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A STUDY ON PARTIAL LEAST SQUARES STRUCTURAL EQUATION MODELING (PLS-SEM) AS EMERGING TOOL IN ACTION RESEARCH

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ABSTRACT— Structural equation modeling (SEM) depicts one of the most salient research methods across a variety of disciplines, including educational management. Recent research advocates the use of partial least squares structural equation modeling (PLS-SEM) as an attractive tool in action research. The purpose of this paper is to systematically examine how PLS-SEM has been applied in action research with the aim of investigating the effect of teacher's leadership styles (transformational and transaction) and student's motivational factors (intrinsic and extrinsic) on student engagement for implementation of Communicative Language Teaching (CLT) in classrooms as well as explore the mediating role of motivational factors of student between the relationship of teacher's leadership styles and student engagement. A cross-sectional survey design was used for the study featuring a self-administrated questionnaire among the students of some selected schools in Bangladesh. The transactional leadership style of teachers influences student engagement, intrinsic, and extrinsic motivation while the transformational leadership style of teachers influences the intrinsic and extrinsic motivation of the student. Both motivational factors mediated the relationship between leadership styles and student engagement. This study contributes to the literature by providing teachers with the updated guidelines for action research by using PLS-SEM. The study also suggests the way for increasing student engagement for CLT implementation in classrooms.

Keywords— Partial Least Squares Structural Equation Model (PLS-SEM), Action Research, Teacher's Leadership Style, Student's Motivation and Engagement.

I. INTRODUCTION

To test whole theories as well as concepts, the acceptance and recognition of structural equation modeling (SEM) has developed (Rigdon, 1998). Copious of SEM's accomplishment can be accredited to the technique's capability to assess the measurement of latent variables whereas correspondingly testing connections amongst latent variables (Babin et al., 2008). Formerly established through Wold (1974, 1980, 1982) PLS is an SEM procedure grounded on an iterative method that take advantage of the elucidated discrepancy of endogenous constructs (Fornell and Bookstein, 1982). Essentially, PLS- SEM functions considerably similar to a multiple regression analysis (Hult et al., 2018). In around 1940s and 50s action research introduced by famous Kurt Lewin and his associates as a cooperative problem resolving sequence for refining administrations (Lewin 1947, 1948; Corey 1953). The expression action research, apprehended the conception of well-organized examination in the circumstance of concentrated determinations to progress the excellence of an institute in addition to its action. Nowadays, action research vestiges as an authoritative instrument for instantaneously refining the practice and the well define structure of an institution.

II. LITERATURE REVIEW

Partial least squares structural equation modeling

PLS-SEM has in recent times established substantial consideration in a diversity of disciplines comprising human resource management (Ringle et al. 2019); hospitality and tourism (Usakli and Kucukergin, 2018); hospitality (Ali et al. 2018) management information systems (Hair et al. 2017a); international business (Richter et al. 2016); accounting (Nitzl, 2016); tourism (do Valle and Assaker, 2016); supply chain management (Kaufmann and Gaeckler, 2015); marketing (Hair et al. 2012b); strategic management (Hair et al. 2012a); management information systems (Ringle et al. 2012); operations management (Peng and Lai, 2012) and accounting (Lee et al. 2011). Over-all 875 research have been directed grounded on PLS-SEM from the period of 1980 to 2017 conferring to Sarstedt (2020). No research has been directed based on action research with PLS-SEM. The all-inclusive learning groups can be invigorate by the using of Action research, in addition to it assistance educators in altering or reproducing on their classroom practices. This can assist resourcefulness of every individual educators, educational institutions, and institutes functioning with societies, as well as regions, districts. The PLS – SEM method has incredible capability to manage the problematic modeling issues that routinely take place in the social sciences such as unusual data characteristics like non-normal data and highly complex models. Consequently, published research has frequently accentuated that PLS – SEM is predominantly engaging for applied science by consenting the testing of hypothesized connections in taking a extrapolation or prediction emphasis in the model estimation (Evermann and Tate, 2016; Sarstedt et al., 2017). PLS – SEM accordingly incapacitates the obvious dichotomy amongst clarification, which academic research generally accentuates, in addition to prediction which is obligatory to derive managerial implications (Hair et al., 2019). Furthermore, different controversial views about the merits and demerits of method, witnessed in various fields of research (Khan et al., 2019), have enhanced the understandings of it (Petter, 2018).

Action Research for Communicative Language Teaching Implementation

CLT syllabus emphasis on communication which encourages students to learn a language better with the meaningful prospect and change the traditional classroom practice.

The prominent features of Communicative Language Teaching methodology are

- Language learning with real communication based
- Create opportunities for students to have experimentation
- Be patience for learners errors
- Make changes and give chance students to develop accuracy and fluency in language use
- Make a real connection between language skills, like listening, speaking and reading
- Make opportunities for students to find out grammatical rules.
- Teachers as a facilitators and students oriented classroom

With these new principals, new student's oriented lessons where they can negotiate meaning and interact in communication are required.

Alam (2016) identified the lack of motivation among the students, Rahman et al. (2019) and Alam (2016) investigated that lack of trained teachers and their appropriate supervision are challenges in implementing CLT at secondary schools in Bangladesh. Savignon (2018) also detailed that the suitable teachers' authority in the classroom with students' active participation can motivate the pedagogy for CLT implementation.

In the continues popularity and expected growth of PLS-SEM, this study intends to discuss the method and steps used to test a model of action research about implementation of CLT in the classrooms of Bangladeshi Secondary Schools using PLS-SEM.

Language management theory argues to address that language planning at first must find out the problems in the related context, and the planning process must solve all the problems as well as give suggestions to manage every aspect to complete the planning (Neustupný, 1994). According to the theory if hindrances persist then language implementation is not possible. So CLT implantation of Bangladeshi Secondary Schools is not possible if the problems like minimum motivation of the students and inappropriate leadership style of the teachers exist.

Using PLS-SEM, this study is going to investigate:
(1) The effect of Teacher's leadership style (transformational and transactional) on student's motivation (intrinsic and extrinsic) in classroom.
(2) The influence of Teacher's leadership (transformational and transactional) on student's engagement in classroom.
(3) Student motivation (intrinsic and extrinsic) plays mediating role between the relationships of teacher's leadership style (transformational and transactional) and student's engagement in classroom.

WHY TO USE PLS-SEM FOR ACTION RESEARCH

The PLS-SEM methodology is used because of gaining the acceptance of many business discipline (Sarstedt, 2020). Many scholars have published their papers by summarizing and using the PLS-SEM in the field of their research. This paper presented the three major reasons for applying PLS-SEM in the field of action research that are data distribution, sample size, and the usages of formative indicators (Lin, et al. 2020).

Non-normal data

Collection of data for action research often is unsuccessful to pursue multivariate normal distribution. PLS-SEM is flexible to work with non-normal data due to PLS algorithm's transformation of non-normal data in accordance with central limit theorem (Beebe et al., 1998; Cassel et al., 1999). Hence, the caveat to PLS-SEM is to provide the complete solutions to models by using the non-normal data is twofold.
First, the researchers need to be careful that the highly skewed data can weaken the statistical power of the analysis. More specifically it is said that the valuation of the model parameters' significance depends on normal errors from bootstrapping that may be inflated in case highly skewed data (Henseler et al., 2016). Second, because CB-SEM is concerned with many alternatives to estimate procedures that may be problematic causes of assuming the PLS-SEM when data distribution is the automatic choice (Hair et al., 2012b).

Small sample size

PLS-SEM is useful when it works with small sample sizes (Chin & Newsted, 1999). Though the sample size brings impact on the different aspects of SEM that contains parameter estimates, model fit, and statistical power (Shah and Goldstein, 2006).
Hair et al. (2017) presented that the PLS is distribution free and good for studying the difficult models that have sample sizes. PLS-SEM is able to achieve the higher rate of statistical power and shows the superior convergence behaviour (Henseler, 2010). A popular heuristic indicates that small sample size for PLS model should be equal to ten times biggest number of formative indicators that are used to detect one construct or ten times the biggest number of inner model paths conducted at a particular construct in the inner model (Barclay et al., 1995).

Formative indicators

There is a difference between reflective and formative constructs. The formative measures shows the cases where the indicators cause the construct (i.e. the arrows point from the indicators to the construct), On the other hand construct causes the reflective indicators (i.e. the arrows point from the construct to the indicators).Hence, the PLS-SEM and CB-SEM are able to measure the models by using formative indicators, PLS-SEM has gained the mentionable support as the recognized method (Hair et al., 2014). Formative indicators with CB-SEM creates the problems of identification while being analyzed (Jarvis et al., 2003), it is common to researchers in believing that PLS-SEM is the finest option.

III. METHODOLOGY

A cross-sectional survey design was used for the study featuring a self-administrated questionnaire. The quantitative research design is applied and the survey instrument for the study was questionnaire. The population was the students of some selected higher secondary schools in Bangladesh. Partial random sampling had followed because it is the modified version of simple random sampling where researchers focused on every subgroup (every class) of the given population. The total sample was 387. In this present study, every construct in the questionnaire has three or more items where responses would be elicited using the Five-Point Likert Scale.

IV. DATA ANALYSIS & RESULTS

The researchers are required to follow the multi stage- process that is concerned with specification of the inner and outer models, data collection and assessment, the actual model estimation, and the valuation of results while applying the PLS-SEM.

This study is centered by the three major steps that are given below:

(1) Model specification;

(2) Outer model evaluation; and

(3) Inner model evaluation.

Hair et al. (2014) presents the details introduction into every stages of PLS-SEM use.

(1) Model specification

The model specification stage involves with setting up of the inner and outer models. The inner model or structural model shows the interactions between the constructs being appraised. The outer models are also acknowledged as the measurement models that are used in evaluating the interactions between the indicator variables and their corresponding construct.

On the basis of theory and logic the first step of using PLS-SEM is concerned with creating a path model which connects variables and constructs (Hair et al., 2014). In preparing the path model which is shown in Figure 1, it is foremost thing to differentiate the location of the constructs and the interactions between them. Constructs are regarded as either exogenous or endogenous. Exogenous constructs act as independent variables and which do not have any arrow pointing at them (transformational and transactional leadership style of teacher in Figure 1), other construct explain endogenous constructs (student engagement in Figure 1).

Whereas regularly regarded as the dependent variable within the relationship, endogenous constructs are also acted as independent variables at the time of placing between two constructs (student extrinsic and intrinsic motivation act as mediator in Figure 1). Researchers are required to be aware of setting up the model in its basic form, the PLS-SEM algorithm can only handle models having no rounded relationship between the constructs. This requirement would be violated if researchers reversed the relationship teacher's transformational leadership ->student engagement and teacher's transactional leadership -> student engagement in Figure 1. In this situation, transformational and transactional leadership of teacher would predict student extrinsic and intrinsic motivation, student extrinsic and intrinsic motivation would predict student engagement, and student engagement would predict teacher's transformational and transactional leadership again, yielding a circular loop (i.e. teacher's transformational and transactional leadership ->student's extrinsic and intrinsic motivation -> student's engagement ->teacher's transformational and transactional leadership).

After designing the inner model, the researcher must identify the outer models. in this stage the researchers are required to make several decisions like as whether to use a multi-item or single-item scale (Diamantopoulos et al., 2012; Sarstedt and Wilczynski, 2009) or whether to specify the outer model in a reflective or formative manner (Diamantopoulos and Winklhofer, 2001; Gudergan et al., 2008). The sound specification of the outer models is vital because of hypothesizing the relationships in the inner model which are only as valid and reliable as the outer models. In Figure 1, all the constructs are concerned with having a reflective measurement specification and there have no formative measurement items.

On the other hand, the number of items per construct/statement is much higher in action research, while formative measures involve as by definition, need to confine the entire field of the construct (Diamantopoulos and Winklhofer, 2001; Diamantopoulos et al., 2008).

(2) Outer model evaluation

After specifying the inner and outer models, then PLS-SEM algorithm is run and on the basis of the results and evaluating the reliability and validity of the construct measures in the outer models.

The researcher can trust the construct by instituting with the assessment of the outer models that create the basis for the assessment of the inner model interactions, are precisely valued and signified. The researcher must differentiate between reflectively and formatively measured constructs after apprising the outer models (Ringle et al., 2011; Sarstedt and Schloderer, 2010). Different concepts are based on the two approaches to measurement. Hence, it needs the consideration of various evaluative measures.

Reflective indicators

PLS-SEM include two types of measurement model one is reflective and another is formative measurement model. Therefore, the researchers differentiate between these two types of models to assess them (Henseler, Ringle, and Sinkovics 2009). Here, this study is concerned with employing only the reflective measurement model as there are no item suitable for formative measurement.

Reflective indicators form a representative of all probable items in the conceptual field of a construct (Diamantopoulos and Winklhofer, 2001). Therefore, reflective items are identical, extremely interrelated and capable of omitting without changing meaning of the construct. Reflective indicators are connected to construct through loadings that are the bivariate correlations between the indicator and the construct.

Researchers should validate both the reliability and validity during assessing the reflective outer models. The first step of measuring the composite reliability is to evaluate the construct measures' internal consistency reliability. While generally assessed using Cronbach's alpha (Cronbach and Meehl, 1955), composite reliability provide a more suitable measure of internal consistency reliability for minimum two reasons. First, unlike Cronbach's alpha, composite reliability are not assumed that all indicator loadings are equal in the population that is concerned with working principles of the PLS-SEM algorithm. It focuses on the indicators based on every reliabilities at the time of model judgment. Second, Cronbach's alpha is also responsive to the quantity of items in the scale and normally attempt to misjudge internal consistency reliability. PLS-SEM can accommodate different indicator reliabilities by using composite reliability (i.e. differences in the indicator loadings), as also avoids the underestimation connected with Cronbach's alpha.

Table 1: Composite reliability and Validity

	Outer loadings	**CA**	**CR**	**AVE**
STUDENT ENGAGEMENT		0.624	0.799	0.571
ee5	0.764			
ee8	0.726			
ee9	0.775			
EXTRINSIC MOTIVATION		0.749	0.857	0.667
em11	0.855			
em18	0.831			
em21	0.762			
INTRINSIC MOTIVATION		0.832	0.878	0.550
im26	0.594			
im27	0.821			
im29	0.612			
im35	0.785			
im36	0.777			
im37	0.823			
TRANSACTIONAL LEADERSHIP		0.744	0.836	0.563
tal51	0.812			
tal52	0.847			
tal55	0.663			
tal56	0.661			
TRANSFORMATIONAL LEADERSHIP		0.782	0.851	0.538
tfl43	0.713			
tfl45	0.566			

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tfl47	0.699
tfl48	0.823
tfl49	0.835

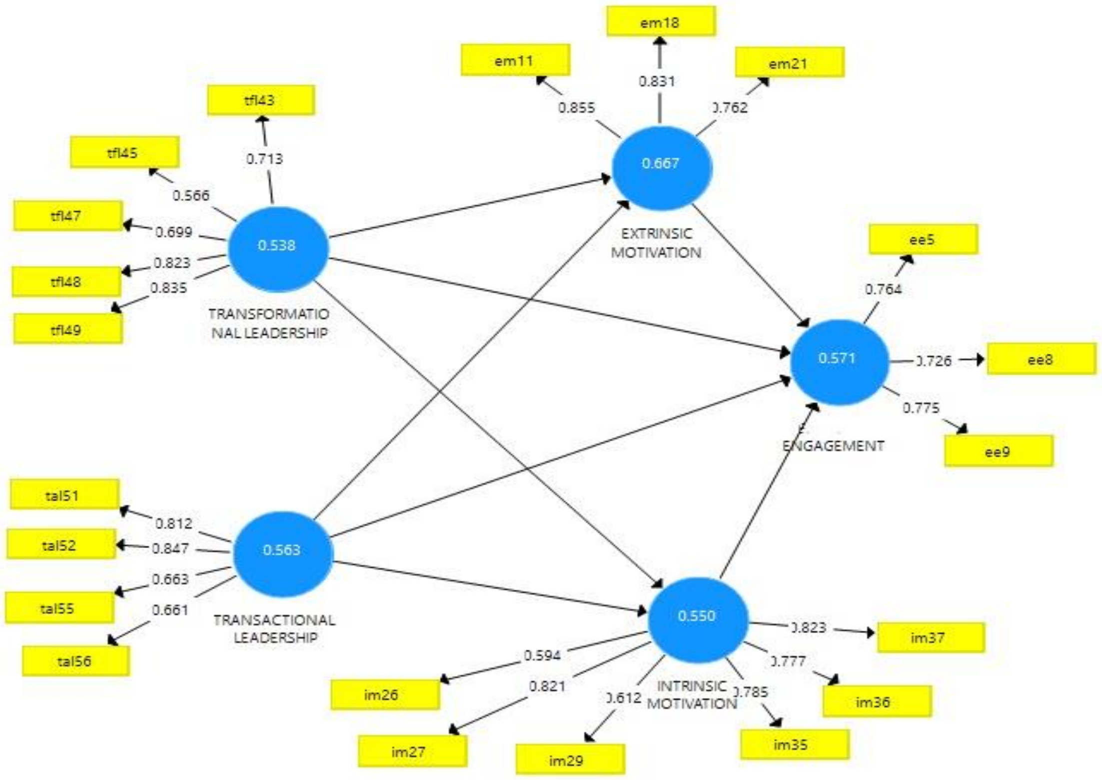

Figure 1. Measurement model

The second step of evaluation of reflective indicators is the assessment of validity. Construct's convergent validity and discriminant validity examines validity by noting. Convergent validity is supported during each item has outer loadings above 0.70 (Hair et al., 2014) and each construct's average variance extracted (AVE) is 0.50 or higher (Haier et al., 2017). The AVE is the total mean value of the squared loadings of a set of indicators (Hair et al., 2014) and is related to the communality of a construct. In a brief, an AVE of 0.50 presents that the construct elucidate more than half of the variance of its indicators (Table 1). The value of AVE slightly lesser than 0.5 is accepted (based on previous studies such as Lam, 2012) at the time of composite reliability is more than 0.60 for all construct. Therefore, the entire prerequisite for convergent validity, construct reliability, Cronbach alpha or internal reliability, and communality is attained. After that the instigator carries on the next step for discriminant validity.

Discriminant validity shows the level where construct is empirically discrete from other constructs or, in another way, the construct appraise what are the measures. Three criteria are used in Smart PLS to study discriminant validity that are cross loading, Fornell and Larcker, and HTMT criterions.

Fornell and Larckercriterion (1981) is the method of assessing the existence of discriminant validity. This method presents that the construct that shares more variance with its indicators than with any other construct. The AVE of each construct should be higher than the highest squared correlation with any other construct to measure the requisite. According to previous studies (for example, Tanaka & Huba, 1989), it should be ignored if the difference is too small (refer Table 2).

Table 2: Fornell and Larcker criterions.

CONSTRUCT	Y1	Y2	Y3	Y4	Y5
STUDENT ENGAGEMENT (Y1)	0.755				
EXTRINSIC MOTIVATION (Y2)	0.654	0.817			
INTRINSIC MOTIVATION (Y3)	0.690	0.737	0.732		
TRANSACTIONAL LEADERSHIP (Y4)	0.612	0.625	0.691	0.751	
TRANSFORMATIONAL LEADERSHIP (Y5)	0.543	0.730	0.673	0.470	0.727

The second option of verification for discriminant validity is to examine the cross loadings of the indicators. This method is considered as more liberal (Henseler et al., 2009) requiring the loadings of each indicator on its construct that are higher than the cross loadings on other constructs (Table 3).

Table 3: Cross loadings

ITEMS	STUDENT ENGAGEMENT	EXTRINSIC MOTIVATION	INTRINSIC MOTIVATION	TRANSACTIONAL LEADERSHIP	TRANSFORMATIONAL LEADERSHIP
ee5	0.764	0.518	0.534	0.541	0.467
ee8	0.726	0.469	0.489	0.416	0.374
ee9	0.775	0.495	0.540	0.423	0.384
em11	0.544	0.855	0.627	0.468	0.645
em18	0.534	0.831	0.563	0.436	0.611
em21	0.524	0.762	0.611	0.625	0.530
im26	0.409	0.328	0.594	0.504	0.211
im27	0.575	0.666	0.821	0.508	0.623
im29	0.510	0.393	0.612	0.519	0.323
im35	0.534	0.567	0.785	0.553	0.476
im36	0.488	0.581	0.777	0.460	0.600
im37	0.541	0.668	0.823	0.546	0.658
tal51	0.489	0.500	0.605	0.812	0.437
tal52	0.537	0.604	0.632	0.847	0.447
tal55	0.329	0.278	0.327	0.663	0.160
tal56	0.447	0.417	0.432	0.661	0.285
tfl43	0.291	0.468	0.472	0.213	0.713
tfl45	0.279	0.376	0.269	0.124	0.566
tfl47	0.471	0.492	0.483	0.367	0.699
tfl48	0.487	0.630	0.642	0.519	0.823
tfl49	0.418	0.654	0.523	0.390	0.835

The Heterotrait-monotrait (HTMT) ratio of correlations is a up to date procedure which is presented by (Henseler, Ringle & Sarstedt, 2015) as a prescribed means of examining the the discriminant validity (Table 4). This is because the Fornell and larcker criterion is seemed to be accurate in calculating discriminant validity in modern research. In addition, Henseler, Ringle&Sarstedt, (2015) explained the supremacy of the MTMT criterion with the use of the Monte Carlo simulation the consequences presented that the HTMT criterion is concerned with higher sensitivity and specificity rates of between 97-99%, against the Fornell larcker that belongs percentage of 20.82%, and that of cross loading method 0%.

There are two initial approaches to detect discriminant validity using HTMT. Initial approaches are involved with examining the ranges of HTMT, proposed by Kline (2011) as 0.85 while Gold, Malhotra & Segars (2001) proposed HTMT value of

0.90 to show the challenge of discriminant validity if the values go beyond the predetermined threshold.

Table 4: HTMT criterions

	Y1	Y2	Y3	Y4
STUDENT ENGAGEMENT (Y1)				
EXTRINSIC MOTIVATION (Y2)	0.906			
INTRINSIC MOTIVATION (Y3)	0.957	0.87		
TRANSACTIONAL LEADERSHIP (Y4)	0.874	0.802	0.856	
TRANSFORMATIONAL LEADERSHIP (Y5)	0.758	0.936	0.799	0.544

(3) Inner model evaluation

Several steps are needed to take to evaluate the hypothesized relationship in the inner model after establishing the reliability and validity of the outer models.

Latent variable scores are treated as precise linear combinations of their associated indicators in PLS-SEM model estimations that regarded as error-free substitutes for the indicators. On the contrary, factor-based approach, PLS-SEM is not imposing strong common factor-related assumptions (Henseler, Ringle & Sarstedt, 2015). Furthermore, PLS-SEM is a non parametric bootstrap method that makes no distributional assumption and can be estimated with small sample sizes (Hair, Hult, et al., 2017). Hence, PLS-SEM is not concerned with standard goodness-of-fit statistic and prior efforts of establishing a matching statistic that has proved highly problematic (Henseler and Sarstedt, 2013).

The following criteria facilitate this assessment: Coefficient of determination (r square), cross-validated redundancy (Q square), path coefficients, and the effect size (f square). Prior to this assessment, the researchers are needed to measure the inner model for potential collinearity issues. As the inner model estimates effect from sets of regression analyzes, their values and significances may be subject to biases if constructs are highly correlated (Ringle, 2020).Hair, Ringle, & Sarstedt (2011) recommends a VIF value of 5 or more indicates Collinearity challenge. From the table 5, it can be observed that the inner VIF values for each construct are within the established range of 5. Hence implying the PLS-SEM can proceed with the proceeding tests.

Table 5: Inner VIF

	Y1	Y2	Y3
EXTRINSIC MOTIVATION (Y2)	3.005		
INTRINSIC MOTIVATION (Y3)	2.992		
TRANSACTIONAL LEADERSHIP (Y4)	2.054	1.284	1.284
TRANSFORMATIONAL LEADERSHIP (Y5)	2.370	1.284	1.284

While the Fornell-Larcker criterion generally express collinearity limitations in the inner model earlier in the model evaluation process which is not the case when formatively measured constructs are involved. This is because that the AVE forms the basis for the Fornell-Larcker assessment which is not a meaningful measure for formative indicators. Hence, collinearity assessment in the inner model is of fundamental importance where the model belongs to formatively measured constructs.

Coefficient of determination (R square)

The R square quantifies the predictive accuracy of model. On the other hand R square explains the exogenous variable's united effect on the endogenous variable(s). This effect presents the ranges from 0 to 1 where 1 shows the total predictive accuracy. As R square embraces different disciplines, scholars relies on a "rough" rule of thumb considering an standard R square, with 0.75, 0.50, 0.25, respectively. It indicates the large, modest, or weak levels of predictive accuracy (Hair et al., 2011; Henseler et al., 2009). Generally R square is a useful technique to assess the quality of PLS model but heavy dependency on r square can create problem. Specifically, if the researchers want to compare models with various specifications of the identical endogenous constructs, dependency on R square may create the problem of selecting the weak efficient model. For example, the R square increases the non-significant yet slightly correlated construct is belongs to the model. Therefore, if the goal of researchers is to improve the R square, the researcher will be benefited by adding the supplementary exogenous constructs even if the interactions are not consequential. Relatively, the decision for a model will be based on the adjusted R square that will penalizes updated model and complexity by reducing the (adjusted) R square where supplementary constructs are added to the model.

The value of R square of student engagement, extrinsic motivation and intrinsic motivation of students are 0.543, 0.634 and 0.632 respectively that indicates the medium effect of the exogenous variables on endogenous variables (Table 6).

Table 6: R Square

	R Square	R Square Adjusted
STUDENT ENGAGEMENT	0.543	0.539
EXTRINSIC MOTIVATION	0.634	0.632
INTRINSIC MOTIVATION	0.632	0.630

Cross-validated redundancy (Q square)

The Q square is a means that measure the predictive relevance of inner model. The assessment builds on a sample re-use technique where it skip over a part of the data matrix, assess the parameters of model and predicts the skipped element with uses of estimates. The smaller difference between predicted and original values indicates the larger Q square and thus predictive accuracy of the model. More distinctively, the value of Q square is larger than zero of particular endogenous construct which shows the predictive relevance of path model for this particular construct (Table 7). Therefore it should be mentioned that by comparing the value of Q square to zero is investigative whether an endogenous construct can be predicted, it does not mean anything about the quality of the prediction (Rigdon, 2014; Sarstedt et al., 2014).

Table 7: predictive relevance (Q square)

	SSO	SSE	Q^2 (=1-SSE/SSO)
STUDENT ENGAGEMENT	1161.000	809.426	0.303
EXTRINSIC MOTIVATION	1161.000	676.405	0.417
INTRINSIC MOTIVATION	2322.000	1523.586	0.344

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Effect size (f square)

The size of effect for each path model can be measured by calculating Cohen's f square. On the basis of f square value, the size of effect of a construct for a specific endogenous construct, can be measured such that 0.02, 0.15, and 0.35 show small, medium, and large effects, respectively (Cohen, 1988).

Table 8: f Square

	Y1	Y2	Y3
STUDENT ENGAGEMENT (Y1)			
EXTRINSIC MOTIVATION (Y2)	0.046		
INTRINSIC MOTIVATION (Y3)	0.086		
TRANSACTIONAL LEADERSHIP (Y4)	0.044	0.278	0.490
TRANSFORMATIONAL LEADERSHIP (Y5)	0.001	0.667	0.422

Path coefficients

Path coefficients are provided the estimation by running the PLS model that shows the hypothesized relationships connecting the constructs. Path coefficient values standardizes ranges from the +1 to – 1, with coefficients close to + 1 that indicates vigorous interactions and coefficients close to - 1 presenting the huge negative interactions. While values close to - 1or + 1 are statistically significant always, a standard error is attained with the uses of bootstrapping to examine the significance (Helm et al., 2009). After measuring the significant relationships the researchers need to justify the relevance of significant relationships. In a brief are the sizes of the structural coefficients meaningful? As stated by Hair et al. (2014), many studies overlook this step and merely rely on the significance of effects. If this important step is omitted, researchers may focus on a relationship that, although significant, may be too small to merit managerial attention. If the p value is less than 0.05 and the t-value is higher than 1.96 then the effect will be significant at confidence level 95%. Table 9 presented extrinsic motivation (b=0.250, t= 3.421, p= 0.000), intrinsic motivation (b=0.342, t= 5.364, p= 0.000), transactional leadership (b=0.204, t= 3.866, p= 0.000) have significant effect on student engagement. Furthermore, transactional leadership has significant effect on extrinsic motivation (b=0.361, t= 10.340, p= 0.000) and intrinsic motivation (b=0.481, t= 13.790, p= 0.000). Transformational leadership has significant effect on extrinsic motivation (b=0.560, t= 15.567, p= 0.000) and intrinsic motivation (b=0.446, t= 11.914, p= 0.000) according to table 9 and figure 2; While, transformational leadership style has no effect on student engagement (b=0.034, t= 0.532, p= 0.601).

Table 9: Path coefficient

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
STUDENT EXTRINSIC MOTIVATION -> STUDENT ENGAGEMENT	0.250	0.257	0.073	3.421	0.000
STUDENT INTRINSIC MOTIVATION -> STUDENT ENGAGEMENT	0.342	0.340	0.064	5.364	0.000
TRANSACTIONAL LEADERSHIP -> STUDENT ENGAGEMENT	0.204	0.200	0.053	3.866	0.000
TRANSACTIONAL LEADERSHIP -> STUDENT EXTRINSIC MOTIVATION	0.361	0.362	0.035	10.340	0.000
TRANSACTIONAL LEADERSHIP -> STUDENT INTRINSIC MOTIVATION	0.481	0.479	0.035	13.790	0.000

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TRANSFORMATIONAL LEADERSHIP -> STUDENT ENGAGEMENT	0.034	0.035	0.064	0.532	0.601
TRANSFORMATIONAL LEADERSHIP -> STUDENT EXTRINSIC MOTIVATION	0.560	0.562	0.036	15.567	0.000
TRANSFORMATIONAL LEADERSHIP -> STUDENT INTRINSIC MOTIVATION	0.446	0.450	0.037	11.914	0.000

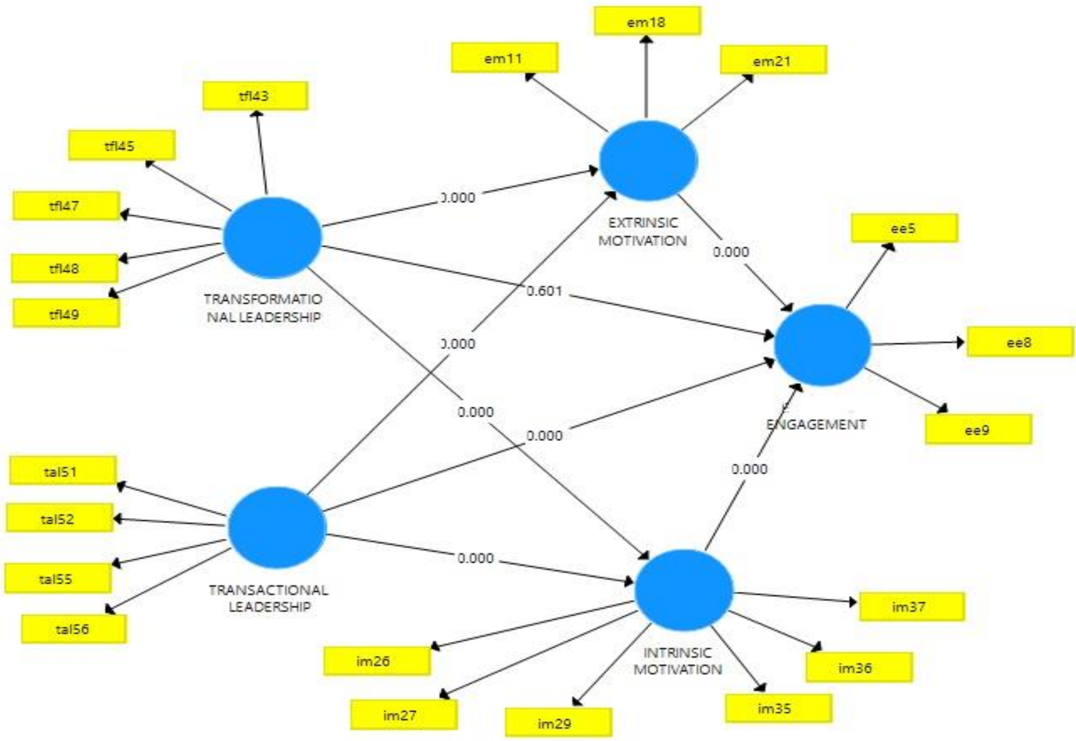

Figure 2. Structural model

V. MEDIATION

Mediation represents a situation in which a mediator variable to some extent absorbs the effect of an exogenous on an endogenous construct in the PLS path model. For example, in this study on the student engagement, the relationship between teacher's leadership style (transformational and transactional) and student engagement is sequentially mediated by student motivation (intrinsic and extrinsic). As such, this analysis – opposed to a simple evaluation of direct effects – provides a more appropriate picture of action research performance. Several authors have criticized the far-reaching neglect of explicitly examining mediating effects in PLS path models, which can easily lead to erroneous conclusions when interpreting model estimates (Hair et al., 2013, 2012a, b). A potential reason for this neglect might be that there is still some ambiguity on how to evaluate mediating effects in PLS-SEM. Hair et al. (2014) provide an initial illustration on how to analyze mediating effects. According to the table 10, extrinsic motivation mediates the relationship between transactional leadership and student engagement (b=0.090, t= 0.090, p= 0.001), transformational leadership and student engagement (b=0.140, t= 3.251, p= 0.001). Again, intrinsic motivation mediates the relationship between transactional leadership and student engagement (b=0.165, t= 4.680, p= 0.000), transformational leadership and student engagement (b=0.153, t= 5.132, p= 0.000) because of the value of p is less than 0.05 and the t-value is higher than 1.96.

Table 10: Specific indirect effect

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
TRANSACTIONAL LEADERSHIP -> STUDENT EXTRINSIC MOTIVATION ->STUDENT ENGAGEMENT	0.090	0.093	0.027	0.090	0.001
TRANSFORMATIONAL LEADERSHIP -> STUDENT EXTRINSIC MOTIVATION ->STUDENT ENGAGEMENT	0.140	0.145	0.043	3.251	0.001
TRANSACTIONAL LEADERSHIP -> STUDENT INTRINSIC MOTIVATION ->STUDENT ENGAGEMENT	0.165	0.163	0.035	4.680	0.000
TRANSFORMATIONAL LEADERSHIP ->STUDENT INTRINSIC MOTIVATION ->STUDENT ENGAGEMENT	0.153	0.153	0.030	5.132	0.000

VI. DISCUSSION

SEM is very influential tool of analysis to measure the cause and effect relationships models with latent variables. The aim of this analysis is to gather extensive knowledge about the drivers of (for example, teacher's leadership style, student engagement or student motivation) SEM which is the method of choice. Many researchers consider the SEM as carrying out multiple regression analysis when they have the fundamental knowledge of regression analysis. But most of them may have insufficient understanding about the other functional technique like PLS-SEM for action research.

The most prominent contribution of action research to education is in giving teachers a researcher role. Action research provides teachers with a methodology for conducting their own studies in their classrooms and schools. Rather than being only a practitioner of curricula and programs developed by others, the teacher engages in research on the curriculum and programs being applied, thereby empowering them. This would include teachers in the curriculum development process. Being involved would increase the responsibility and motivation of teachers to apply the curriculum and engage in better teaching. Since teachers are now part of curriculum development and can see that they can make a difference, they can contribute to the development of their own profession (Baum, MacDougall, & Smith, 2006; Bellman, Bywood, & Dale, 2003; Chain, 2011; Philips & Carr, 2009) and focus on the engagement of the students in class room.

The leadership style of teachers is very important for student engagement at the time of CLT implementation. The transactional leadership style of teachers increase student engagement in class room as well as this type of leadership rise the intrinsic and extrinsic motivation among the student. The transformation leadership style of the teachers have no influence on student engagement but it grow the both kind of motivation among the students.

Further, teachers should continuously follow the literature so that their knowledge and skills are up-to-date with respect to their field. Consequently, action research increases the effectiveness of teaching and learning (for example, extrinsic motivation of the student mediates the relationship between transactional leadership and student engagement; transformational leadership and student engagement. Again, student's intrinsic motivation mediates the relationship between transactional leadership and student engagement; and transformational leadership and student engagement) through interventions (Chain, 2011; Philips & Carr, 2009; Thompson, 2011).

Moreover, action research seeks conditional knowledge; therefore, it is not possible to generalize its results. However, this does not mean that information derived from action research cannot be used by or for the benefit of other teachers. Action research reports are systematic tools to use in the dissemination of useful information derived from practice. The teacher/researcher can share their experiences with their colleagues, just like doctors sharing treatment methods and tactics used in individual cases. Teachers can reach different solutions; action research enables them to publish these solutions and archive these in a systematic way. Through systematic reporting and archiving, action research provides a valuable resource for teachers. Further, action research enables the transfer of experience among teachers for CLT implementation. Teachers can benefit from each other's ideas and applications to improve their own practices (Afify, 2007; Baum, MacDougall, & Smith, 2006; Bellman, Bywood, & Dale, 2003; Philips & Carr, 2009).

VII. CONCLUSION AND LIMITATION

In conclusion, in addition to effects on instructional activities, action research enables teachers to work as researchers, too. As practitioners of curriculum and educational programs teachers are also a variable in education settings (like, CLT implementation). The teaching process is a dynamic, humane process. People have the ability to change and improve the environment and conditions in which they live—and in the case of education, in which they are educated. In the quest to improve the effectiveness of educational programs practitioner/researchers are very valuable because they "live" the problems preventing effectiveness in the curriculum or program. As a result, they are in the best position to develop the best solutions to situations. Partial least squares structural equation modeling (PLS-SEM) can be used as an emerging tool for this kind of research.

This study has not discussed one of the benefits of PLS-SEM which allow the use of formative measures and differentiate from the reflective measures. Formatively measured constructs are effective in the research for illustrating and forecasting basic constructs like sources of competitive advantage or success of organization (Albers, 2010). Further study will focus on providing the guidance about apprising the more multifaceted effects such as moderation or moderated mediation.

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