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# A Comparison Of Partial Least Square Structural Equation Modeling (PLS-SEM) and Covariance Based Structural Equation Modeling (CB-SEM) for Confirmatory Factor Analysis

Wan Mohamad Asyraf Bin Wan Afthanorhan
Department of Mathematics, Faculty of Science and Technology,
Universiti Malaysia Terengganu, 21030 Kuala Terengganu, Malaysia

***Abstract--In several years, structural equation modeling or popularly known as SEM is the first generation path modeling widely used by researchers and practitioners nowadays to analyze the interrelationship among variables in a model. Some of the researchers classify SEM as the covariance-based SEM (CB-SEM). However, this method have been argued since its application should achieved the criterion before conducting the measurement and structural model. Thus, partial least square SEM (PLS-SEM) has been established to solve this problems. This paper aims to examine which one of the structural equation modeling is appropriate to use for confirmatory factor analysis by using SMARTPLS and AMOS. In this instance, the data of volunteerism program is chosen as a research subject to prove this issue. The author revealed that PLS-SEM path modeling using SMARTPLS is appropriate to carry on the confirmatory factor analysis which is more reliable and valid.***

***Index Terms***- **AMOS, Confirmatory factor analysis, CB-SEM, PLS-SEM, Reliability and Validity, SMARTPLS.**

## I. INTRODUCTION

Structural equation modeling (SEM) is first applied by Bollen (1989) and Joreskog (1973) in social sciences which is the academic advisor for Herman wolds (1973, 1975), the one who establish LISREL CB-SEM software package. Then, PLS-SEM were develop much better by (Ringle, Wende, and Will 2005). According to Hair et. al (2010) explain CB-SEM is used to evaluate focuses on goodness of fit which is focusing on minimization of the discrepancy (differences) between the observed covariance matrix and the estimated covariance matrix. Its application is suggested appropriate to testing and confirmation where prior theory is strong or have a good reason to do so. However, the researchers or practitioners should achieve the assumption when conducting CB-SEM. The first one is the sample size of data should be large which is more than 200. Hair et. al. (2010) offer the minimum sample size depending on the model complexity and basic measurement model characteristics. According to Goodhue, Lewis and Thompson (2006), sample size should not be used as a main reason for employing PLS-SEM because it does not have adquate statistical power at small sample size. They recommend PLS is a powerful method when a small sample size could be carry on compare to CB-SEM. The statistical software package for CB-SEM can be obtained in AMOS, LISREL, MPLUS and EQS while PLS-SEM in SMARTPLS and PLS Graph. Basically, each constructs should has more than three items (indicators) in order to avoid the identification problem. In the case where three indicators left in the model cannot be computed since the model 'just-identified' and all values obtained from factor loadings are meaningless. Secondly, only the reliable and valid variance is useful for testing causal (direct) relationships. Means that, the structural model cannot be conducted when prior of reliability and validity cannot be achieved. Thus, partial least square SEM (PLS-SEM) has been established to solve this problems. Its application is aimed to maximize the explained variance of the endogenous latent constructs (dependent variables) and minimize the unexplained variances. This method have several advantages which is include the normality of data distribution not assummed. Means that, the data with nonnormal can be conducted in structural equation modeling since its application is performed the non parametric method. Besides, indicators (items) with fewer than three for each constructs could be carry on since the identification issues has been overcomed. In addition, this models can be include a larger number of indicator variables even higher than 50 items. Instead, CB-SEM just accept several indicator variables to conducting the analysis since its limited.

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## II. LITERATURE REVIEW

### *A. Evaluation of Measurement Models*

CB-SEM have performed three types of fitness indexes to achieve the fitness of measurement models before conducting the structural models. Three categories of fitness is absolute, incremental and parsimonous fit besides ensure the reliability and validity could be achieved. According to Hair et. al. (1995, 2010) and Holmes-Smith (2006) recommend the use of at least three fit indexes by including one index from each category of model fit. Absolute fit present three types of index which is chisquare, Root Mean Square Error Approximation (RMSEA) and Goodness Fit Index (GFI). Incremental fit proposed four types of index which is Adjusted Good of Fit (AGFI), Comparative Fit Index (CFI), Tucker Lewis Index (TLI), and Normed Fit Index (NFI). Last but not least, parsimonious fit indicates only one of index namely chisquare over degree of freedom. All of the fitness category should be achieved depending on their literature supported. Thus, the information concerning the fitness index category, their level acceptance, and comments are presented in following table as suggested by Zainudin Awang (2010).

| Name of Category | Index | Level of acceptance | Literature | Comments |
|---|---|---|---|---|
| Absolute fit | Chisquare | P > 0.05 | Wheaton et. al. (1997) | Sensitive to sample size > 200 |
| | RMSEA | RMSEA < 0.08 | Browne and Cudeck (1993) | Range 0.05 to 1.00 acceptable |
| | GFI | GFI > 0.90 | Joreskog and Sorbom (1984) | GFI = 0.95 is a good fit |
| Incremental fit | AGFI | AGFI > 0.90 | Tanaka and Huba (1985) | AGFI = 0.95 is a good fit |
| | CFI | CFI > 0.90 | Bentler (1990) | CFI = 0.95 is a good fit |
| | TLI | TLI > 0.90 | Bentler and Bonett (1980) | TLI = 0.95 is a good fit |
| | NFI | NFI > 0.90 | Bollen (1989) | NFI = 0.95 is a good fit |
| Parsimonious fit | Chisq/df | Chisq/df < 5.0 | Marsh and Hocevar (1985) | Should be beyond 5.0 |

**Table 1**

Given PLS-SEM have more potential compared to CB-SEM which is less strict assumption to be followed especially the fewer indicators can be conducted. Thus, the identification issue could be avoided. For example Joreskog and Wold (1982) explain these result corroborate earlier writting and theorems, which indicated that PLS-SEM 'are asymptotically correct in the joint sense of consistency (large number of cases) and consistency at large (large number of indicators for each latent variable). In PLS-SEM have two types of measurement model which is reflective and formative measurement model. Thus, the researchers distinguish between these models to evaluate them (Henseler, Ringle, and Sinkovics 2009). In this case, this study would employ the reflective measurement model only since there are non item appropriate for formative measurement. Reflective measurement model should be assessed with the reliability and validity in order to achieve their consistency. Construct reliability can be classify as composite reliability. According to Zainudin Awang, (2012) explain reliability is the extent of how reliable is the said measurement model in measuring intended latent constructs. Unlike Cronbach alpha that has been proposed by Nunally (1978) offer the value greater than 0.70 indicate the mesurement model is reliable. Composite reliability values of 0.60 to 0.70 in exploratory research and values from 0.70 to 0.90 in more advanced stages of research are regarded as satisfactory (Nunally and Bernstein 1994) whereas values beyond 0.60 indicate a lack of reliability. Given validity is the measure of the accuracy of an instrument used in a study (Linn, R.L., 2000.; Stewart, C.D., 2009). There are three types of validity which is convergent, discriminant, and construct validity as the presented below:

| Name of Category | Index | Level of acceptance | Comments |
|---|---|---|---|
| Convergent Validity | AVE | AVE > 0.50 | The validity is achieved when all items in a measurement model are statiscally significant. |
| Construct Validity | GFI<br>CFI<br>RMSEA<br>Chisq/Df | GFI > 0.90<br>CFI > 0.90<br>RMSEA < 0.08<br>Chisq/Df < 5.0 | This validity is achieved when the fitness indexes achieve the following requirements |
| Discriminant Validity | Square Root of AVE | All the correlation | This validity is achieved when the |

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| | | |
|---|---|---|
| and correlation of latent constructs | between these construct should below 0.85. | measurement model is free from redundant items. |

**Table 2**

Reflective measurement model's validity assessment focuses on convergent and discriminant validity. For convergent validity, researchers needs to examine the average variance extracted (AVE). According to Fornell and Larcker (1981), an AVE value of 0.50 and higher indicates a sufficient degree of convergent validity, meaning that the latent variable (constructs) explains more than half of its indicators variances. They also postulates that a latent constructs shares more variance with assigned indicators than with another latent variable in the structural model. For discriminant validity, two measures heve been empoyed which is the square root of AVE and the correlation of latent constructs. The correlation values for each constructs should be lower than the square root of AVE in order to obtain the validity of measurement model (Afthanorhan, 2013). In this instance, the powerful between these two method to be tested according the reliability and validity of measurement model. Once again, measurement model is commonly used for confirmatory factor analysis (CFA) and the researchers should obey the requirement needed to achieve the true model. Besides, the assesement model reqiured after done the unidimensionality procedure. According to Zainudin Awang, (2010), unidimensionality procedure is achieved when the measuring items have acceptable factor loadings for the respective latent constructs. In order to ensure unidimensionality of a measurement model, any items with a low factor loading should be deleted. For a new developed scales, the factor loading for an item should be 0.50 or higher. Means that, indicators with factor loadings greater than 0.50 should be retained in the model and remove indicator beyond this requirements. However, its depends on their literature supported since some of the reseacrhers prefer to use already established scales which is 0.60. The deletion should be made one item at a time with the lowest item to be deleted first. After an item deleted, the reseacrhers needs to respecify and run the new measurement model. The process continues until the unidimensionality requirement is achieved (Zainudin Awang, 2010). The importance of unidimensionality has been stated succinctly by Hattie (1985 p.49): " That a set of items forming an instruments all measure just one thimg in common is a most critical and basic assumption of mesurement theory." Moreover, unidimensionality refers to the existence of a single trait or construct underlying a set of meausres (Hattie 1985;mcdonald 1981).

$$\text{AVE} = \frac{\textit{Sum of Standardized Loadning Square}}{\textit{Sumof Standardized Loadning Square} + \textit{measurement error}}$$

$$\text{Measurement error} = 1 - (\text{Stadardized Loading})^2$$

**Fig 1: Average Variance Extracted (AVE)**

$$\text{CR} = \frac{\textit{Square of Total Standardized Loadning}}{\textit{Square of Total Standardized Loadning} + \textit{measurement error}}$$

**Fig 2: Construct reliability/ Composite Reliability**

$$\text{DV} = \sqrt{\text{AVE}}$$

**Fig 3: Discriminant Validity**

## III. RESULTS

This study to examine which one of the structural equation modeling is appropriate to use for confirmatory factor analysis by using SMARTPLS and AMOS. These application play a different function. For example SMRTPLS is developed for partial least square structural equation modeling (PLS-SEM). Indeed, there are many application provided to analyze this method but this software is the newest and more efficient with interesting graphical. For AMOS has been established since 2004 and is provided for covariance based structural equation modeling. Thus, objective research should be achieved by using both software.

***Measurement Model of PLS-SEM After Unidimesionality***

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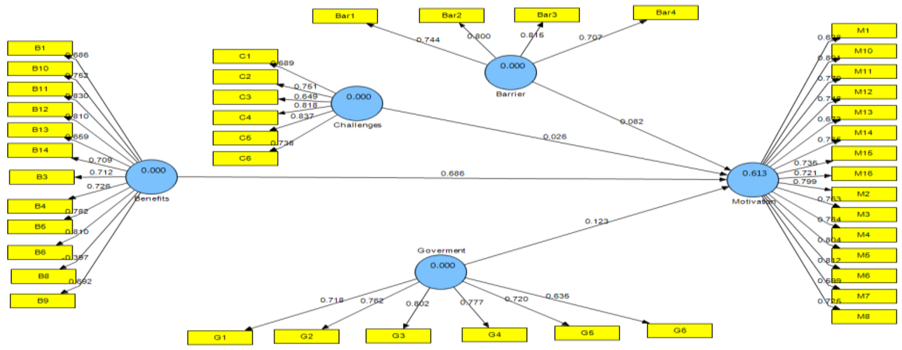


**Fig 4 Outer Loadings After Unidimensionality Procedure**

| Barrier | Loadings | Benefits | Loadings | Challenges | Loadings | Goverment | Loadings | Motivation | Loadings |
|---|---|---|---|---|---|---|---|---|---|
| | | | 0.6833 | | | | | | 0.6284 |
| Bar1 | 0.7437 | B1 | | C1 | 0.6885 | G1 | 0.7178 | M1 | |
| Bar2 | 0.7995 | | | C2 | 0.7511 | G2 | 0.7624 | M2 | 0.7990 |
| Bar3 | 0.8151 | B3 | 0.7090 | C3 | 0.6492 | G3 | 0.8017 | M3 | 0.7633 |
| Bar4 | 0.7069 | B4 | 0.7277 | C4 | 0.8181 | G4 | 0.7773 | M4 | 0.7843 |
| | | B5 | 0.7856 | C5 | 0.8368 | G5 | 0.7196 | M5 | 0.8045 |
| | | B6 | 0.8143 | C6 | 0.7379 | G6 | 0.6350 | M6 | 0.8127 |
| | | B7 | 0.7832 | | | | | M7 | 0.5992 |
| | | | | | | | | M8 | 0.7250 |
| | | | 0.6848 | | | | | | |
| | | B9 | | | | | | | |
| | | B10 | 0.7521 | | | | | M10 | 0.8016 |
| | | B11 | 0.8267 | | | | | M11 | 0.7702 |
| | | B12 | 0.8045 | | | | | M12 | 0.7476 |
| | | B13 | 0.6473 | | | | | M13 | 0.6720 |
| | | B14 | 0.7038 | | | | | M14 | 0.7853 |
| | | | | | | | | M15 | 0.7346 |

**Table 3**

The figure and table above presented the measurement model from the output of SMARTPLS. This value can be obtained from the *outer loading* indicates the factor loading for each indicator included. Early, author has suggest to use the new developed scales which is 0.50 or higher should be retain in the measurement model. Thus, the outer loadings below 0.50 should be removed from the measurement models since its indicates this indicator have less contribution towards these factors. In this case, 2 items from latent barrier, benefits and motivation have been removed from these latents. Otherwise, all indicator in challenge latent are accepted while goverment have removed three items. This procedure can be known as unidimensionality procedure. After the researchers have done this process, the model asssessmen should be applied in order to improve their reliability and validity. Thus, convergent and discriminat validity employed in this process. Other than that, the construct reliability or composite reliability also to be tested.

***Convergent Validity and Construct Reliability***

| Variables | AVE | Composite Reliability | Cronbachs Alpha | Communality |
|---|---|---|---|---|
| Barrier | 0.5891 | 0.8511 | 0.7662 | 0.5891 |
| Benefits | 0.5258 | 0.9217 | 0.8944 | 0.5258 |
| Challenges | 0.5623 | 0.8844 | 0.8491 | 0.5623 |
| Goverment | 0.5441 | 0.8769 | 0.8361 | 0.5441 |
| Motivation | 0.5564 | 0.9492 | 0.9422 | 0.5564 |

**Table 4**

The table presented above show the result of AVE and construct reliability. Besides, the internal reliability which is cronbach alpha also presented as a tradisional method to determine the reliable of measurement model. Thus, this method still required to helps the researchers obtain the true model. According to Fornell and larcker,

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(1981) proposed the AVE can be accepted when the value is greater than 0.50. Other than that, Nunally (1978,1994) suggest value greater than 0.70 for composite reliability and crobach alpha. Futhermore, some of the researcher required the communality to determine the acceptable of measurement model. According to James Gaskin, (2012) the value of communality is accepted when greater than 0.50. Hence, all the requirement for convergent validity, construct reliability, cronbach alpha or internal reliability, and communality is achieved. Then, author proceed the next step for discriminant validity.

***Discriminant Validity***

| **Variables** | **Barrier** | **Benefits** | **Challenges** | **Goverment** | **Motivation** |
|---|---|---|---|---|---|
| Barrier | **0.7675** | | | | |
| Benefits | 0.2660 | **0.7251** | | | |
| Challenges | 0.3457 | 0.2117 | **0.750** | | |
| Goverment | 0.2556 | 0.4401 | 0.2524 | **0.7376** | |
| Motivation | 0.3038 | 0.6654 | 0.2283 | 0.4551 | **0.7459** |

**Table 5**

The table presented above is the discriminant validity according on PLS-SEM. According to Hamdan said et.al. (2011) explain that discriminant validity test shows how much variance in the indicators that are able to explain variance in the construct. Discriminant validity value obtained from the square root of AVE value. The diagonal values (in bold) are the square root of AVE while other values are the correlation between the respective constructs. In this case, the discriminant validity is achieved when a diagonal value bold is higher than the value in its row and column.

***Measurement Model of CB-SEM After Unidimensionality Procedure***

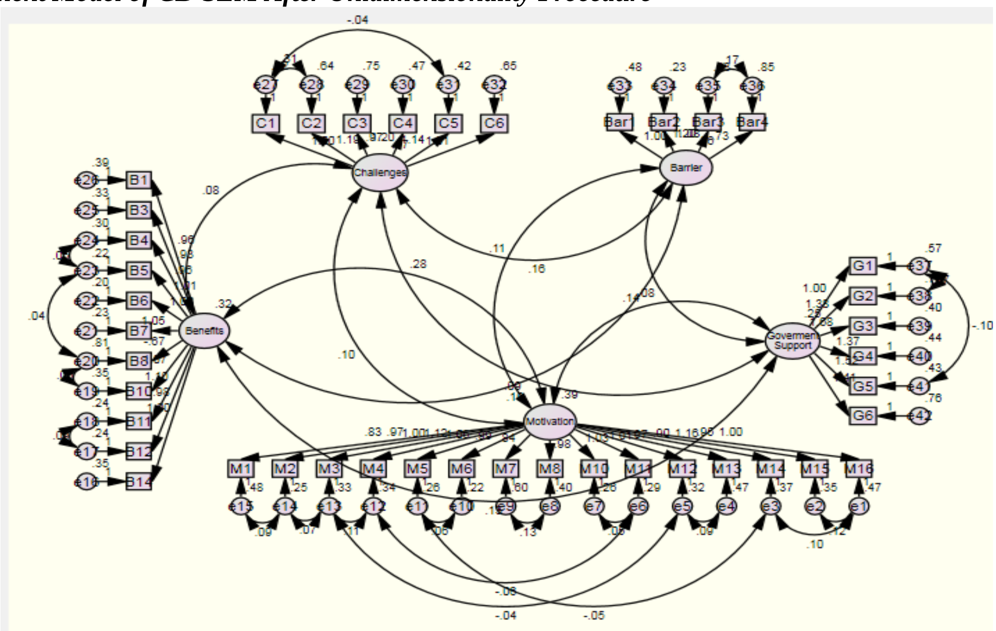


**Fig 5**

| **Barrier** | **Loadings** | **Benefits** | **Loadings** | **Challenges** | **Loadings** | **Goverment** | **Loadings** | **Motivation** | **Loadings** |
|---|---|---|---|---|---|---|---|---|---|
| | | | 0.636 | | 0.688 | | 0.688 | | 0.591 |
| Bar1 | 0.627 | B1 | | C1 | | G1 | | M1 | |
| Bar2 | 0.765 | | 0.669 | C2 | 0.798 | G2 | 0.798 | M2 | 0.783 |
| Bar3 | 0.775 | B3 | 0.711 | C3 | 0.595 | G3 | 0.595 | M3 | 0.755 |
| Bar4 | 0.522 | B4 | 0.775 | C4 | 0.748 | G4 | 0.748 | M4 | 0.777 |
| | | B5 | 0.811 | C5 | 0.721 | G5 | 0.721 | M5 | 0.799 |
| | | B6 | 0.772 | C6 | 0.635 | G6 | 0.635 | M6 | 0.809 |
| | | B7 | 0.643 | | | | | M7 | 0.569 |

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| | | | |
|---|---|---|---|
| | 0.726 | M8 | 0.702 |
| B9 | 0.824 | | 0.777 |
| B10 | 0.776 | M10 | 0.742 |
| B11 | 0.644 | M11 | 0.715 |
| B12 | 0.636 | M12 | 0.634 |
| B13 | 0.669 | M13 | 0.767 |
| B14 | 0.711 | M14 | 0.709 |
| | | M15 | 0.698 |

**Table 6**

The figure and table presented above show the result of factor loadings provided in CB-SEM. Based on the result above, indicator for each construct retained in the measurement model is similar PLS-SEM. However, most the value of factor loading obtained in CB-SEM is lower than PLS-SEM even author use the same scales when apply the unidimensionality procedure. Thus, PLS-SEM show that this method is to maximize the explained variance of endogenous latent constructs (dependent variable) and minimize the unexplained variances.

***Convergent Validity and Construct Reliability***

| Variables | AVE | Composite Reliability | Cronbachs Alpha |
|---|---|---|---|
| Barrier | 0.452 | 0.758 | 0.761 |
| Benefits | 0.503 | 0.898 | 0.923 |
| Challenges | 0.477 | 0.844 | 0.849 |
| Goverment | 0.467 | 0.838 | 0.835 |
| Motivation | 0.519 | 0.941 | 0.941 |

**Table 7**

For convergent validity and constrcut reliability, AVE value for latent barrier, challenge, and goverment is below 0.50. This construct do not achieve the requirement as Fornell and Larcker (1981) proposed. This can prove that validity for this measurement model is less accepted even the composite reliability and cronbach alpha fulfill the requirement as the literature supported. Finally, author proceed for the discriminant validity.

***Discriminant Validity***

| Variables | Benefits | Motivation | Challenges | Barrier | Goverment_Support |
|---|---|---|---|---|---|
| Barrier | 0.709 | | | | |
| Benefits | 0.690 | 0.721 | | | |
| Challenges | 0.219 | 0.229 | 0.691 | | |
| Goverment | 0.287 | 0.297 | 0.390 | 0.672 | |
| Motivation | 0.451 | 0.449 | 0.277 | 0.261 | 0.683 |

**Table 8**

Given discriminant validity is accepted since a diagonal value bold is higher than the value in its row and column. Repeatedly, the bold value is represented for square root of AVE while teh other value is the correlation of latent constructs.

## IV. CONCLUSION

On the basis of calculations and modeling, it can be perceived that PLS-SEM path modeling using SMARTPLS is appropriate to carry on the confirmatory factor analysis which is more reliable and valid. Based on the result section, the value of factor loadings/outer loadings, and average variance extracted (AVE) in PLS-SEM is better than CB-SEM even use the same data provided. To date, AVE with greater than 0.50 indicates the value for each factor capture more than half of variances or minimize the error variances. In this case, convergent and discriminant validity from PLS-SEM is success for fulfill the requirement needed.Thus, the researchers could carry on the future step which is structural model since the evaluation of measurement model is achieved. Confirmatory Factor Analysis (CFA) is the extension of exploratory factor analysis that can be obtained from SPSS since this method can be indicated by regression weight. Moreover, Hair et. al (2011) had suggest this method to be known as silver bullet since there are a lot of advantages compare to CB-SEM. Hence, this paper

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work proved that the PLS-SEM is used to maximizing the explain variance of latent constructs which is more reliable and valid besides help the reasearchers or practitioners to conduct their research in perfectly.

## V. ACKNOWLEDGEMENT

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## AUTHOR BIOGRAPHY

Wan Mohamad Asyraf Bin Wan Afthanorhan is a postgraduate students in mathematical science (statistics) in the Department of Mathematics, University Malaysia Terengganu. He ever holds bachelor in statistics within 3 years in the Faculty of Computer Science and Mathematics, UiTM Kelantan. His main area of consultancy is statistical modeling especially the structural equation modeling (SEM) by using AMOS, SPSS, and SmartPLS. He has been published several articles in his are specialization. He also interested in t-test, independent sample t-test, paired t-test, logistic regression, factor analysis, confirmatory factor analysis, modeling the mediating and moderating effect, bayesian sem, multitrait multimethod, markov chain monte carlo and forecasting. His publication:

- Modeling The Multigroup Moderator-Mediator On Motivation Among Youth In Higher Education Institution Towards Volunteerism Program in **International Journal of Scientific and Engineering Research (IJSER). (Impact Factor = 1.40)**
- Modeling The Multimediator On Motivation Among Youth In Higher Education Institution Towards Volunteerism Program in **Journal Of Mathematical Theory and Modeling (MTM). (Impact Factor = 5.53)**
- Modeling A high Reliability and Validity By Using Confirmatory Factor Analysis On Five Latent Constructs: Volunteerism Program in **International Research Journal Advanced Engineering and Science Technologies (IRJAEST).**