American Journal of Humanities and Social Sciences Research (AJHSSR)
e-ISSN :2378-703X
Volume-08, Issue-01, pp-175-182
www.ajhssr.com
Research Paper Open Access

The Implementation of Structural Equation Modelling Partial Least Squares (SEM-PLS) to Examine the Mediation of Job Satisfaction in the Effect of Career Development and Work Engagement on Turnover Intention

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ABSTRACT: This research aims to underscore the critical significance of employing Structural Equation Modeling Partial Least Squares (SEM PLS) in investigating complex relationships within human resources. In the intricate landscape of workforce dynamics, where variables such as career development, work engagement, and turnover intention intertwine, SEM PLS emerges as an indispensable analytical tool. This study navigates through the intricate web of latent constructs by adopting SEM PLS, allowing for a more nuanced understanding of the underlying mechanisms. The relevance of SEM PLS lies in its unparalleled ability to model latent variables, offering a robust solution to the measurement of intangible constructs such as job satisfaction, work engagement, and turnover intention. Highlighted that SEM PLS not only accommodates the complexities of human resource phenomena but also offers flexibility in handling non-normal data distributions, a common characteristic of workforce datasets. Moreover, the utility of SEM PLS extends to its prowess in capturing interactions and mediating effects among variables. By employing SEM PLS, this research endeavors to unravel the simultaneous influences of career development and work engagement on job satisfaction, subsequently mediating their impact on turnover intention. Such a holistic approach enables a comprehensive exploration of intricate relationships often obscured by traditional analytical methods. The empirical application of SEM PLS in this study transcends statistical analysis; it represents a contextual approach aligned with the realities of human resource data. In an era where organizational decisions hinge upon a comprehensive understanding of the factors influencing employees, SEM PLS stands out as a strategic framework that resonates with the intricacies of human resource management. In conclusion, this research contributes not only to the empirical understanding of human resource dynamics but also serves as a testament to the practical applicability of SEM PLS in navigating the complexities of workforce relationships. As organizations increasingly seek evidence-based insights for informed decision-making, SEM PLS emerges as a vital ally, providing depth and clarity in unraveling the intricacies of human resource phenomena.
Keywords - Structural Equation Modelling, Career Development, Work Engagement, Turnover Intention, Job Satisfaction.

I. INTRODUCTION

Structural Equation Modeling Partial Least Squares (SEM PLS) has become a powerful analytical tool, especially in Human Resource Management (HRM) research. Its application in studies focusing on complex relationships, such as those within the HRM domain, is essential for several reasons.

Firstly, SEM PLS provides a robust method for analyzing latent constructs, enabling researchers to model unobservable variables like job satisfaction or career development accurately. Hair et al. (2017) argued that SEM PLS excels in handling latent variables, making it particularly suitable for investigations involving intricate psychological and behavioral dimensions in HRM.

Secondly, the flexibility of SEM PLS is crucial in accommodating non-normal data distributions commonly encountered in HRM research. Traditional SEM methods often rely on the assumption of multivariate normality, which may not hold in the complex and diverse field of human resources. By relaxing these assumptions, SEM PLS allows for more realistic analyses of HRM datasets, promoting the applicability of findings to real-world scenarios (Hair et al., 2017).

Moreover, SEM PLS is well-suited for models with a small sample size or complex relationships. In HRM research, where data collection may be challenging due to turnover and confidentiality, SEM PLS's ability to handle smaller sample sizes becomes advantageous (Chin, 2010). This is especially relevant in studies aiming to understand the dynamics of career development, work engagement, and turnover intention, where intricate relationships may exist within a limited pool of participants.

Furthermore, the method's suitability for examining mediating effects and interactions between latent constructs is paramount in HRM investigations. As organizational dynamics become more nuanced, understanding how variables mediate or interact with each other is crucial. SEM PLS facilitates this examination, providing insights into the complexities of relationships within HRM frameworks (Hair et al., 2017).

Structural Equation Modeling Partial Least Squares (SEM PLS) in the context of quantitative research can be seen as a complementary approach. Experts have provided views and research related to the relationship between quantitative methods and the use of SEM PLS. in the article "Estimation of Structural Equation Models for Ordinal Variables by the Method of Partial Least Squares" (Wiedermann, 1999) explains that SEM PLS can be used effectively in dealing with ordinal variables, which often appear in quantitative research. PLS proves its flexibility in handling different data scales. The same thing was also stated by Ringle et al. (2012) who stated that PLS-SEM can be used for segmentation in quantitative research, helping to identify differences in model structure between groups.

The choice of quantitative methods and PLS-SEM in research can be understood as a response to the complexity of the phenomenon under investigation, the need for objectivity, and the specific challenges researchers face. Both help provide effective analytical tools to answer research questions and better understand complex inter-variable relationships. This is supported by previous research that uses the same method, namely research from Bawono, W., & Lo, S. J. (2020). And the same method is also in the research of Memon et al., (2018). The same thing was also done by Elian et al. (2020). In conclusion, the use of SEM PLS in this research is pivotal because it can model latent constructs accurately, handle non-normal data distributions, adapt to smaller sample sizes, and explore intricate relationships and interactions between variables. These features make SEM PLS a method of choice for unraveling the complexities inherent in HRM research and contribute to the richness and depth of insights generated in this study.

II. LITERATURE REVIEW

Developing empirical studies in business research is often faced with complex research models. In the quantitative paradigm (positivism), hypothesis testing is a crucial stage to confirm or develop theory, answer research problems, and provide solutions to research subjects (Jogiyanto, 2011: 47). In regression techniques, the research model is built based on one dependent variable and several independent variables. Another tool or analysis method is needed when the research model uses more than one dependent variable. A method that can solve the problem without having to create several regression equations because analyzing separately is inappropriate.

One method that can be used in analyzing the path equation model is Structural Equation Modeling (SEM). According to Chin in Ghozali&Latan (2015), SEM has the advantage of conducting path analysis (phat analytic) with latent variables. Furthermore, Wright in Jogiyanto (2011: 47) suggests that SEM is one of the analytical techniques used to test and estimate causal relationships by integrating path and factor analysis.

According to Fornell and Bookstein in Ghozali&Latan (2015: 19) there are two types of SEM, namely Covariance-Based Structural Equation Modeling (CB-SEM) and Partial Least Squares Path Modeling (PLS-SEM). CB-SEM requires a strong theoretical basis, fulfills various parametric assumptions, and meets the goodness of fit test. Therefore, CB-SEM is suitable for testing theories and justifying the tests with a series of complex analyses. Meanwhile, PLS-SEM aims to test the predictive relationship between constructs by seeing if they have a relationship or influence.

Next, we look at the sample size and measurement scale. CB-SEM requires a relatively large sample size for accurate estimation and uses continuous and interval measurement scales. PLS-SEM does not require a large sample size.

Construct development procedures in various literatures are recommended to use constructs with reflective indicators because they are assumed to have similar content domains. However, they can also use constructs with formative indicators (Ghozali&Latan, 2015: 57). In building constructs with reflective indicator models, the covariance between model measurements is assumed by the variance that manifests the latent construct. In the reflective model, the direction of the indicator starts from the construct to the indicator, where each indicator has error terms or measurement errors. For example, Y, Y, and Y are indicators, and e is an error term. 123 illustrates a reflective construct.

III. METHOD

General Background

Path analysis (McDonald, 1996; Wright, 1921) allows for estimating an equation system where every variable is observable. Path models, also commonly called system regression models, can contain more than one dependent variable, in contrast to regression models. Path model variables can be entered as single-item constructions in Smart-PLS. A variable based on several indicators is equally weighted to get a construct score. Theoretically, only structural relationships between observable variables (or equally weighted constructs) are modeled with or without control factors. When one or more variables moderate the link between two other variables, this model is frequently employed (mediation model). Moderated mediation can be modeled concurrently.

Path models can undergo significance testing thanks to bootstrapping in Smart-PLS. As a result, the PROCESS module offers every modeling and computation option that PROCESS has historically provided (Hayes, 2018). According to Sarstedt et al. (2020), PROCESS models are automatically built by Smart-PLS and the results are output instantly, thus no additional computations are needed outside of Smart-PLS. An illustration of a PROCESS model in Smart-PLS is provided in the accompanying image.

Evaluation of the Measurement Model

Because the latent variable indicators have an impact on the indicators, reflective indicators are included in the measurement model in this study. The measurement model's assessment by examining the value in Yamin (2022):

a. The correlation coefficient between each measurement item and the variable is known as the outer loading (LF) or loading factor. The item's ability to reflect or characterize the variable measurement is indicated by this measure. As a general guideline, Hair Jr et al. (2021) and Henseler et al. (2009) state that LF values ≥ 0.70 are acceptable; however, Chin (1998) expresses a different opinion, stating that LF values > 0.50 are acceptable (valid).
b. According to Heseler et al. (2009), internal consistency of reliability, as represented by composite reliability (CR), is a measure of the variable's reliability where the value is not less than 0.6. In the meantime, > 0.70 is the appropriate Composite Reliability value, according to Hair et al. (2011) (numbers between 0.60 - 0.70 are acceptable in exploratory study).
c. The average variation of each measurement item that the variable contains is known as the average variance extracted, or AVE. To what extent the variation in measurement items can be explained by the main variable. This measure also shows how well the variable's convergent validity is. AVE value (Hair et al., 2021) above 0.50.
d. The degree to which the developed variables or constructs differ from other variables or constructs that are statistically tested is known as discriminant validity. Testing for discriminant validity is done at the indicator and variable levels. The cross loadings measure is applied at the indicator level, while the Fornell-Lacker Criterion, which contrasts the correlation between variables and the AVE root, is applied at the variable level. HeterotraitMonotrait Ratio, or HTMT (Heterotrait) validity value <0.9 is another way to assess discriminant validity (Henseler et al., 2015; Hair et al., 2021).

Structural Model Evaluation

The purpose of this structural model evaluation is to examine the hypothesis (or causality). The bootstrapping procedure is used for hypothesis testing (percentile method). The t test is the statistical test applied in this methodology. The two-way test's (two-tailed test) t-values show that the test is 1.96 (significant threshold = 5%). The t-test test requirements state that a link between variables is considered to have a significant effect if the value of $tstabstik > ttael$ or the significance value <0.05 (Yamin, 2022).

Evaluation of Model Quality and Fit

Assessing the model is the best way to determine its quality. This assessment is evident from several metrics, including R square, Q square, F square, and SRMR, and this are employed to declare the model acceptable (Yamin, 2022).

1. R square

The overall impact of exogenous and endogenous variables on other endogens in the model is depicted by the R square value. The R square values are 0.67 (high), 0.33 (moderate), and 0.19 (poor), according to Chin (1998).

2. Q Square

The predictive relevance (prediction accuracy) of the model is demonstrated by Q Square, which also indicates how well each change in exogenous variables can predict its endogenous variables. Exogenous variables are predictively relevant to endogenous variables if the Q square value is greater than zero. According to Hair Jr. et al. (2019), Q Square indicates low, moderate, and high predictive accuracy whether it is 0, 0.25, or 0.50.

3. F square

Describes how much influence the variables in the structural model have or how much influence the exogenous latent variables have on the endogenous variables. This measure is calculated by comparing the R square value when variables are included/excluded in the structural model. The interpretation of the F square value in Hair et al. (2021) is 0.02 (low) 0.15 (medium) 0.35 (high).

IV. RESULTS

Items' ability to reflect or represent varied measurements is called outer loading. Chin (1998) states that, as a rule, an outer loading value greater than 0.50 is acceptable (legal). Table 1 below displays the study's outer loading value:

Table 1. Outer Loading

No	Variables	Item	*Outerloadings*	
1	Career Development (X1)	X1.1	**0.766**	Valid
		X1.2	**0.861**	Valid
		X1.3	**0.778**	Valid
		X1.4	**0.837**	Valid
		X1.5	**0.802**	Valid
		X1.6	**0.854**	Valid
		X1.7	**0.791**	Valid
		X1.8	**0.794**	Valid
		X1.9	**0.753**	Valid
		X1.10	**0.813**	Valid
		X1.11	**0.791**	Valid
		X1.12	**0.804**	Valid
		X1.13	**0.810**	Valid
		X1.14	**0.794**	Valid
		X1.15	**0.800**	Valid
2	WorkEngagement(X2)	X2.1	**0.656**	Valid
		X2.3	**0.704**	Valid
		X2.5	**0.582**	Valid
		X2.6	**0.646**	Valid
		X2.7	**0.612**	Valid
		X2.8	**0.690**	Valid
		X2.9	**0.641**	Valid
		X2.10	**0.535**	Valid
3	Turnover Intention(Y)	Y1	**0.765**	Valid
		Y2	**0.712**	Valid
		Y3	**0.952**	Valid
		Y4	**0.922**	Valid
		Y5	**0.742**	Valid
		Y6	**0.955**	Valid
		Y7	**0.952**	Valid
		Y8	**0.808**	Valid
		Y9	**0.946**	Valid
4	JobSatisfaction(Z)	Z1	**0.804**	Valid
		Z3	**0.813**	Valid
		Z4	**0.784**	Valid
		Z5	**0.692**	Valid
		Z6	**0.789**	Valid
		Z7	**0.792**	Valid
		Z8	**0.796**	Valid
		Z9	**0.779**	Valid
		Z10	**0.683**	Valid

It is clear from this table that all measurement items on the variables—career development, work engagement, turnover intention, and job satisfaction—show an outer loading value more than 0.5, indicating the validity of all the indicators used.

Composite Reliability is a measure to show how far the variable reliability is, while Average Variance Extracted shows how far the overall variable can explain the variation of measurement items. The value of Composite Reliability and Average Variance Extracted can be seen in the following table:

Table 2. Composite Reliability Test Result

	Composite Reliability	**Average Variance Extracted (AVE)**
Career Development	**0.965**	**0.646**
Work Engagement	**0.860**	**0.608**
Turn Over Intention	**0.964**	**0.752**
Job Satisfaction	**0.930**	**0.595**

The Composite Reliability value of all research variables is more than 0.7, as shown in the above table, indicating that the reliability level is acceptable. In general, there is consistency in the measures of the following variables: job satisfaction, work engagement, career development, and turnover intention. In the meantime, all research variables have an AVE value more than0.5, indicating that the degree of variation across all items included in this research variable satisfies the standards of strong convergent validity.

The discriminant validity test illustrates how far the variables or constructs that are built are different from other variables / constructs and are statistically tested. This test can be done by looking at the HTMT (HeterotraitMonotrait Ratio) value in the following table:

Table 3. The Discriminant Validity Test Result

	CD	**WE**	**TI**	**JS**
Career Development				
Work Engagement	**0.336**			
Turn Over Intention	**0.478**	**0.326**		
Job Satisfaction	**0.139**	**0.458**	**0.272**	

The table shows that the HTMT value of all pairs of variables is smaller than 0.9, so discriminant validity is fulfilled. This means that the correlation between measurement items in measuring the same variable is stronger than the correlation between items and other variable items. In other words, measurement items correlate more with the measured construct than other constructs.

Table 4. AVE Test Result

	CD	**WE**	**TI**	**JS**
Career Development	0.804			
Work Engagement	0.024	0.638		
Turn Over Intention	0.479	0.400	0.867	
Job Satisfaction	-0.045	0.480	0.256	0.771

The table above shows the AVE root value of each variable on the diagonal axis, where all variables have an AVE root greater than their correlation with other variables so that the evaluation of the discriminant validity of the research variables is fulfilled.

The bootstrapping procedure evaluates structural models or test hypotheses (percentile approach). The t test is the statistical test applied in this methodology. The two-way test's (two-tailed test) t-values show that the test is 1.96 (significant threshold = 5%). The t-test test requirements state that the hypothesis is accepted if the value $tstabstik > ttael$ or the significance value <0.05. The following tables and figures show the structural model testing results:

Figure1. Structural Model Testing Results:

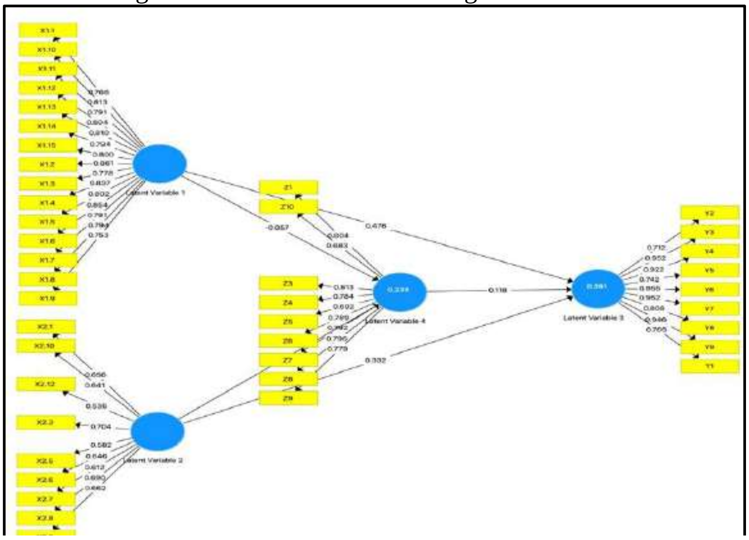

Table 5. Hypothesis Test Results

	Original Sample (O)	T Statistics (|O/STDEV|)	P Values
Career Development -> Turnover Intention	0.476	5.108	**0.000**
Career Development -> Job Satisfaction	-0.057	0.547	**0.584**
Work Engagement -> Turnover Intention	0.332	2.409	**0.016**
Work Engagement -> Job Satisfaction	0.481	5.307	**0.000**
Job Satisfaction -> Turnover Intention	0.118	1.058	**0.291**

According to the table and figure. The following explanation applies to the link between variables (hypothesis test results) mentioned above:

1.Career Development has a significant and positive impact on Turnover Intention, as evidenced by the P value of 0.000 < 0.05, the t-statistic value of 5.108 > 1.96, and the coefficient value of 0.476.

2.With a P value of 0.584 > 0.05, a t-statistic value of 0.547 < 1.96, and a coefficient value of -0.057, Career Development had no discernible impact on Job Satisfaction.

3.With a t-statistic value of 2.409> 1.96, a P value of 0.016 <0.05, and a coefficient value of 0.332, work engagement positively and substantially impacts turnover intention.

4. Work Engagement positively and significantly impacted job satisfaction, as evidenced by a t-statistic value of 5.307 > 1.92, a P value of 0.000< 0.05, and a coefficient value of 0.481.

5. With a P value of 0.291 > 0.05, a t-statistic value of 1.058 < 1.96, and a coefficient value of 0.118, Job Satisfaction had no discernible impact on Turnover Intention.

The R square value describes the whole effect of extraneous and endogenous parameters on other endogens in the framework. A table presenting the R square values from this investigation is provided below:

Table 6. R Square Test Results

	R Square	R Square Adjusted
Turnover Intention	0.391	0.367
Job Satisfaction	0.233	0.213

The table above shows that the influence of career development, work engagement, and job satisfaction on turnover intention is 39.1 percent. Meanwhile, the magnitude of the influence of Career Development and Work Engagement on Job Satisfaction is 23.3 percent, which is included in the low category.

Table 7. F Square Test Results

	Turnover Intention	Job Satisfaction
Career Development	0.371	0.004
Work Engagement	0.139	0.301
Job Satisfaction	0.018	

The table shows that Career Development, Work Engagement, and Job Satisfaction have a low influence (F square = 0.371, 0.139, 0.018) on Turnover intention and the mediating role of Job Satisfaction on the influence of Career Development. Work Engagement has a low influence (F square = 0.004, 0.301) on purchase intention.

V. DISCUSSION

The use of Structural Equation Modeling Partial Least Squares (SEM PLS) in this study has relevance and advantages that cannot be ignored. Through the application of SEM PLS, this research can reveal the nuances and complexities of inter-variable relationships in the context of human resources. This discussion will highlight some key points that confirm the success and advantages of SEM PLS in meeting the challenges of this research.

First, PLS-SEM provides the ability to model latent variables that cannot be measured directly, such as job satisfaction, work engagement, and turnover intention. This is crucial in understanding the psychological and behavioral dimensions of employees that cannot be measured visibly. Successful measurement of these latent variables will open the door to a deeper understanding of the factors that influence employee performance and retention.

Secondly, the PLS SEM's advantage of flexibility with statistical assumptions provides significant advantages in handling human resource datasets that tend to be complex and do not always adhere to the normal distribution assumption. This creates an opportunity to apply analytical methods that are more realistic and relevant to the characteristics of the data at hand.

Furthermore, by utilizing the advantages of PLS-SEM in interaction and mediation measurement, this study can provide further insights into how variables such as career development and work engagement simultaneously affect job satisfaction, which mediates the relationship with turnover intention. This modeling opens opportunities to explore more detailed pathways of influence, providing a more complete picture of the dynamics in the context of human resources.

Fourth, applyingPLS-SEM in this study is a statistical analysis tool and a strategic approach to answering complex research questions. PLS-SEM provides a highly relevant and applicable framework in business and organizational contexts, where strategic decisions are often made based on a comprehensive understanding of the factors that influence employees.

To conclude, using PLS-SEM in this study represents a significant step forward in understanding the dynamics of relationships between variables in human resources. The successful application of this method makes a real contribution to the scientific literature and practice of human resource management by opening new insights and expanding our understanding of the complex interactions among key factors in the work environment.

VI. CONCLUSION

The conclusions of this study highlight the successful use of Structural Equation Modeling Partial Least Squares (SEM PLS) in exploring the dynamics of relationships between variables in the human resources context. The findings provide an in-depth understanding of the key factors influencing job satisfaction, work engagement, and employee turnover intention. This research's practical and theoretical implications can be summarized as follows: This study significantly contributes to the human resource literature by exploring the validity and reliability of critical constructs, such as career development, work engagement, job satisfaction, and turnover intention. The findings complement and enrich our understanding of the multidimensional relationships among these variables. The application of PLS-SEM is not just a statistical analysis method but also a contextual approach relevant to the reality of human resource data. The success of this method in handling complex datasets that do not always follow classical statistical assumptions shows that PLS-SEM is an appropriate analytical tool in this study. The results of the SEM PLS analysis show how variables such as career development and work engagement can simultaneously influence job satisfaction and how job satisfaction mediates the relationship with turnover intention. The practical implication of this deep understanding is that organizations can positively direct employee development efforts to influence employee retention and well-being. An in-depth understanding of the key factors in employee decision-making, job satisfaction, and retention can help design more appropriate and effective human resource management strategies. Organizations can leverage these findings to design more targeted development policies and programs, increase employee satisfaction, and reduce the propensity to leave.

VII. ACKNOWLEDGEMENTS

This research is supported by Mataram University, where the author pursued education. We express our gratitude to H. AkhmadSaufi, SE., M. Bus., Ph.D., and EmbunSuryani, SE., M.Si., Ph.D., the thesis adviser, for providing moral support, valuable advice, and consistent supervision, which are essential to the realization of the study. We thank the American Journal of Humanities and Social Sciences Research (AJHSSR) for allowing the author to share insights with the community through its scholarly journal. Our appreciation also goes to all parties who guided and assisted in completing this research.

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