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Non-Linear Impact of Organizational Structure on Schedule Management for R&D Project Success: An ANN Approach

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ABSTRACT

To attain project success in R&D (Research & Development) public sector environment, the aspects of an OS (Organizational Structure) play a vital role in the successful implementation of R&D projects. Nevertheless, not meeting proposed timelines and inadequatem management of schedules of R&D projects is the intrinsic hurdle in R&D projects. However, the study gauging the impact of OS on the SM (Schedule Management) of R&D projects has never been discussed before. Therefore, this study aims to gauge the effectiveness of OS and SM dimensions upon each other by employing predictive modeling technique i.e. ANN (Artificial Neural Network). This study is based on a quantitative approach and the model followed is non-linear regression. A simple random sampling technique is used to collect data from 285 respondents (in two rounds) from various R&D public sector set-ups. The robustness and homogeneity of data is checked by carrying out F and T-tests. Subsequently, data is pre-processed; ANN model is trained and validated by choosing appropriate tuning parameters and quantitative performance measures like RMSE (Root Mean Square Error) and MAPE (Mean Absolute Percentage Error) are analyzed. The results clearly indicated that formalization, decentralization and authority of managers are strongly correlated; differentiation, specialization, coordination mechanism, departmentalization are positively but weakly correlated with some sub-constructs and centralization also constitutes positive but weakly correlated among all. The results also imply that decentralized OS are more preferable than centralized structures for the execution of R&D projects when proposed timelines are to be met timely.

Key Words: Project Success, Project Management, Organizational Structure, Schedule Management, R&D Projects, Artificial Neural Network, Predictive Modeling.

1. INTRODUCTION

Differences in the nature, complexity and size make each and every project unique [1]. For that reason, it is very challenging to realize that projects will attain successful completion by meeting a prescribed set of success criteria or not [2]. Number of perceptions and absolute importance of project's success vary by number of phenomena; for instance, nature of projects (e.g. R&D, commercial, non-R&D etc.) and the dispersion with respect to the population distributed at several geographical locations [3]. The

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sustainable development of organizations requires the introduction of new and innovative products that provides vitality and strength. The attributes of R&D projects are distinct and are coped differently than non-R&D projects. However, the criteria for the success and failure of R&D projects are hard to predict. Considering the challenges in globalization; for demanding organizations like industrial-technology, the successful execution of R&D projects is the most-valued contributing factor [4].

In order to get hold of promising technologies; advanced methods and techniques, new information, to attain efficiency against opponnents R&D projects are the valuable source for a corporate management and organization to attain efficiency against opponents [5]. Classically, the products develop in irregular time periods and rarely from R&D processes. The reason is the existence of uncertainties and unpredictability involved in the R&D products' development to a great extent. However, because of the widely used state-of-the-art technologies and dynamic technological environment globally, uncertainty acts as a major hurdle in new product development/R&D. Therefore, the presence of uncertainty in R&D projects leads to massive R&D risks and becomes a further source of R&D projects' failures [6]. It is evident that most of the R&D projects tend to diverge critically from the unit and project costs, performance parameters of the final product and planned schedules i.e. time-to-market. Unfortunately, due to these reasons, customers' demands and expectations are not fulfilled [7]. Nonetheless, delays are frequent in R&D projects and schedule pressures hamper the overall success and productivity [8-11]. The outcomes of previous literature studies demonstrate that the R&D projects taken up in various OS experience a variety of schedule delays related problems. The problems stated above are highlighted because of the incongruous selection of OS and SM factors and becomes the reason of undesirable outcomes. A schedule slippage most prominently on the critical activity is one of the foremost undesirable outcomes that creates a negative impact on the performance and success of R&D projects. Hence, the selection of right OS dimensions for the right project and for the achievement of in-time execution is a crucial phenomenon for the successful management of R&D projects. In this study, an AI (Artificial Intelligence) based mechanism is developed that links the factors of OS to the SM through ANN technique necessary for the prudent execution of R&D projects in public sector environment. There is a lack of such predictive modelling example in the existing literature that links up the OS and SM factors for the in-time completion of projects in R&D environment. This research explores the impact of different aspects of OS and SM in research and development surroundings not identified previously. Therefore, following research questions are formulated for this study:

RQ-1: What are the various sub-constructs and dimensions of OS and SM that influence R&D project success?

RQ-2: To what extent the data collected in two rounds is reliable, robust and homogeneous?

RQ-3: How the impact of OS on the SM of R&D projects can be predicted?

RQ-4: To what extent the proposed predictive modeling method is valid?

The research question 1 and 2 are addressed in Step 1 and Step 2; "Data Collection and Measurement of Variables & Checking the Robustness and Homogeneity of Data", research question 3 in Step 3 and Step 4; "Data Pre-processing and Predictive Modeling (ANN Training)" and research question 4 in Step 5; "Model Validation".

2. LITERATURE REVIEW

ANN is one of the prominent non-linear regression techniques of supervised learning. NNs (Neural Networks) are the mathematical or computational models based on the technique of biological nervous system. A typical NN is composed of various layers and in return each layer is made up of a number of interconnected 'units' or 'nodes'. The input layer receives the input data, processes it, sends the processed data further to the inner layers (hidden layers; one or more) and the last layer (output layer) generates the output of ANN model [12]. An ANN model development consists of two stages; learning (or training) and predicting (or testing). The network adjusts the weights between the nodes and 'learns' through this alteration during learning stage [13]. Conventionally, data are divided into two separate segments; the first is used to train the network and the second is to test the predictive ability of the network. The basic theme of ANN is to reduce the RSS (Residual Sum of Squares) or SSR (Sum of Squared Residuals) or SSE (Sum of Squared Errors) of prediction. There is no restriction on the number of input variables and hidden units/nodes and layers used in the model, so it is easy to initialize ANN modeling with the help of any random values for solving the complex mathematical optimization problems.

There are different types of NN architectures; most commonly used are RNN (Recursive Neural Network), MLP (Multilayer Perceptron), Self-Organizing Maps, RBF (Radial Basis Function), LSTM (Long/Short-Term Memory), CNN (Convolutional Neural Networks) etc. [14]. In this study, NN having one input layer (comprising of multiple input nodes/ variables), one or more layers of intermediate or hidden layers and an output layer (comprising of multiple output nodes/variables) known as MIMO (Multi-Input Multi-Output) MLP is used. Generally, these types of networks use BP (Back-Propagation) Learning Algorithm. There are variety of applications (test, predict and classify) of ANN in the field of management. ANN addresses several problem types in management sciences; for example, manufacturing, strategic management, finance and marketing [15].

It is quite obvious that in a practice driven environment, the facets of OS creates a massive impact on the SM of R&D projects. Hence, this field requires a systematic investigation to address the impact of various contexts e.g. team coordination, decision-making at different hierarchical levels, SM, and following rules and regulations in an OS. Largely, the type of a project determines the success and failure of a project [16]. In this regards, the major success factors were differentiated between R&D and construction projects by [17]. Later on, a framework was proposed by [18] that linked competitive advantage with the success of projects. Many dimensions were discussed and included in this framework which was related to; business success, creating new market and technological opportunities, impact on the customers, and efficiency related to budget and schedule requirements. However, the above-mentioned dimensions are embedded in R&D projects and reliant on schedule and uncertainties related to technology. Clark et. al. [19] also highlighted the association of OS and project leaders with the speed of R&D/NPD projects. There are several other factors suggested by researchers, for example 'teamwork' as an essential element of project success [1-2,20-23]. Similarly, teamwork creates a substantial effect on the reduction of cycle time in R&D/NPD projects [24]. Balachandra and Friar [25] identified almost seventy-eight factors for the success and failure of R&D/NPD projects. Overall four categories were identified by the researcher; organization, environment, technology and market. Afterwards, [26] also explored that the ability of organizations that promotes innovation (R&D) and the production of new products, is affected by several key factors that created immense impact e.g. innovation processes, resources, OS, knowledge management, leadership and management style. Recently, [27] also carried out an extensive research and explored many factors related to product development and R&D. To meet the technical requirements and success criteria of projects on the basis of time, cost and quality only, the traditional methods of project management have become ineffective and outdated [28-29]. However, the paradigm of project management was shifted by some other researchers towards the perspective of people-focused from the traditional iron-triangle in late 1990s. Therefore, in this context, the measurement of project success can be carried out with respect to the interpersonal and behavioral skills of project teams, and customer and stakeholder satisfaction as well [30-31].

During last 20 years, a significant importance can be witnessed related to the competitiveness of a firm based on technological innovation and associated with the relationship among structure, performance and strategy [32]. In technology-intensive organizations, three organizational designs are being used as far as different types of OS are concerned that are networked, integrated and decentralized [33]. Argyres and Silverman [32] carried out a research and inquired a connection between firm's organization of research (de-centralized or a centralized) and the sort of innovation produced by the opted R&D structure. The empirical results advocated the centralized R&D structure more productive and innovative than the other R&D structure; decentralized. Recently, researchers have developed an interest in recognizing those factors that create a great impact on the competency of performance of project management and on OS as well [34]. However, some other researchers discovered various causes of projects' (including R&D projects) failures that include; unclear role of authorities, scarcity of resources, lack of definition of objectives, ineffective coordination/communication modes, deficient project schedule, uncontrolled change and inadequate control and not having top management support [35-37].

The findings of literature review show that the success/failure factors of R&D projects considerably vary and appear to be contradictory as well [38]. In spite of that, for the successful execution and management of projects, choosing significant dimensions of OS is an important area to consider, especially for R&D projects. From the perspective of product management, [39] explored the notion of OS and environmental uncertainty by establishing the fact that degree of centralization of decision-making, differentiation, and formalization of rules and procedures perform a significant role. Lately, [40] claimed that OS is an indispensable undertaking that requires robust communication, determined management, and prudent decision mechanisms. A number of various variables and dimensions of OS are discussed; specialization, formalization, attitude of managers, vertical complexity and differentiation, coordination mechanism, limited/ slack resources, division of work (distribution of tasks and activities), control, centralization and internal and external communication [41-46].

In different OS, the concept of project scheduling is placed under the domain of project management. Most of the organizations do not succeed in delivering product or the service with respect to the committed timelines and hence inadequate project schedules becomes source of considerable delays. Engwall and Jerbrant [47] carried out a qualitative analysis of various R&D projects and concluded that many complications of resource allocation become apparent because of the failure in project scheduling. Most of the studies appraise scheduling and planning as the foremost processes of new product introduction and an R&D project [48-51]. However, the disorder of resource allocation becomes a source of delays in project schedules and considers as a crucial factor for dispute in OS. SM planning [52] is considered as a process of formulating rules, policies and procedures, plan, develop, maintain and control project schedules and one of the most significant factors of SM. Frinsdorf et. al. [53] conducted a research in the defense environment and examined the critical factors related to project efficiency. He deduced from the results and analysis that handling multiple projects is challenging with respect to the managing of a single project due to the shared scope and resources. As a result, in such environment the prioritization of projects is fundamental to attain the project efficiency. Jun-Yan [54] discussed several particulars of uncertainty linked with a project schedule. The unpredictability and risks can be affiliated with the equipment and labor productivity, weather, and conditions at sites and workplace etc. On the other hand, [55] proposed a solution for an automobile R&D problem related to the multi-project resource scheduling. A multi-project schedule method was suggested by the researchers based on evidence reasoning, task priority and critical chain. As it is clear that uncertainty is inherent in project schedules, other researchers have concluded that project managers working for R&D projects come across uncertainty related issues frequently about schedules and the performance of the product [56]. However, evaluating success of an R&D project is an intricate and a complex task. It is stated earlier that complexity, uncertainty and interdependencies are the prominent features of R&D projects. With the application of traditional project management methods, it is not possible to predict the success or failure prior to and during the implementation of an R&D project.

In this study a gap has been identified after conducting an extensive research on the proposed topic. Up to the present time, no comprehensive predictive model to calculate the impact of dimensions of OS on time management has been formulated. The objective of this research is to minimize propose in-advance a predictive model for project/engineering managers and decision makers to opt for the suitable dimensions of OS and SM in interdependent and complex R&D public sector environment for R&D projects' execution.

3. RESEARCH METHODOLOGY

A quantitative approach is followed in this research. In quantitative method, the investigator applies several strategies of inquiry/investigation, for example, instruments/surveys and experiments, and data collection is done on the constructed questionnaire and statistical data and analysis is yielded [57].

Quantitative methods use deductive logic that emphasizes representing empirical components of social world into variables. These variables can be expressed as frequencies or rate and their relationships can be explored with the help of statistical techniques [58]. There are several advantages of quantitative methods; firstly, these involve large samples which are randomly selected and the researcher can make claims and generalizations samples to a population [59]. Secondly, developing theories, mathematical models and/or hypotheses development are the objective of quantitative research. The measurement process is the key to quantitative research because it provides the basis to connect the empirical observation and mathematical/statistical analyses. Thirdly, quantitative methods use surveys/instruments/questionnaires in which researcher asks questions in the same order (e.g. likert scale, etc.). This characteristic of quantitative method allows drawing meaningful comparison of responses. In this study, the constructs used in quantitative methodology have been conceptualized as multi-dimensional [60]. A construct is known as multi-dimensional when it contains various divergent but interrelated dimensions which are treated as a single theoretical concept and makes it distinguishable from unidimensional constructs [61]. Two or more than two underlying dimensions make the constitution of a single multi-dimensional construct. Two multi-dimensional constructs; OS and SM have been used in this research. Each multi-dimensional construct is composed of related sub-constructs and each sub-construct consists of interrelated dimensions. The details of the data sets are presented in section 4.1.2 and 4.1.3. Afterwards, the quantitative data is collected, the variables are measured and the proposed sub-constructs and relevant dimensions are trained and validated through predictive modelling.

In this research, a non-linear regression model is followed. The rationale of using ANN is that firstly, the model of this study is based on multiple non-linear regressions. It can be used to identify the particular features/characteristics of non-linearity within the data set. Secondly, this study is multifaceted/multi-dimensional in nature. Another rationale of using ANN is that it follows a non-parametric model unlike other statistical methods that are based on parametric models and required high statistical background. However, ANN uses a diverse and appealing family of machine learning algorithms when confronting with complex multi-dimensional problems and solves them with a high degree of accuracy. However, ANN also has the ability to detect the complex non-linear associations/relationships between the independent and dependent variables, handle large/complex data-sets and identify all probable interactions between variables (predictor variables, etc.). In a comparative study conducted [62], it was analyzed that NN models outperform traditional statistical methods e.g. logistic regression, discriminant analysis, factor analysis (maximum likelihood) etc. Another comparative study [63] revealed that neural networks performed better than other statistical approaches; e.g. PLS (Partial Least Squares) and MLR (Multiple Linear Regression). The complexity of this research lies in the number of variables involved in the input layer (eight) - which should be more and the number of variables involved in the output layer is (eight) - which should be less. Therefore, capturing the complexity from this sort of data, NN are known to cater for this complexity better than other algorithms. The research process is described in detail as below:

3.1 Research Process

John [64] suggests choosing survey design to examine the relationships between and among variables. As a part of data collection, information about actual instrument is made available. Afterwards, data analysis and interpretation consists of a series of steps that involves a detailed discussion of data analysis procedures. The number of steps involved in a research process depends on the nature of study. The research process steps for quantitative method in this study are based on [64]. In the first step, the data are collected through a survey design and measurement of research is carried out by computing descriptive statistics. In the second step, the robustness and homogeneity of data is checked by conducting a comparative analysis between the samples of two rounds of data collection. Subsequently, in the third step, data pre-processing is conducted in R. In the fourth step, an ANN model is developed and trained. Finally, in the fifth step, the ANN model is validated. The output of steps involved in the research process becomes the input of the next step. Hence, there is a presence of feedback in the research process but the whole process does not follow a closed loop feedback process. The research process is shown in Fig. 1.

3.1.1 Step-1: Data Collection and Measurement of Variables

Study Participants and Sampling: All participants from R&D organizations in this research had fifteen or more years of professional experience and were actively involved in the dynamics of decision making, managing and controlling project schedules, project management and OS related issues of R&D projects. The respondents of questionnaire survey were project directors (21%), senior managers (program and project managers) (18%), design engineers (22%), quality assurance and control officers (10%), configuration management officers (9%), junior managers (6%) and others (14%).

In this study, a sampling technique named as "simple random sampling" technique is used. This study estimates OS and SM dimensions using reflective multi-item seven-point scales questionnaire, where (1 = Strongly Disagree), (2 = Disagree), (3 = Disagree Somewhat), (4 = Undecided/Neutral), (5 = Agree Somewhat), (6 = Agree), and (7 = Strongly Agree). In

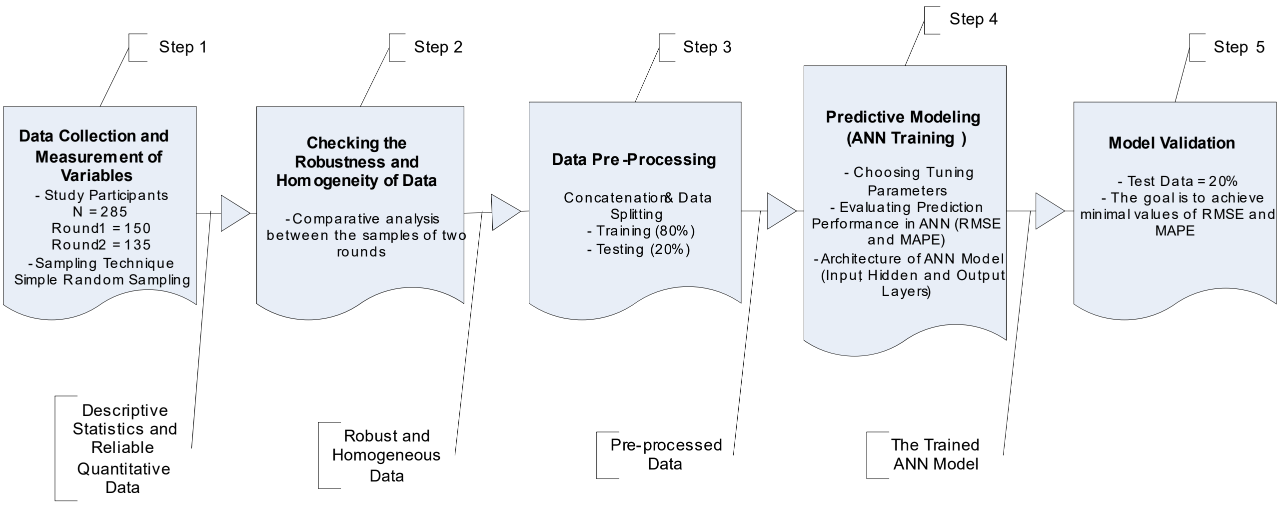

FIG. 1. THE RESEARCH PROCESS

order to ensure that the questions of the questionnaire are not linked to each other, face and content validity is checked thoroughly.

Data Collection: Initially, 480 questionnaires were distributed to various R&D set-ups. The relevant point of contacts were contacted within the main organization and sister public sector organizations. Almost 8-9 head of the departments were identified as the prime source of data collection. Number of copies of questionnaire was handed over to the HODs and requested them to distribute/float the survey in their departments/ organizations.

In order to avoid survey bias during data collection, following points were taken care of:

(i) The phrasing/wording of survey questions were kept neutral and language used was appropriate for the targeted audience.

(ii) Respondents were offered with the interval questions (Likert scale (1-7)).

(iii) The surveys/questionnaire was structured and personalized appropriately by keeping the target audience in mind.

There were 285 valid questionnaires received in two consecutive rounds of data collection and effective response rate was 59.37%. Total 150 questionnaires were collected in the first round and 135 in the second round. Collecting data from public sector organizations specifically on R&D projects was a challenging task. To achieve the maximum and optimal data collection, assistance was required from people who were familiar with the characteristics of the population of interest. Based on the availability of data, the data were collected in two rounds:

(i) In the first round, the data were collected within the main public sector organization.

(ii) In the second round, the data were collected from constituent/sister public sector organizations working on R&D projects.

Data Analysis: The measurement of variables is carried out by performing descriptive statistical and reliability analysis in R and SPSS respectively. The measures for acceptable levels of Cronbach's alpha qualify a value of 0.8 and above are considered as good, 0.7 and above as satisfactory and 0.6 and above as acceptable for measurement [71].

3.1.2 Step-2: Checking the Robustness and Homogeneity of Data

In order to check the robustness of data, a comparative analysis between the samples of the first and second round is carried out. F-test and T-test are conducted to check the robustness [66] and homogeneity of data in this study. The F-test [67] is performed to compare the variances of two samples (batches) from normal populations. Whereas, the Student's t-test is a test in which the test statistic follows t-distribution under the null hypothesis. T-test was developed by William Sealy Gosset in 1908 and is also used to infer whether the means of the two samples (batches) are significantly different from each other.

3.1.2 Step-3: Data Pre-Processing

During data pre-processing in this study, the data from two files (OS and SM data files) are loaded in R. Means are calculated for all sub-constructs of OS and SM and are concatenated together before the training and testing of ANN models.

3.1.4 Step-4: Predictive Modeling (ANN Training)

Before finalizing the ANN model with respect to the whole training set, it is essential to find the optimal tuning parameters using cross validation.

Optimizer – Adam: In this study, a stochastic optimization method known as 'Adam' is used. This algorithm is efficient in doing complex computations and well suited for the problems that involve large number of parameters/ data [68].

Evaluating Prediction Performance in ANN: The criteria to evaluate prediction performance in ANN are by using several measures. A comparative analysis is carried out on both samples (first and second round) with respect to RMSE and MAPE in this study. RMSE (also known as a 'loss function') is the standard deviation of the prediction errors (residuals). Other metrics include MAPE; it is the measure of forecast error or of prediction accuracy of a forecasting method. Also there is no rule of thumb to predict if the prediction errors are too large. The value of MAPE or MAE is normally smaller than the value of RMSE [69]. On the basis of the selection of tuning parameters, quantitative performance measures like RMSE and MAPE are minimized thus yielding the optimum results. It is worth mentioning here that with the increase in the number of hidden nodes and layers, the value of train RMSE and train MAPE gets smaller and tends to approach zero. On the other hand, the optimal number of hidden layers and nodes in the hidden layers is dependent on the problem [70]. The procedure of adding hidden nodes and layers continued until the suitable value (lower values) of both measures were attained.

Activation Function - ReLU (Rectified Linear Unit): In NNs, activation functions are also known as transfer functions. Activation functions are used in NNs to impart non-linearity. Now-a-days, the rectifier is the most popular activation function for deep machine learning (NNs). A unit that is used to employ the rectifier is known as ReLU. ReLU is expressed in the form of following notation:

$$f(x) = \max(0,x)$$

The threshold in this function is set at zero. ReLU is zero when $x < 0$ and gradually increases in a linear fashion with slope 1 when $x > 0$. In this study, all the desired predictions are positive and greater than zero. Therefore, it may not make sense to use transfer function other than ReLU because it outputs positive values only.

Other Tuning Parameters: Other tuning parameters are; number of iteration (epoch), batch size and validation split. An ANN model is setup and a resampling-based performance measure for cross validation is calculated on the basis of 285 responses enclosed in a training set.

3.1.5 Step-5: Model Validation

The ANN model is validated after training. As test data, 20% of the data will be used for testing purposes. After passing through trained ANN model, predictions will be computed and validation will be stopped after getting smaller values of performance measures (RMSE and MAPE).

4. RESULTS AND ANALYSIS

4.1 Step-1: Data Collection and Measurement of Variables

Environment/Tool Used for this Study: In this study, the software RStudio (Version: 1.0.143.0) is used for data processing that is a powerful and flexible platform for the evaluation of predictive modeling, performance and data analysis. RStudio is an open-source IDE (Integrated Development Environment) for R. The keras package available in R is used in this study for building feed-forward ANN. It uses an open-source software library for deep machine learning/machine intelligence used for complex numerical computations with the help of stateful data flow graphs known as 'TensorFlow™' developed by 'Google Brain Team and released in February, 2017.

Overview of the Data Set: The characteristics of data sets are presented in Table 1. The datasets are provided in SAV files (SPSS files).

Description of the Data Set: As shown in Table 1, the data set has been divided into two SPSS data files; OS and SM files. The data set of OS and SM is composed of eight sub-constructs and each sub-construct consists of several variables/dimensions. The variables are represented as columns and responses as rows. The main constructs 'OS' consists of 30 variables and 'SM' consists of 39 variables. The type of all variables is 'Numeric'. A brief description of data sets is presented in Appendix-A.

Measurement of Variables: The measurements of variables are shown in Table 2. In totality, eight sub-constructs and relevant dimensions of OS and SM are derived from the literature study. Each sub-construct in this study is comprised of multiple items/dimensions. A mean value of all sub-constructs is calculated with respect to their respective items. For example, first sub-construct of OS is 'Formalization' and contains five items. Now, in order to measure this sub-construct (Form-1), a single mean value is calculated which is an average of five items. Finally, these measures (mean value) are used for the computation of ANN model.

The mean values show that on average the respondents selected the answers of OS (Section-I) on a Likert scale (1-7) between 3.364 and 5.332 and of SM (Section-II) between 4.107 and 4.765. However, standard deviation values of OS varies between 0.992 and 1.457 and of SM varies between 1.047 and 1.336 which means that on average the individual responses are almost one point and a little over 1 point far away from the mean value.

The reliability coefficients (Cronbach's alpha (α)) of all sub-constructs have been computed and are acceptable. The overall computed value of Cronbach's alpha for organizational instrument is 0.917 and for SM instrument is 0.962 that represents acceptable values of reliability and holds good internal consistency among items of both instruments. Also, the questionnaire used in this study has high face and content validity.

TABLE 1. OVERVIEW OF DATA SETS

No.	File Name	Variables (Columns)	Responses (Rows)	Size (KB)
1.	OS - DataFile	30	285	14
2.	SM - DataFile	39	285	17

APPENDIX-A: BRIEF DESCRIPTION OF TWO DATASETS USED IN THIS STUDY

Organizational Structure (Data Set # 1)					
No.	Variables Name	Label	No.	Variables Name	Label
1	Existence of Formalization	Form11	16	Functional Differentiation Vertical Differentiation	FDVD41
2	Enforcement of Formalization	Form13	17	Specialized Differentiation	SD41
3	Standardization of Work Processes	SWP11	18	Coordination Mechanism Horizontal Coordination1	HC51
4	Standardization of Skills Training and Indoctrination	SSTI12	19	Personal Communication	PC51
5	Standardization of Output	SO13	20	Team Coordination	TC51
6	Participation in Decision Making	PDM21	21	Direct Supervision	DS51
7	Participation in Decision Making2	PDM22	22	Decentralization 1	Decentral 61
8	Participation in Decision Making3	PDM23	23	Vertical Decentralization	VD61
9	Specialization1	Special31	24	Horizontal Decentralization	HD61
10	Specialization2	Special32	25	Departmentalization 1	Depart71
11	Specialization3	Special33	26	Departmentalization 2	Depart72
12	Functional Specialization	FS31	27	Departmentalization 3	Depart73
13	Functional Differentiation Horizontal Differentiation	FDHD41	28	Authority of Project Managers	APM81
14	Functional Differentiation Horizontal Differentiation	FDHD42	29	Authority of Functional Managers	AFM81
15	Functional Differentiation Horizontal Differentiation	FDHD43	30	Authority of Technology Managers	ATM81
Schedule Management (Data Set # 2)					
1	Plan Schedule Management Project Management Plan	PMP11	21	TaskPriorityParameters3	TPP33
2	Project Charter	PC11	22	TaskPriorityParameters4	TPP34
3	Environmental Factors 1	EF11	23	TaskPriorityParameters5	TPP35
4	Environmental Factors 4	EF14	24	TaskPriorityParameters6	TPP36
5	Organizational Process Assets 1	OPA11	25	Resource Availability and Estimation Resource Factor	RF41
6	Organizational Process Assets 2	OPA12	26	Resource Availability	RA42
7	Organizational Process Assets 3	OPA13	27	Activity Resource Estimation	ARE43
8	Tools and Techniques 2	TT12	28	Resource Breakdown Structure	RBS44
9	Schedule Management Plan 1	SMP11	29	Schedule Constraints Temporal Constraints	TC51
10	Schedule Management Plan 3	SMP13	30	Precedence Constraints	PC52
11	Activities Definition 1	AD21	31	Availability Constraints	AC53
12	Activities Definition 2	AD22	32	Schedule Development 1	SD61
13	Activities Definition 3	AD23	33	Schedule Development 2	SD62
14	Activities Definition 4	AD24	34	Schedule Uncertainty 2	SU72
15	Activities Definition 5	AD25	35	Schedule Uncertainty 3	SU73
16	Activities Definition 6	AD26	36	Schedule Uncertainty 4	SU74
17	Activities Definition 7	AD27	37	Schedule Control 1	SC81
18	Activities Definition 8	AD28	38	Schedule Control 2	SC82
19	Task Priority Parameters 1	TPP31	39	Schedule Control 3	SC83
20	Task Priority Parameters 2	TPP32			

4.2 Step-2: Checking the Robustness and Homogeneity of Data

F-test (Fisher Test) and Student's T-test: The hypotheses of F-test and T-test are described as in Table 3.

F-test and T-test for the sub-constructs of OS and SM are calculated through the software R. After analyzing F-Test and T-test results, it can be deduced that robustness of this study is acceptable. It is evident from the Table 4 that the means and variances of the eight sub-constructs of OS and SM between the samples in the two rounds are not significantly different. The difference of means between two rounds is also shown in Table 4.

4.3 Step-3: Data Pre-Processing

After calculating the means, both files are concatenated. Now, in order to train and test the data, it is split into 80% for training and 20% for testing. The data in the

TABLE 2. DESCRIPTIVE STATISTICS

Main Construct - Organizational Structure				
Sub-Constructs	Number of Items	Mean Value	Standard Deviation	Cronbach's Alpha
Formalization (Form1)	5	4.655	1.153	0.794
Centralization (Central2)	3	3.364	1.457	0.805
Specialization (Special3)	4	5.332	0.992	0.762
Differentiation (Diff4)	5	4.404	1.129	0.805
Coordination Mechanism (CoMech5)	4	4.607	1.106	0.715
Decentralization (Decentral6)	3	4.064	1.112	0.611
Departmentalization (Depart7)	3	4.795	1.091	0.642
Authority of Managers (AOM8)	3	4.619	1.306	0.855
Total Number of Variables	30			
Main Construct - Schedule Management				
Sub-Constructs				
Plan Schedule Management (PSM1)	10	4.224	1.078	0.895
Activities Definition (AD2)	8	4.600	1.047	0.875
Project/Task Priority Parameters (TPP3)	6	4.631	1.153	0.876
Resource Availability and Estimation (RAE4)	4	4.765	1.095	0.789
Schedule Constraints (SC5)	3	4.215	1.292	0.801
Schedule Development (SD6)	2	4.723	1.336	0.754
Schedule Uncertainty (SU7)	3	4.107	1.205	0.714
Schedule Control (SC8)	3	4.202	1.307	0.798
Total Number of Variables	39			

training set are used to train the ANN and the testing set is utilized for the verification of the accuracy of trained NN for the prediction of SM of R&D projects. Data is duplicated and shuffled, afterwards for training purpose. The flow chart of data pre-processing is shown in Fig. 2.

TABLE 3. HYPOTHESES OF F-TEST AND T-TEST

F-test	T-test
F-distribution assumes that the null hypothesis is true.	Student's T-test assists in analyzing if two population means are equal. When p-value is greater than 0.01, we will be fail to reject null hypothesis.
Null Hypothesis: True ratio of variances for the two batches is equal, H_0: $\sigma_1^2 \neq \sigma_1^2$	Null Hypothesis: True difference in means for the two batches is equal or zero, H_0: $\mu_1 = \mu_2$ or $\mu_1 - \mu_2 = 0$
Alternative Hypothesis: True ratio of variances is not equal to 1, H_a: $\sigma_1^2 \neq \sigma_1^2$	eAlternative Hypothesis: True difference in mans is not equal to 0, H_a: $\mu_1 \neq \mu_2$ or $\mu_1 - \mu_2 \neq 0$

TABLE 4. VARIANCE (F-TEST) AND MEAN DIFFERENCE COMPARISON (T-TEST) OF THE SAMPLES IN TWO ROUNDS

Constructs	F Test (Fisher Test)			T Test (Student's T-Test)						
	F Score*	p-value*	Accept/ Reject*	T Value	df (Degrees of Freedom)	p-value*	Mean of (first round) (A) N=150	Mean of (second round) (B) N=135	Diff of Means	Accept/ Reject
Form1	1.182	0.322	Accept	-0.464	283	0.642	4.625	4.689	-0.064	Accept
Central2	1.248	0.191		-0.005	283	0.995	3.364	3.365	-0.001	
Special3	0.977	0.887		0.343	283	0.731	5.352	5.311	0.041	
Diff4	1.047	0.785		0.647	283	0.517	4.445	4.359	0.086	
CoMech5	0.990	0.950		-0.046	283	0.963	4.605	4.611	-0.006	
Decentral6	1.260	0.172		-0.993	283	0.321	4.002	4.133	-0.131	
Depart7	1.116	0.517		0.112	283	0.910	4.802	4.788	0.014	
AOM8	1.188	0.307		-2.442	283	0.015	4.442	4.817	-0.375	
PSM1	1.403	0.046		-1.665	283	0.096	4.124	4.336	-0.212	
AD2	1.247	0.192		-0.935	283	0.350	4.546	4.662	-0.116	
TPP3	1.028	0.868		0.173	283	0.862	4.642	4.619	0.023	
RAE4	1.467	0.023		-1.479	280.95	0.140	4.675	4.865	-0.190	
SC5	1.226	0.228		0.249	283	0.803	4.233	4.195	0.038	
SD6	1.139	0.440		-1.866	283	0.063	4.583	4.878	-0.295	
SU7	1.070	0.690		-0.571	283	0.568	4.069	4.151	-0.082	
SC8	1.665	0.002		-2.067	277.02	0.039	4.053	4.368	-0.315	

F Score* = Ratio of Variances, p-value* = Significance level (α) = 0.01 (99% confidence interval), Accept/ Reject* = if p-value > 0.01 then 'Accept', otherwise 'Reject'

4.4 Step-4: Predictive Modeling (ANN Training)

Layers/Nodes (Architecture): The main building blocks/ architecture of ANN model includes one input and output layer and four hidden layers. The input nodes in the input layer includes eight OS sub-constructs; formalization, centralization, specialization, differentiation, coordination mechanism, decentralization, departmentalization, and authority of managers, which are the independent variables in this study. All of these sub-constructs encompass their relevant dimensions as well. The output nodes in the output layer are the eight sub-constructs of SM; plan SM, activities definition, project/task priority parameters, resource availability and estimation, schedule constraints, schedule development, schedule uncertainty and schedule control. There are four hidden layers in this BPNN model. All of the four hidden layers consist of 90

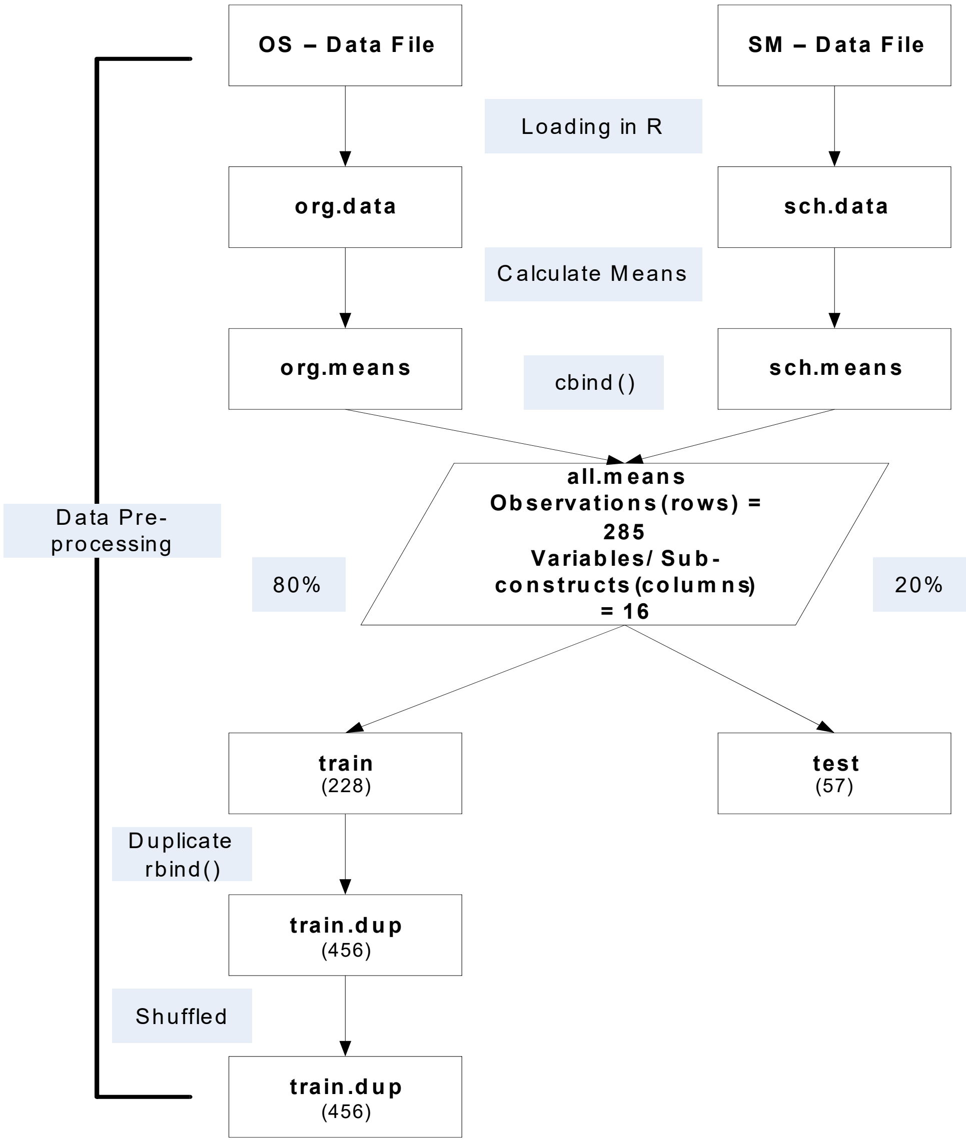

FIG. 2. DATA PRE-PROCESSING IN R

nodes. Regarding the selection of transfer function, the hidden and output nodes both works on the basis of ReLU transfer function as explained earlier as well.

After data pre-processing, an ANN model is built and training results are attained. Given the amount data, the research problem is very complex. It was observed that the ANN was not able to map that complexity for N=228 observations initially. The limitation of small dataset in this research have been overcome by incorporating following steps to get better ANN training performance:

(i) First of all, in this study, the size of dataset and amount of data collected is constrained by the availability of large datasets on R&D projects in public sector organizations.

(ii) Therefore, the training dataset was duplicated (N=456) in order to facilitate the mapping of the complexity of ANN.

(iii) To check the quality of our datasets and extract the maximum available useful information without overfitting from it [72]. We have performed analysis checks by checking the robustness and homogeneity of datasets (explained in section 4.2) and also data pre-processing is done (explained in above section 4.3).

(iv) The fit () function has been individually run (for ANN training) more than 100 times to select the best tuning parameters which give desired results consistently. Hence, the strategy for multiple runs was adopted to monitor the prediction performance in terms of errors and convergence curves of network errors (RMSE and MAPE) [73].

To start with the training process, the initial weights are chosen randomly. If satisfactory values of RMSE and MAPE are attained, the final model of ANN will be attained. Otherwise, weights will be adjusted again iteratively through the forward and backward propagation procedures. Fig. 3 shows the training flow chart of ANN.

4.5 Step-5: Model Validation

When ANN is trained, it has trained ANN weights. 20% of the data will be used as test data for the validation of ANN after training. The test data will pass through trained ANN model. It will generate the ‘predictions’ (results of OS sub-constructs).These predictions will be compared with the actual results of SM sub-constructs. The schema is to minimize the error. ANN validation will be stopped on getting the smallest RMSE and MAPE values. Fig. 4 shows testing flow chart of ANN.

In total, the results of 54 ANN Models (RMSE) are attained and corresponding values are plotted in Fig. 5(a-b). The upper line shows the testing results of RMSE and the lower line shows the training results of RMSE. It was observed that lowest value of test RMSE in all models is 0.537. The values of train and test MAPE for different ANN models are plotted in Fig. 5(a-b). Among all models, the lowest value of test MAPE is 0.061.

Final Results of ANN Model: The convergence curves of the network errors (RMSE and MAPE) are shown in Fig. 6(a-b). It is evident from Fig. 6(a-b) that the algorithm is converged on 7000 epochs. Also, the value of MAPE is getting smaller as the number of epochs is increasing. Therefore, it shows that the ANN model is convergent in this study.

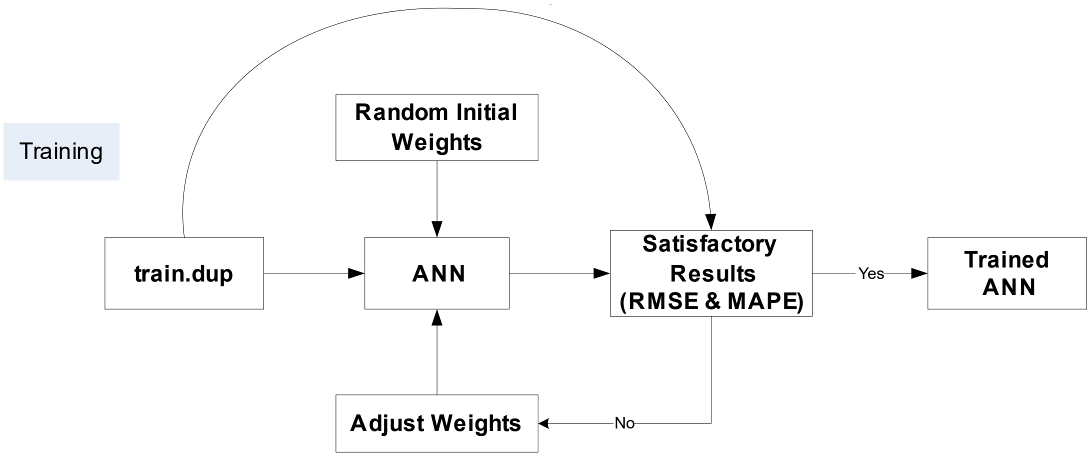

FIG. 3. ANN TRAINING FLOW CHART

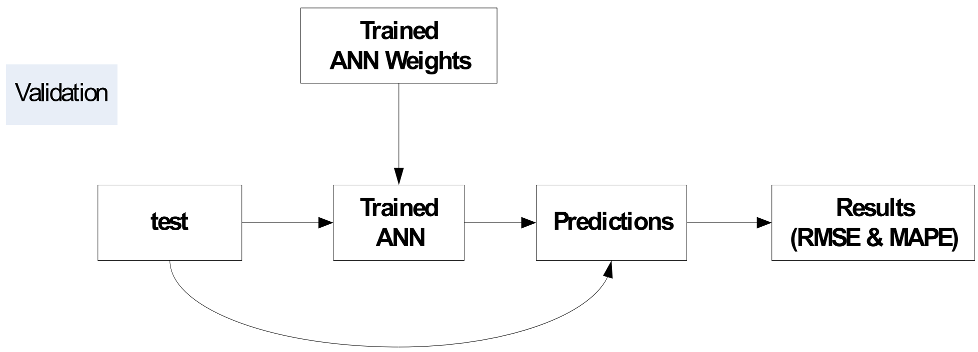

FIG. 4. ANN VALIDATION (TESTING) FLOW CHART

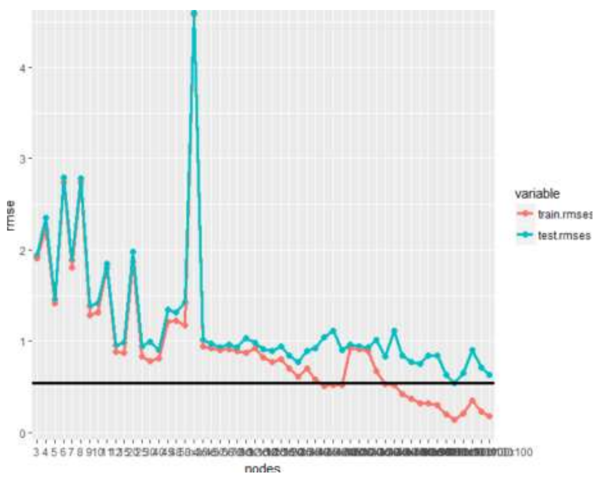

FIG. 5(a). TRAINING AND TESTING OF DIFFERENT ANN MODELS AND CORRESPONDING MSE

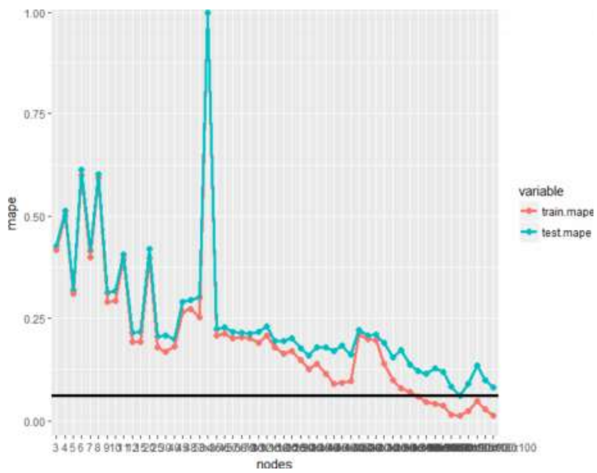

FIG. 5(b). TRAINING AND TESTING OF DIFFERENT ANN MODELS AND CORRESPONDING MSE

The optimal values of MAPE and RMSE are presented in Table 5. The best RMSE and MAPE results are in the last model i.e., MAPE = 0.061 and RMSE = 0.537; which are the lowest among all ANN models.

The final ANN model with one input layer (eight nodes), four hidden layers; each comprised of 90 nodes and one output layer (eight nodes) is shown in Fig. 7.

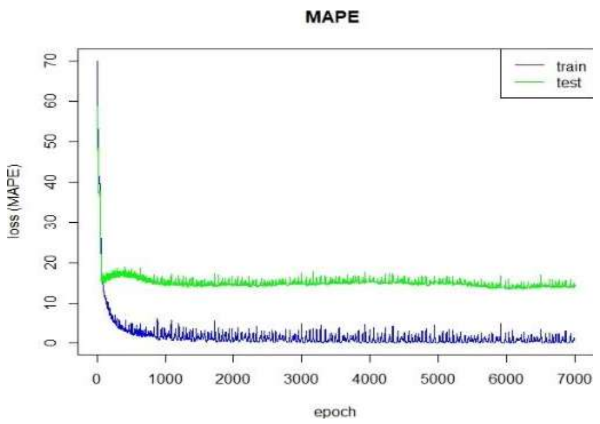

FIG. 6(a). THE CONVERGENCE CURVE OF MAPE IN ANN

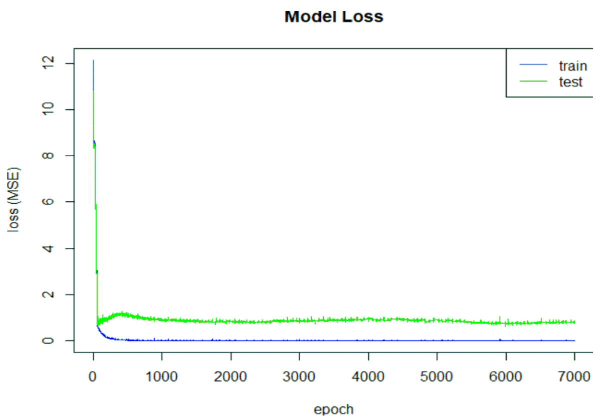

FIG. 6(b). THE CONVERGENCE CURVE OF MSE IN ANN

The values of MAPE and RMSE for both rounds are approximately the same as shown in Table 6. It can also be concluded that samples in both rounds are convergent. Therefore, with respect to MAPE and RMSE, robustness of data in both rounds is acceptable in this study. The formation of an ANN model is based on finding the optimal (lower) values of RMSE and MAPE and number of trials.

5. DISCUSSION

In this research, the impact of critical dimensions of OS on SM is methodically examined through predictive modeling using ANN. However, predictive modeling helped to take into consideration a wide range of concepts at organizational and project levels both. Especially in a R&D environment of public sector organizations, less significance is given in computing the impact of OS dimensions on the scheduling of projects which hampers the success of R&D projects, in the long run.

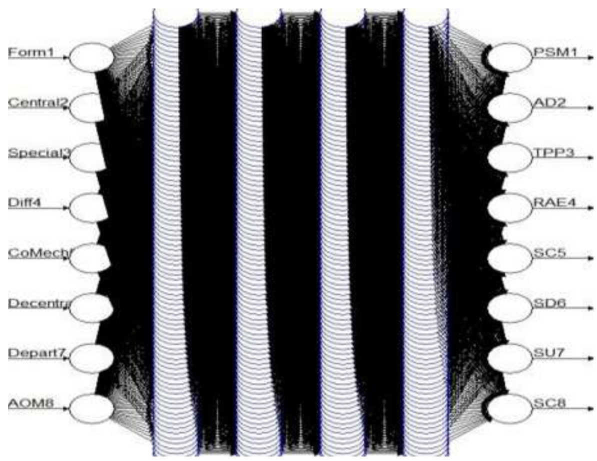

FIG. 7. THE FINAL ANN MODEL OF THIS STUDY

TABLE 5. THE TRAINING AND TESTING RESULTS OF ANN MODEL

	Training Results	Testing Results
Data size	228	57
Percentage	80%	20%
MAPE	0.012	0.061
RMSE	0.137	0.537

In this study, a graphical method is used to draw graphs i.e. 'LOESS'. LOESS stands for Local Regression [65] and is based on non-parametric regression method. It combines multiple regression models by using k-NN (k-Nearest Neighbor) algorithm based meta-model. A 'LOESS curve' is a smooth curve made up from a set of data points generated with the help of this statistical technique. This curve is also known as 'spline' that simply connects one or more points. The gray band around the smooth local regression line represents 'confidence interval'. A confidence band represents the uncertainty regarding regression line and can wiggling differently within the band (top and lower limits of band). The 95% confidence limits are obtained for model predictions. The gray area is the confidence region for the fitted curve (prediction) and not for the data points. The findings are results show that one of the vital identified SM' sub-construct critical for R&D project success i.e. plan SM and its dimensions show that this sub-construct has a high value of internal consistency among its items (Cronbach's alpha = 0.895). Other sub-constructs; activities definition, project/task priority parameters, resource availability and estimation, schedule constraints, development, uncertainty and control also reveals significant results of reliability (0.875, 0.876, 0.789, 0.801, 0.754, 0.714 and 0.798). The findings also show that, on one hand, the identified sub-constructs of SM are crucial for the success of R&D projects whilst, on the other hand, the industry practitioners are fully aware that the acknowledged factors of OS creates immense impact on the SM of R&D projects. Among, eight sub-constructs of OS, formalization is one of the most vital dimensions of OS acknowledged by researchers and practitioners in R&D environment. Formalization also known as standardization is a key factor influencing the projects' schedules. The value of Cronbach's alpha (0.794) indicates that formalization is a strong sub-construct of OS.

Fig. 8 shows eight different loess curves among formalization and eight sub-constructs of SM. The loess fit captures an increasing trend in data for all the eight sub-constructs of SM (PSM1, AD2, TPP3, RAE4, SC5, SD6, SU7 and SC8). The loess curve depicts that the existence of formalization in an OS has a strong impact and relationship with the SM of R&D projects. If R&D organizations develop formalized official rules, regulations and procedures, goals of the projects can be achieved within the defined timelines. The more rules and procedures are standardized in an OS; more prudently scheduling of R&D projects can be done.

Usually, centralization has been given less importance in an organic structure due to inflexible processes of decision making. Fig. 9 shows different loess curves among centralization and eight sub-constructs of SM. The loess fit captures a slow increasing trend in the data for all the eight sub-constructs of SM (PSM1, AD2, TPP3, RAE4, SC5, SD6, SU7 and SC8). It is obvious that there is a weak positive relationship between centralization and all SM sub-constructs.

TABLE 6. THE ANN RESULTS OF THE SAMPLES IN THE TWO ROUNDS

	The sample in the first round	The sample in the second round
Data size	150	135
Percentage	52.63%	47.37%
MAPE	0.1232	0.1064
RMSE	0.5841	0.5538

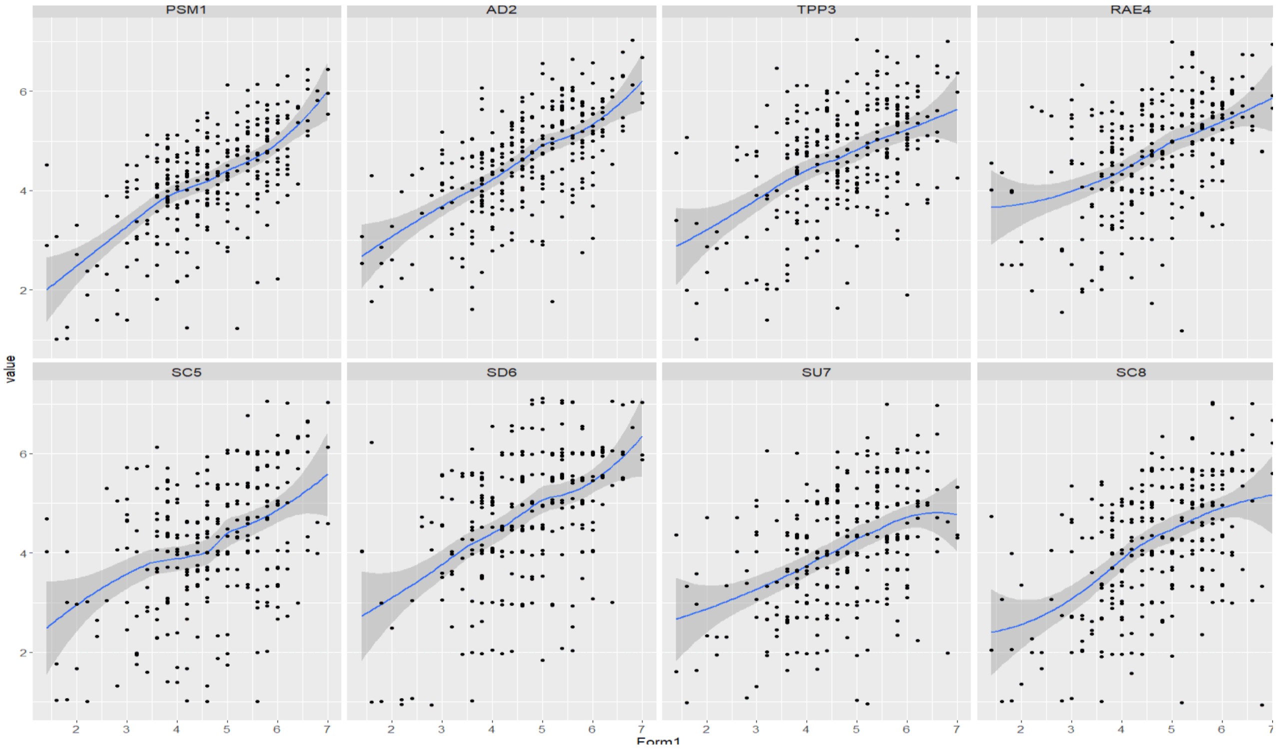

FIG. 8. LOESS CURVE BETWEEN FORM1 AND SM SUB-CONSTRUCTS

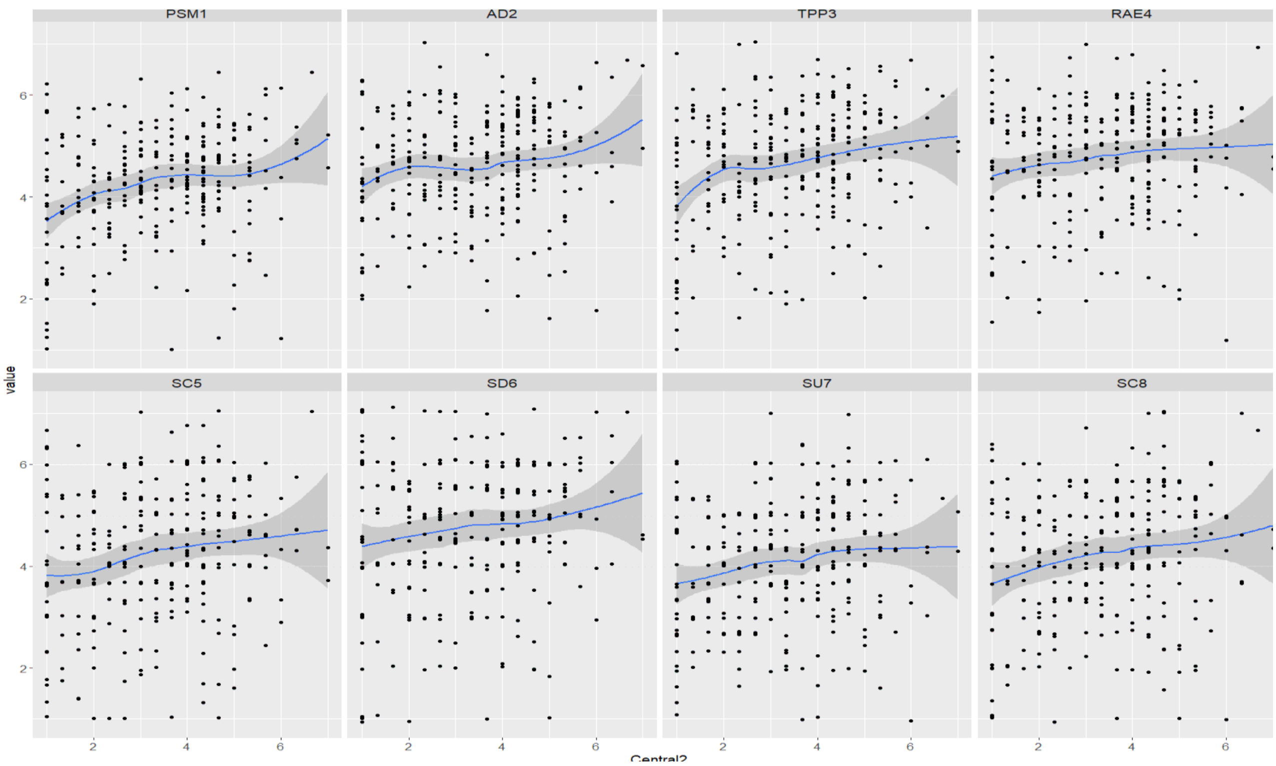

FIG. 9. LOESS CURVE BETWEEN CENTRAL2 AND SM SUB-CONSTRUCTS

While considering the success in R&D environment, specialization is another important dimension of OS that affects R&D project success enormously. The value attained in reliability analysis advocates the inclusion of specialization as an important sub-construct of OS. By deploying specialized skill-sets in R&D environment for the execution of R&D projects, the development and planning of schedules, analyzing resource availability, identifying different project and task parameters, and finding uncertainties in schedule, can be achieved successfully. Fig. 10 shows different loess curves among specialization and eight sub-constructs of SM. It is clear from the loess curves that there is a positive relationship between specialization and SM sub-constructs.

Similarly, the impact of division of labor with regards to the number of hierarchical levels, and spatial dispersion on the schedule of R&D projects is also computed in predictive modeling. The results of predictive modeling revealed that differentiation is also an important dimension of OS and is directly proportional to R&D project success. The value of Cronbach's alpha (0.805) suggests differentiation to be an integral part of the OS' sub-constructs. If most of the work in an organization is divided into further sub-units with respect to the responsibility and authority, segregation of tasks according to manager' goal orientation, geographic dispersion, the chances of an efficient execution of R&D projects will be guaranteed within proposed timelines. Fig. 11 shows different loess curves among differentiation and eight sub-constructs of SM. It is apparent from the loess curves that there is a positive relationship between differentiation and SM sub-constructs. However, RAE4 (Resource Availability and

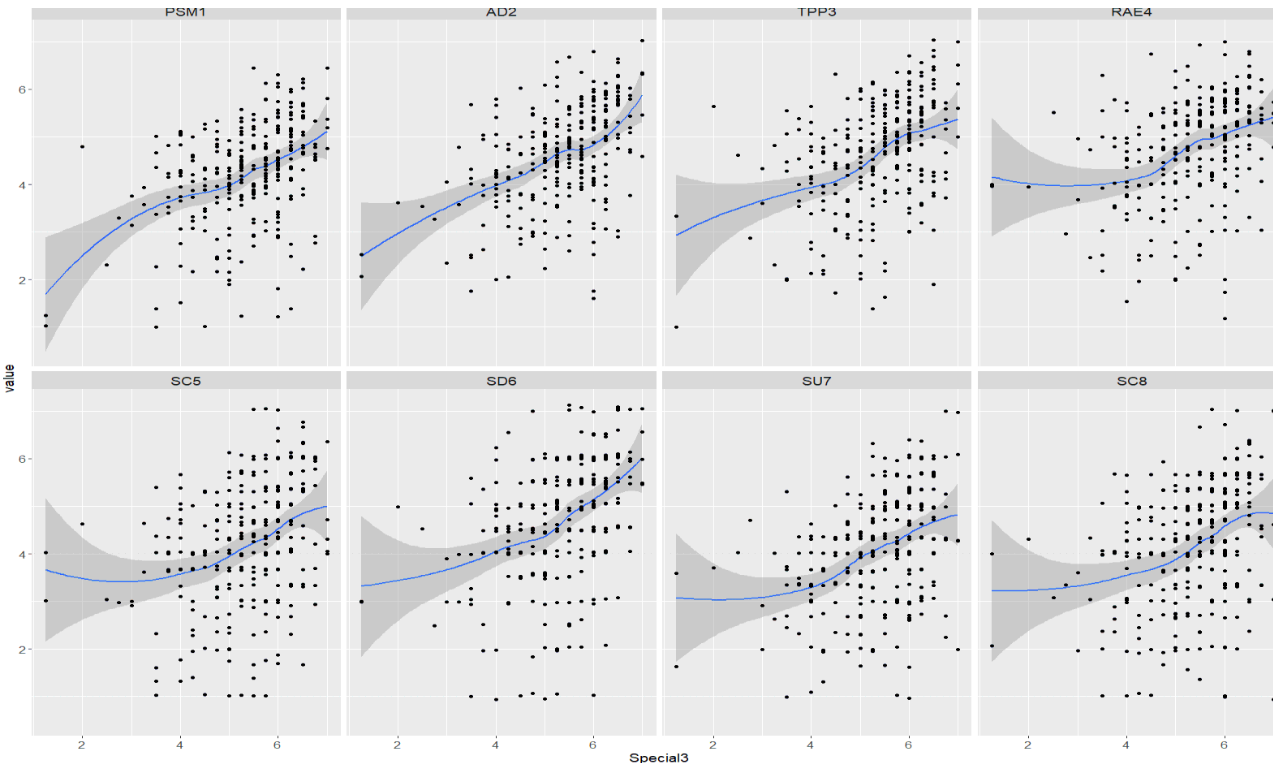

FIG. 10. LOESS CURVE BETWEEN SPECIAL3 AND SM SUB-CONSTRUCTS

Estimation) shows a weak relationship with differentiation in an OS. It means that the influence of differentiation while identifying RAE4 managing schedules is not strong and showing a decreasing trend.

Within an OS in R&D environment, without an effective coordination mechanism, management of stakeholders is not possible. The value of Cronbach's alpha (0.715) indicates the existence of coordination mechanisms as an essential factor of OS. Various mechanisms of coordination help to schedule the resources identify constraints, project/task priority parameters and risk factors. Fig. 12 shows different loess curves among coordination mechanism and eight sub-constructs of SM. It is apparent from the loess curves that there is a positive relationship between coordination mechanism and SM sub-constructs. However, SU7 (Schedule Uncertainty) and SC8 (Schedule Control) show a weak relationship with coordination mechanism in an OS. It means that the effect of coordination mechanism on schedule control and uncertainty while managing schedules is not strong and shows a decline.

Fig. 13 shows different loess curves among decentralization and eight sub-constructs of SM. It is apparent from the loess curves that there is a positive relationship between coordination mechanism and all SM sub-constructs. Therefore, trends in the overall results and analysis of predictive modeling suggest implementing and executing R&D projects in a decentralized structure, i.e. organic environment.

Fig. 14 shows different loess curves among departmentalization and eight sub-constructs of SM. It is apparent from the loess curves that there is a positive

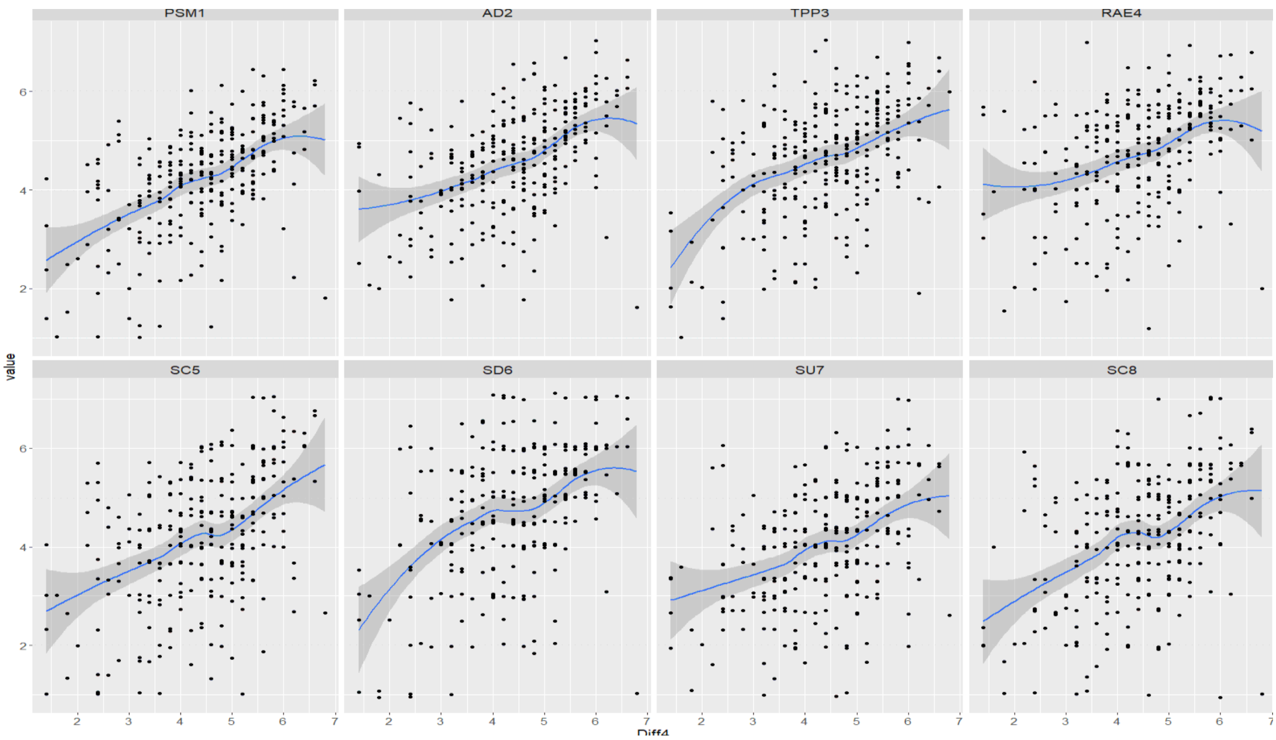

FIG. 11. LOESS CURVE BETWEEN DIFF4 AND SM SUB-CONSTRUCTS

relationship between departmentalization and SM sub-constructs. However, SU7 and SC8 show a weak relationship with departmentalization in an OS. It means that the effect of departmentalization on schedule uncertainty and control while managing schedules is not very strong.

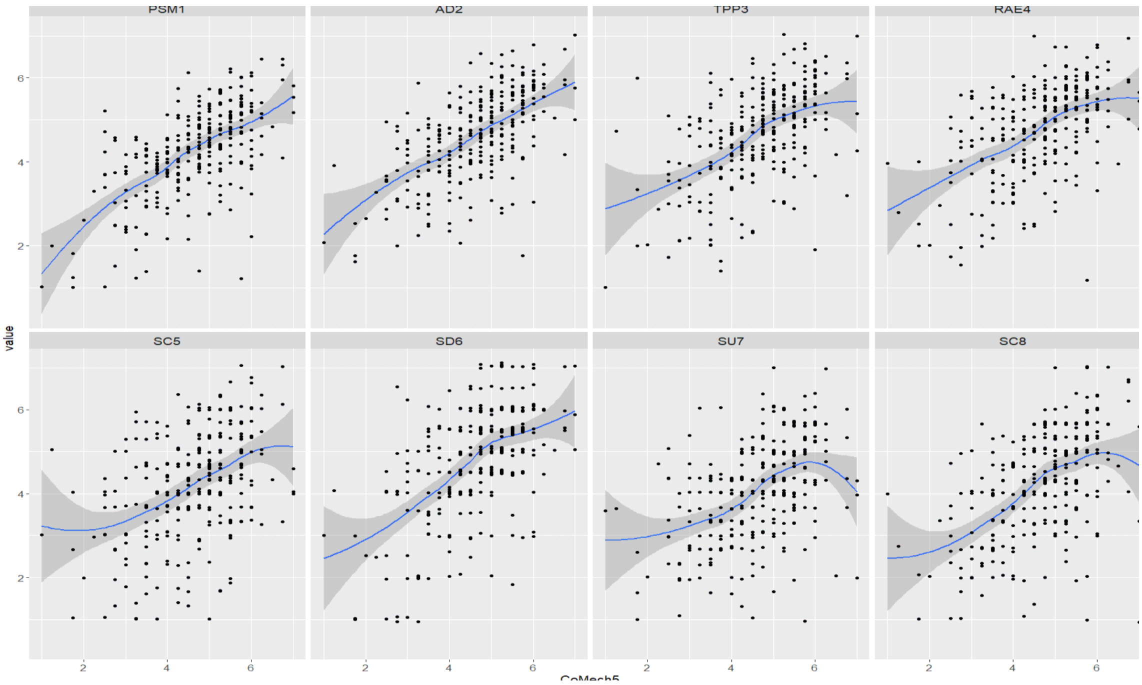

FIG. 12. LOESS CURVE BETWEEN COMECH5 AND SM SUB-CONSTRUCTS

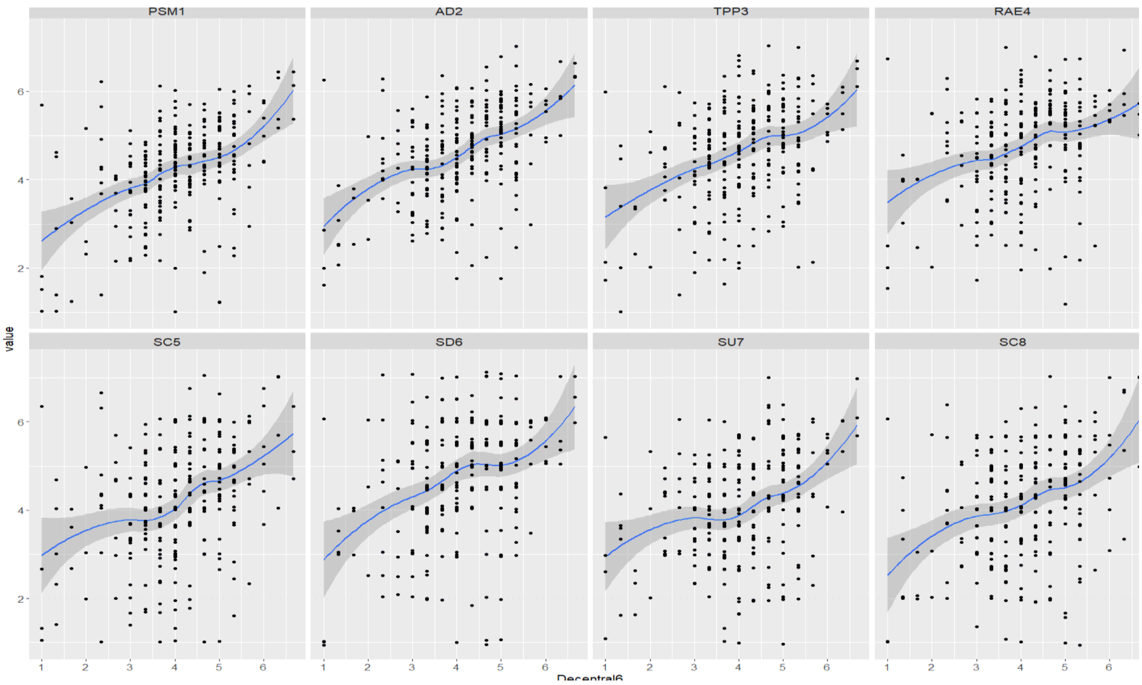

FIG. 13. LOESS CURVE BETWEEN DECENTRAL6 AND SM SUB-CONSTRUCTS

Talking in terms of success and failures; the experience of project manager has an enormous impact on the performance of R&D projects. Massive project delays and failures can be witnessed in the presence of lack of project managers' competence together with the lack of top management support. The high value of Cronbach's alpha (0.855) shows that items of this sub-construct have high internal consistency. From the results and analysis of this study, it is evident that managerial efficiency is an integral part of project management, for the successful execution of R&D projects and to improve the project schedule performance as well. It is the main responsibility of a project manager as a part of project management team, by keeping in view all the uncertainties, constraints, issues related to resources to plan, develop and control the schedule of a project. Fig. 15 shows different loess curves among authority of managers and eight sub-constructs of SM. It is apparent from the loess curves that there is a positive relationship between authority of managers and SM sub-constructs.

Correlogram is also known as the graphical representation of correlation matrix and is used to visualize the data in the form of correlation matrices. The OS and SM sub-constructs are used to compute the correlation matrix in this study. All eight sub-constructs of OS are shown on the left side and other eight of SM are shown on the above side. This helps to highlight the highly correlated variables in the grid. The correlation coefficients are colored according to the values as shown in Fig. 16. The blue color of circles (correlation coefficients) shows that there is a positive correlation between OS sub-constructs and SM sub-constructs. However, the intensity in blue color and circle size are directly proportional correlation coefficients.

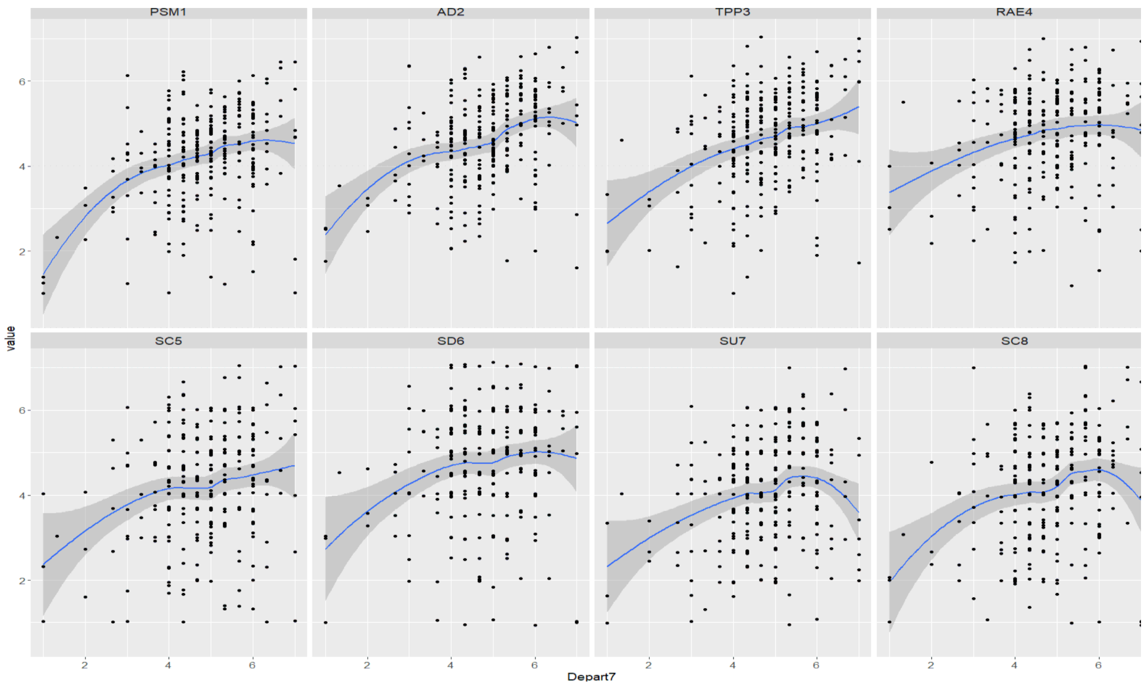

FIG. 14. LOESS CURVE BETWEEN DEPART7 AND SM SUB-CONSTRUCTS

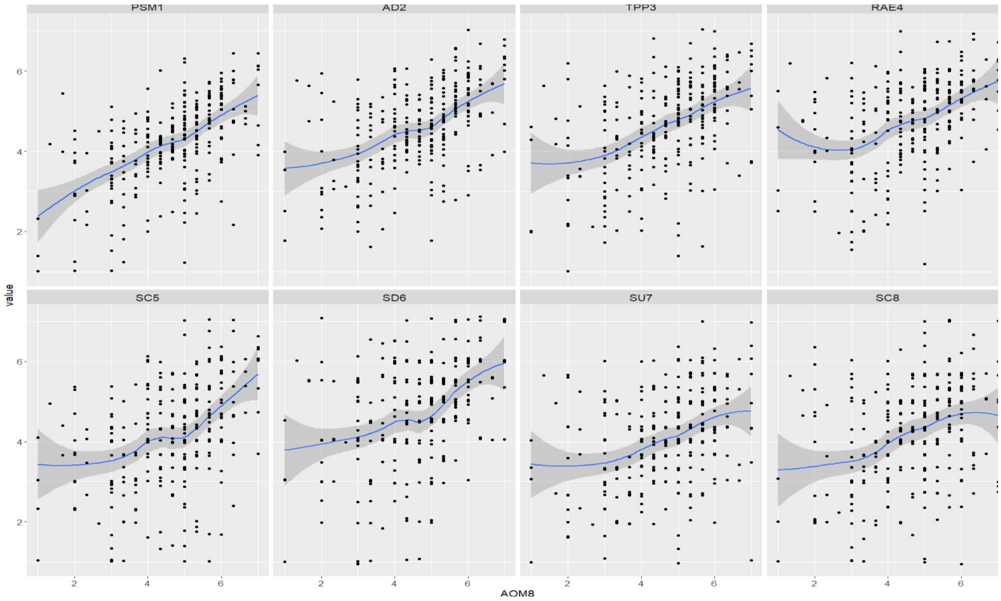

FIG. 15. LOESS CURVE BETWEEN AOM8 AND SM SUB-CONSTRUCTS

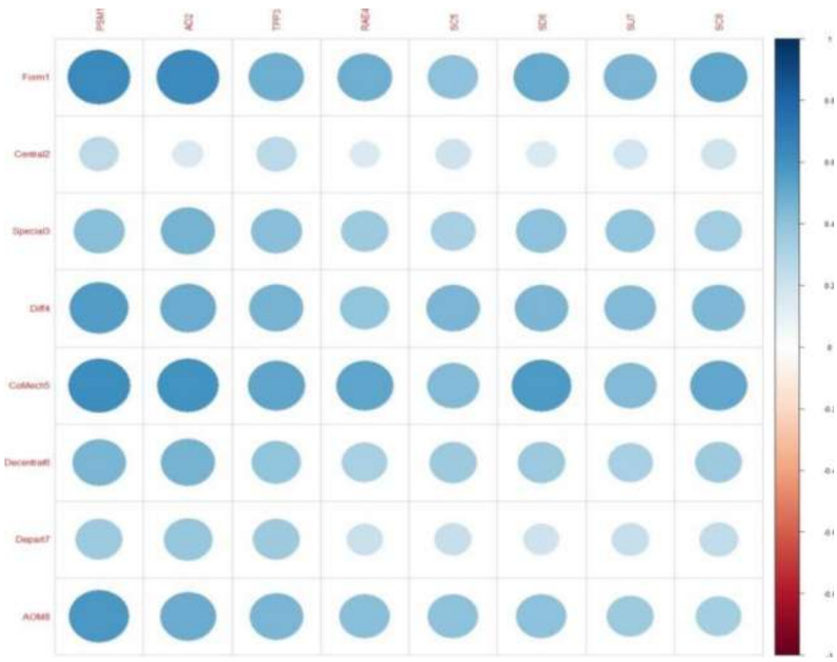

FIG. 16. CORRELOGRAM OF VARIABLES

6. CONCLUSIONS

This research develops literature from the R&D project success/failures, OS, and SM disciplines. It explored the non-linear relationship between the dimensions of OS – formalization, centralization, specialization, differentiation, coordination mechanism, decentralization, departmentalization and authority of managers and SM–plan SM, activities definition, project/task priority parameters, resource availability and estimation, schedule constraints, development, uncertainty and control – by means of predictive modeling using ANN. This groundwork yields a rationale for a set of valid and reliable OS and SM sub-constructs and dimensions. It develops eight sub-constructs for each main construct; thirty dimensions for organizational structure and thirty-nine dimensions for SM.

Moreover, the instrument has passed the standard criteria of reliability for basic research. The robustness and homogeneity of data collected in two rounds was checked through F-test and T-test. After conducting the proposed tests, the homogeneity and robustness of data was confirmed. After running 54 models of ANN, the lower values of RMSE and MAPE were attained and the algorithm was converged on 7000 epochs.

The results showed that formalization, decentralization, specialization and authority of managers builds a positive and strong relationship with all sub-constructs of SM. However, the result of predictive modeling shows that differentiation also establishes a positive correlation with the sub-constructs of SM, except resource availability and estimation. It infers that the division of labor in an OS does not support the phenomenon of resource availability and estimation, for example, activity resources and resource breakdown structures will not be estimated and defined, respectively, for the management of schedules very strongly. Other sub-construct, coordination mechanism also constitutes a positive relationship except with schedule control and uncertainty. It can be deduced that presence of coordination methods in an OS does not promote much the handling of unforeseen events, risks, and constraints of schedule. The sub-construct, departmentalization also constitutes positive relationship with all sub-constructs of SM except, schedule uncertainty and control. It implies that the impact of departmentalization's dimensions will not eradicate the uncertainties while managing schedule and also will not impact on schedule control. The sub-construct, centralization observed a positive but weak relationship especially with four sub-constructs; task/priority parameters, resource availability and estimation, schedule constraints and uncertainty. The results shows that if decision making processes in the structure of an organization will be centralized, there will be an inverse impact on the above-mentioned sub-constructs of SM and time lags, schedule delays and slippages will be observed in R&D projects' execution. Thus, public sector organizations facing challenges about R&D project schedule based problems, should appraise the significant role played by the dimensions of an OS. The stated dimensions of OS are positively related to SM explored for R&D projects. The results specify that decentralized structure (organic) may operate better than centralized structure (inorganic) when SM practices are applied.

7. IMPLICATIONS FOR INDUSTRY PRACTITIONERS

The practitioners of R&D industry frequently manage strategically important R&D projects in distinct OS. In order to deal with the challenges of selecting the optimal variables of OS and their impact on the schedules of projects and overall success of R&D projects, team leaders should be vigilant. The application of theory has been explored practically in this research. To begin with, the model proposed in this research provides a holistic approach that will assist professionals to correlate the organizational design with the time-bound factors of R&D projects where they encounter uncertainty and risks issues frequently. The practical suggestions recommended by this study will also help them to stay away from unwanted results in highly uncertain environment like; unsuitable allocation and selection of resources, ambiguous role of authorities, lack of formalized procedures and policies, time delays and slippages, improper resource allocation and estimation, not prioritizing the project and activity parameters, deficient coordination mechanism etc. in an OS. If the practitioners take care of the right amalgamation of indicated factors identified in this research and create a paradigmatic organizational environment, reliable R&D products will be their ultimate success.

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