergraduate and graduate.

Among the participants, there are those who continue their professional life in a single business as well as those who has worked in more than one business. In order to determine the effects of this situation on the decision process, the total experience and working periods in the last workplaces are considered separately.

In Table 2, the total experience times taken from the participants as open-ended are categorized. Accordingly, 139 people with less than 6 years of experience make up 20.1% of the total, 134 people with 6-10 years of experience make up 19.4% of the total, 88 people with 11-15 years of experience make up 12.7% of the total, 83 people with 16-20 years of experience make up 12% of the total, 73 people with 21-25 years of experience make up 10.5% of the total, and finally 175 people with more than 25 years of experience make up 25.3% of the total.

Table 2.
Experience variables summary

Variable	Category	Frequency	Percentage
Total Experience	Less than 6	139	20.1
	6-10	134	19.4
	11-15	88	12.7
	16-20	83	12.0
	21-25	73	10.5
	More than 25	175	25.3
Experience in the current work	Less than 6	177	25.6
	6-10	146	21.1
	11-15	85	12.3
	16-20	82	11.8
	21-25	74	10.7
	More than 25	128	18.5
Working Rate	0.00-0.25	11	1.6
	0.26-0.50	34	4.9
	0.51-0.75	203	29.3
	0.76-1.00	444	64.2

The experience of the participants where they are currently working were also categorized the results in Table 2 were obtained. Accordingly, 177 people working less than 6 years in the last place make up 25.6% of the total, 146 employees between 6-10 years make up 21.1% of the total, 85 employees between 11-15 years make up 12.3% of the total, 16-20 years 82 employees make up 11.8% of the total, 74 people working 21-25 years make up 10.7% of the total, and finally, 128 people working more than 25 years make up 18.5% of the total.

Since the questionnaire form answered by the participants is related to their current job, the variable of working rate = experience in the current work (year) / Total experience (year) was calculated and the results are given in Table 2 in order to take the experience effect into account.

Working rate variable calculated in Table 2 is categorized in quarters. 11 people with a working rate of 0.00-0.25 were 1.6%, 34 people between 0.26-0.50, 4.9%, 203 people between 0.51-0.75, 29.3% and finally 444 people with a range of 0.76-1.00 were obtained as 64.2%. A large number of items were used to measure the factors discussed in the questionnaire. For this reason, in order to determine the each factor load, the averages of the related items were taken. However, this average alone is not sufficient to understand data. In order to understand the distribution of the data, five-number summary tables that are frequently used in data mining techniques have been created and this table is given in table 3.

Table 3.
Five number summary

	Working Ratio	Acquiescent Silence	Defensive Silence	Prosocial Silence	Perceived Organizational Support	Decision Variable
Minimum	0.20	1.00	1.00	1.00	1.00	1.00
Quartile 1	0.67	2.60	2.20	3.20	3.10	5.00
Median	1.00	3.60	3.60	3.60	3.90	6.00
Quartile 3	1.00	4.40	4.30	4.20	4.50	6.00
Maximum	1.00	7.00	7.00	6.20	7.00	7.00

Summary table given here includes the first, median (Q2) and largest values of each variable to be used in the Decision Tree, as well as the Quartile 1 (Q1) and Quartile 3 (Q3) values. The statement directed to the participants as the decision variable is: "The support given to me by the organization I work for affects my perspective on the organization".

In order to model the data obtained within the scope of the study, the data are divided into different clusters as training data and test data as indicated in Table 4. The accuracy of the decision trees created with different training and test sets was evaluated with the correct positive classification rate (accuracy) and under the ROC curve, and is shown in Table 4. Since the highest accuracy rate is obtained when the training data set is 80% of the whole data set, in the study, training and test data were considered as 80% - 20% respectively. While evaluating the rules in decision trees, each branch from the beginning node to the last leaf is specified as a rule. The rules obtained in this way were formed on the tree from left to right, respectively:

Table 4.
Model success summary

Train Set – Test Set	Accuracy	Area under ROC Curve
% 30 - % 70	% 68.801	% 79.10
% 40 - % 60	% 71.325	% 82.80
% 50 - % 50	% 72.543	% 83.30
% 60 - % 40	% 74.368	% 85.10
% 70 - % 30	% 77.404	% 86.40
% 80 - % 20	% 79.710	% 89.30
% 90 - % 10	% 78.261	% 87.60

As a result of the analysis, the decision tree in figure 1 was obtained, and the rules obtained from the decision tree are given in Table 5.

Rule 1:

When the defensive silence, perceived support and prosocial is low, the answer to the decision question was determined as strongly agree. Of the 62 samples that fit this example, 15 are fully consistent with the result. For this reason, the correct classification rate of rule 1 has been calculated as approximately 24%.

Rule 2:

When the defensive silence and perceived support is low but proscoial silence is medium, the answer to the decision question was determined as agree. Of the 56 samples that fit this example, 55 are fully consistent with the result. Hence, the correct classification rate of rule 2 has been calculated as approximately 44%.

Rule 3:

When the defensive silence and perceived support is low but proscoial silence is high and working ratio is <0.25, the answer to the decision question was determined as agree. Of the 26 samples that fit this example, 26 are fully consistent with the result, which indicates a correct classification rate of 100%.

Rule 4:

When the defensive silence and perceived support is low but proscoial silence is high and working ratio is between 0.26 and 0.50, the answer to the decision question was determined as strongly agree. Of the 16 samples that fit this example, 16 are fully consistent with the result, which indicates another correct classification rate of 100%.

Rule 5:

When the defensive silence and perceived support is low but proscoial silence is high and working ratio is between 0.51 and 1.00, the answer to the decision question was determined as agree. Of the 74 samples that fit this example, 35 are fully consistent with the result. Hence, the correct classification rate of rule 5 has been calculated as approximately 47%.

Rule 6:

When the defensive silence and perceived support is medium or high, , the answer to the decision question was determined as agree. Of the 29 samples that fit this example, 10 are fully consistent with the result. Hence, the correct classification rate of rule 6 has been calculated as approximately 35%.

Rule 7:

When the defensive silence is medium and perceived support and prosocial silence are low, the answer to the decision question was determined as agree. Of the 57 samples that fit this example, 32 are fully consistent with the result. Hence, the correct classification rate of rule 7 has been calculated as approximately 56%.

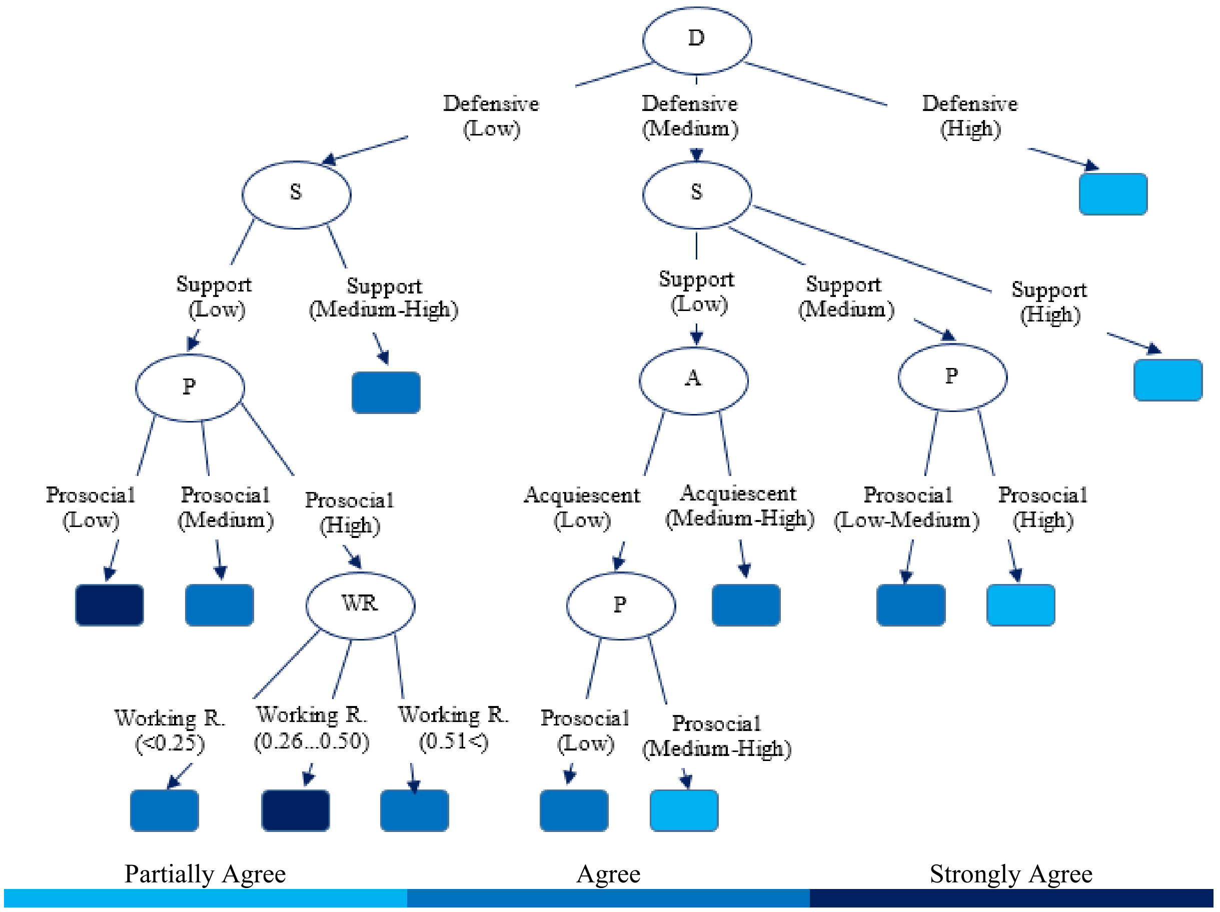

Figure 1. Obtained Decision Tree

Rule 8:

When the defensive silence is medium, perceived support is low and acquiescent silence is low and prosocial silence is medium or high, the answer to the decision question was determined as partially agree. Of the 27 samples that fit this example, all 27 are fully consistent with the result. Hence, the correct classification rate of rule 8 has been calculated as 100%.

Rule 9:

When the defensive silence is medium, perceived support is low and acquiescent silence is medium or high, the answer to the decision question was determined as agree. Of the 19 samples that fit this example, all 19 are fully consistent with the result. Hence, the correct classification rate of rule 9 has been calculated as 100%.

Rule 10:

When the defensive silence and perceived support are medium and prosocial silence is low or medium, the answer to the decision question was determined as agree. Of the 46 samples that fit this example, all 31 are fully consistent with the result. Hence, the correct classification rate of rule 10 has been calculated as approximately 67%.

Table 5.
Rules

	Node 1 (Factor)	Node 2 (Factor)	Node 3 (Factor)	Node 4 (Factor)	Leaf (Decision)	Accuracy Rate
1	Defensive (Low)	Support (Low)	Prosocial (Low)		Strongly Agree	% 24
2	Defensive (Low)	Support (Low)	Prosocial (Medium)		Agree	% 44
3	Defensive (Low)	Support (Low)	Prosocial (High)	Working Ratio (<= 0.25)	Agree	% 100
4	Defensive (Low)	Support (Low)	Prosocial (High)	Working Ratio (0.26...0.50)	Strongly Agree	% 100
5	Defensive (Low)	Support (Low)	Prosocial (High)	Working Ratio (0.51...1.00)	Agree	% 47
6	Defensive (Low)	Support (Med.-High)			Agree	% 35
7	Defensive (Medium)	Support (Low)	Acquiescent (Low)	Prosocial (Low)	Agree	% 56
8	Defensive (Medium)	Support (Low)	Acquiescent (Low)	Prosocial (Med.-High)	Partially Agree	% 100
9	Defensive (Medium)	Support (Low)	Acquiescent (Med.-High)		Agree	% 100
10	Defensive (Medium)	Support (Medium)	Prosocial (Low-Med.)		Agree	% 67
11	Defensive (Medium)	Support (Medium)	Prosocial (High)		Partially Agree	% 36
12	Defensive (Medium)	Support (High)			Partially Agree	% 76
13	Defensive (High)				Strongly Agree	% 47

Rule 11:

When the defensive silence and perceived support are low but prosocial silence is high, the answer to the decision question was determined as partially agree. Of the 23 samples that fit this example, all 8 are fully consistent with the result. Hence, the correct classification rate of rule 11 has been calculated as approximately 36%.

Rule 12:

When the defensive silence is medium but perceived support is high, the answer to the decision question was determined as partially agree. Of the 14 samples that fit this example, all 10 are fully consistent with the result. Hence, the correct classification rate of rule 11 has been calculated as approximately 76%.

Rule 13:

When the defensive silence is high, the answer to the decision question was determined as partially agree. Of the 19 samples that fit this example, all 9 are fully consistent with the result. Hence, the correct classification rate of rule 11 has been calculated as approximately 47%.

5. Conclusions and Suggestions

This study investigates the effects of employee silence and perceived organizational support on decisions of employees through an idiosyncratic perspective and proposes a unique predictive model. By utilizing a data mining technique to trace the hidden patterns or relationships that prior studies haven't been able to reveal, it contributes significantly to the relational literature as it offers insight regarding the antecedents of silence behavior and the impact of perceived organizational support on employees' attitude towards the organization. The present findings confirm that a successful relational framework like the one proposed in this study has a lot to offer in terms of building effective HR strategies and policies. Findings also reveal that perceived organizational support as a part of organizational characteristics and employee silence behavior based on employees' experiences in the workplace have pivotal implications on their decision-making processes. In the suggested model, for instance, 13 rules were obtained with approximately 79% correct classification rate, which exhibits the success of the created model as well as a proper relational framework. The rules 3,4,8 and 9 that has a classification rate of 100% are of particular importance though the other rules also point to critical relationships. Accordingly, these rules reveal unprecedented relationships between the forms of silence, perceived organizational support, and working rate. We would also like to draw attention to a few points for future work. First, the questionnaire surveys reflect the situation of the participants in the current period. However, since the experience levels of the participants are different from each other, similar problems can be examined over their experience levels or the working time in the last workplace. Second, although demographic data were collected in this study, they were not included in the decision tree in order not to break the simplicity of the decision tree. Participants' gender, age, and education level can be added to the model in future studies. Third, the predictive factor in the study is the decision variable. Similar studies can be repeated for different decision variables to examine the effects of organizational silence factors and perceived support factors. Fourth, Decision Trees are very useful for mapping the responses of employees to a decision problem they encounter. For this reason, alternative models can be obtained by utilizing different scales. Finally, the factors discussed in this study are of great importance for businesses and their HRM strategies. The same problem can be evaluated with multi-criteria decision-making methods that can affect decision processes.

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