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THE INTEGRATION OF SUPPLY CHAIN MANAGEMENT AND INDUSTRY 4.0: ANALYSIS OF STRUCTURAL RELATIONSHIPS

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Abstract

In this study, the assessment of major factors that directly impact the success of the Industry 4.0 integration of the supply chain in terms of tangible and intangible business resources as well as the mediating role of work engagement over these business resources was performed. A total of 685 survey questions were distributed to voluntary participants in the supply chain management industry and 182 responses were studied. Structural Equation Modelling using AMOS software was carried out. Analysis such as –variables and their related measurement scales, data screening, replacing missing values, removing outliers and testing normality of data, Harman's single-factor test, and *Confirmatory Factor Analysis –were conducted. Descriptive results of the constructs were discussed.*

Keywords: Supply Chain Management, Industry 4.0, Business Resources, Structural Equation Modelling

I. Introduction

Many organizations aim to integrate Industry 4.0 (I4.0) into their supply chain operations to achieve a more flexible, adaptable, low-cost, fast-service, and competitive supply chain management. To do this successfully, organizations need to start with a strategic plan and integrate it throughout the organization. Shoshanah stated that effective supply chain management strategies involve more than just implementing technological advancements. It also requires designing a framework that enables organizations to achieve their strategic objectives (Shoshanah, 2005). Tajri and Chafi recommended a change management approach that focuses on the supply chain and aligns with strategic goals for integrating new strategies (Tajri and Chafi, 2018). Additionally, Alan Milliken stressed the importance of considering process, technology, and people as critical components for successful supply chain operations, especially when implementing changes (Milliken, 2012).

When it comes to technology, Industry 4.0 initiatives have been planned and adapted in many organizations in the supply chain and manufacturing industries. However, assessing the success rate of I4.0 implementation depends on the strategic alignment of business objectives and technological investments. According to an article by Doug Gates, I4.0 is a development in enhancing performance which, if used in combination and applied to a particular business issue, can offer extraordinary benefits to those who approach it strategically (Gates, 2017). In addition, Mark Brenner stressed the importance of the human element in implementing change management principles and highlighted that profitability is ultimately linked to the performance of individuals, both individually and collectively, in his 2008 publication. (Brenner, 2008).

Therefore, organizations should take the following steps to assess if their I4.0 initiatives have been successfully integrated into the supply chain. The first step is to have organizational resources and capabilities that strategically align with the business goals of the organization. The second step is to adapt to new technological changes that I4.0 brings and make the necessary investments into the current supply chain process. The last step is to consider employee work engagement. The successful integration of any given initiative or change depends largely on the willingness and capabilities of people to perform the subject truly.

Although extensive research has been conducted in various areas related to I4.0 and GSCM, resulting in the development of diverse frameworks and methodologies, there is still ongoing debate about the factors that contribute to the successful integration of I4.0. This is primarily due to factors such as business resources and employee engagement.

This study aims to provide a valuable resource to supply chain organizations, by offering a comprehensive roadmap with practical and scalable I4.0 tools. These tools aim to address the needs of organizations transitioning from traditional supply chain management methods to more agile, flexible, accurate, and efficient digitalized approaches, to achieve a competitive advantage in the industry.

Research Contribution

Major industries, including global supply chain management, have various concerns and a lack of understanding about the integration of Industry 4.0. This gap has been identified as a significant concern in recent literature. Francisco A. Lobo (2020) highlighted the failure aspect of I4.0 integration in Forbes magazine, referencing a Cap Gemini report that revealed only 14% of over 1000 manufacturing companies with a revenue of $1 billion or more, who had ongoing smart manufacturing initiatives, were successful. Lobo's article questions why such huge investments are not paying off. (Lobo, 2020). The research suggests that success factors such as business resources, strategies, I4.0 readiness, and employee engagement throughout the integration process are key catalysts for success. The participants of the research were major organizations in the supply chain management and manufacturing industry. The study aims to evaluate the success factors of I4.0 integration in supply chain management and investigate to what extent business resources and employee work engagement contribute to its success.

Research Hypothesis

The independent variable of the research was determined as "business resources" and the business resources variable was divided into 5 sub-variables. These are Physical resources, Financial Resources, Human Resources, Technological resources, and Organizational resources. The dependent variable of the research was determined as "Industry 4.0 success". There is also an intermediary variable that is thought to have a mediation effect on the research, and this variable was chosen as "work engagement". Also, a single control variable is known as an employee number. The main hypotheses of the research are as follows. The codes and description of the research hypotheses are represented in Table 1.

Table 1. Research Hypotheses Codes and Descriptions

Code	Description	Path
Direct (Causal) Effect Hypotheses		
$H1^+$	Physical Resource (PR) has significant positive effect on Work Engagement (WE)	PR → WE
$H2^+$	Financial Resource (FR) has significant positive effect on Work Engagement (WE)	FR → WE
$H3^+$	Human Resource (HR) has significant positive effect on Work Engagement (WE)	HR → WE
$H4^+$	Technological Resource (TR) has significant positive effect on Work Engagement (WE)	TR → WE
$H5^+$	Organizational Resource (OR) has significant positive effect on Work Engagement	OR → WE
$H6^+$	Physical Resource (PR) has significant positive effect on Industry Success (IS)	PR → IS
$H7^+$	Financial Resource (FR) has significant positive effect on Industry Success (IS)	FR → IS
$H8^+$	Human Resource (HR) has significant positive effect on Industry Success (IS)	HR → IS
$H9^+$	Technological Resource (TR) has significant positive effect on Industry Success (IS)	TR → IS
$H10^+$	Organizational Resource (OR) has significant positive effect on Industry Success (IS)	OR → IS
$H11^+$	Work Engagement (WE) has significant positive effect on Industry Success (IS)	WE → IS
Mediation Effect Hypothesis		
H12	The relationship between Physical Resource (PR) and Industry Success (IS) is mediated	PR→WE→IS
H13	The relationship between Financial Resource (FR) and Industry Success (IS) is	FR→WE→IS
H14	The relationship between Human Resource (HR) and Industry Success (IS) is mediated	HR→WE→IS
H15	The relationship between Technological Resource (TR) and Industry Success (IS) is	TR→WE→IS
H16	The relationship between Organizational Resource (OR) and Industry Success (IS) is	OR→WE→IS

II. Methods and Procedures

Research Model

To specify the research hypotheses targeted in Table 1, a research model was developed in this study. There are 7 variables in total in the research. 5 of them are involved in determining the business sources of companies in the supply chain sector. 1 of them is used to measure the work engagement understanding of companies in the supply chain sector. 1 of them is used to control variables to measure the number of Employees in the company. The last variable determines the success levels of supply chain companies in Industry 4.0 applications. The research model is intended to test the causal and mediation effects between the variables. Figure 1 demonstrates the hypotheses of the research model and the relative paths of these hypotheses.

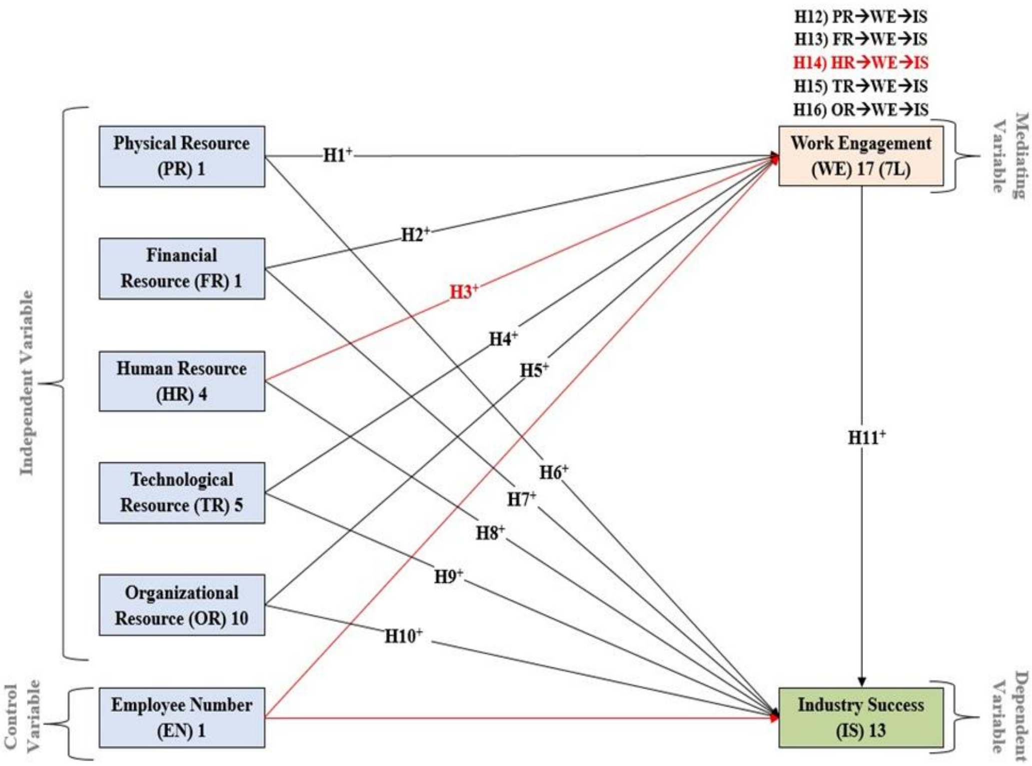

Fig 1. Research Model with Hypotheses

Study Variables

There are 8 variables in total in the research. 5 of them are involved in determining the business sources of companies in the supply chain sector. 1 of them is used to measure the work engagement understanding of companies in the supply chain sector. 1 of them is used to control variables to measure the number of Employees in the company. The last variable determines the success levels of supply chain companies in Industry 4.0 applications.

Physical Resources

The number of fixed assets was used as the measurement of this variable. Based on Barney's (1997) definition of physical resources and his suggestion. To this value not to be affected by the size of the company, the rate per person in the company was taken. Question two was used as a control variable in this part.

1 - How many years has your company been operating in the sector?
2 - What is the number of personnel working in your company?
3 - What is your company's annual fixed assets amount?

Financial Resources

The amount of retained earnings was used as the measurement of this variable. Based on Barney's (1997) definition of financial resources and his suggestion. To this value not to be affected by the size of the company, the rate per person in the company was taken.

4 - What are your company's annual retained earnings?

Human Resources

The Human Capital scale developed in Bontis (1998)'s study and used in Cater and Cater's (2015)'s study is used to measure this variable. The scale consists of 4 items and a 5-point Likert-type rating was evaluated. In the study of Cater and Cater (2015). Participants who evaluate the scale can make assessments as 1-completely disagree and 5- completely agree. High scores on the scale mean that the company's human resources are of high quality and qualified.

Technological Resources

In the research, the expressions used in the study of Zuou and Wu (2010) were used to measure the technological capacities and resources of supply chain companies. In the study of Zuou and Wu (2010), these statements were compiled from the work of Gatignon and Xuereb's (1997) and Song et al. (2005). There are 5 statements to evaluate the technological resources of the supply chain company. These statements are evaluated with a 5-point Likert-type rating (1: much worse; 5: much better) in the study of Zuou and Wu (2010).

Organizational Resources

The concept of "Participative strategic planning" was used to measure the organizational resources of the companies that is taking part in the research. Accordingly, the concept of "participative strategic planning" developed in the study of Collier et al.(2004) and adapted in the study of Kohtamaki et al.(2012), is measured with 10 items. The scale was evaluated with a 5-point Likert-type rating. There is no item to be reverse-coded in the scale.

Work Engagement

Schaufeli and Bakker (2004) created the Utrecht Work Engagement Scale to assess Work Engagement. The scale used to measure the work engagement variable comprises of 17 statements. It was graded using a 7-point Likert-style rating, with scores ranging from 0 (indicating almost never) to 6 (representing always).

Industry 4.0 Success

Stentoft et al. (2019) were inspired by the work of Ruessmann et al.(2015), Salkin (2018), and Saucedo-Martinez et al.(2017) to measure the success of Industry 4.0. In this study, Stentoft et al. (2019). We used the 12-item measurement tool in his study. The scale was evaluated with a 5-point Likert type (1 = to a very low degree and 5 = to a very high degree) rating, and the high scores on the scale indicate that the company has successfully implemented Industry 4.0.

II. Findings

The finding encompasses the analysis of conducted research and displays the results of the hypotheses of this research, using the software program AMOS. This finding covers eight major sections. The initial part of the study presents an introduction, while the second section provides an overview of the variables and the measurement scales associated with them. In the third section, the authors describe the process of data screening, which includes replacing missing data, removing outliers, and checking for the normality of the data distribution. The fourth section employs Harman's single-factor test to confirm that the common method variance is not a significant issue in the research model. In the fifth section, the study uses Confirmatory Factor Analysis (CFA) to assess the reliability, validity, and uni-dimensionality of the constructs. The sixth section reports descriptive statistics of the constructs, and the seventh section presents the results of structural models testing the hypothesized causal and mediation effects. Finally, the eighth section summarizes the study's overall findings and results of the data analysis.

Variable Measures

The primary constructs were gauged using established instruments, and a comprehensive overview of the construct variables and their measurement scale can be found in Table 2.

Table 2. List of Variables and Measurement Items

Code	Variables	Number of Items	Measurement Scale	Question in the Survey
CV	Employee Number (EN)	1	7 Ordinal Groups	Section 4, Question 2
IV1	Physical Resource (PR)	1	9 Ordinal Groups	Section 4, Question 3
IV2	Financial Resource (FR)	1	9 Ordinal Groups	Section 5, Question 4
IV3	Human Resource (HR)	4	5-Point Likert Scale	Section 6
IV4	Technological Resource (TR)	5	5-Point Likert Scale	Section 7
IV5	Organizational Resource (OR)	10	5-Point Likert Scale	Section 8
MV	Work Engagement (WE)	17	7-Point Likert Scale	Section 9
DV	Industry Success (IS)	13	5-Point Likert Scale	Section 10

CV = Control Variable; IV = Independent Variable; DV = Dependent Variable; MV = Mediating Variable

Data Screening

A data screening process is performed to assure that data collected from volunteer participants is correct. Also, performing data screening is an essential aspect of any survey, as it serves the purpose of verifying that the data collected is devoid of missing values and outliers and that the distribution of variables is normally distributed.

Replacing Missing Values

Survey results indicated that some survey participants failed to answer one or more survey questions. Due to the missing values on collected data, the missing value should be treated before running further analysis. As it is stated by various researchers missing values of less than 5% or some cases up to 10% are considered within reasonable limits and unlikely to be problematic for the result of the studies. (Hair et al., 2017; Cohen and Cohen,1983).

To account for any missing data, the Expectation Maximization (EM) algorithm in SPSS was utilized. This iterative process utilizes all other relevant variables associated with the construct of interest to predict the values of any missing variables. Monte Carlo experiments conducted by Graham et al. (1997) were used to showcase the effectiveness of the EM method in imputing data. Results revealed that this method was significantly more accurate and consistent in predicting parameter estimates compared to other methods, such as list-wise deletion (which yielded highly variable results) and mean substitution (which consistently underestimated 343 values). In fact, the EM method often generated identical parameter estimates. Additionally, the EM analysis in SPSS also generates Little's MCAR (Missing Completely At Random) $\chi 2$ statistic. If this statistic is not significant, it can be assumed that the missing data are missing at random. The highest missing value percentage found in this study was 1.6% (3 missing out of 182 cases), below the threshold of 5%. Therefore, EM was adopted to solve the missing value problem. The results of the MCAR test showed Chi-Square: 1288.762, df: 1319, and sig: 0.719.

Removing Outlier

The process of removing outliers from the collected data is an essential step in the data screening process. Outliers are characterized as observations with unique combinations of characteristics that differ significantly from other observations (Hair et al., 1998). Various methods are used to detect outliers, including univariate techniques such as histograms, box plots, and standardized z-scores, as well as multivariate detection methods like Mahalanobis D2 distance. As noted by Hair, Tabachnick, and Fidell, checking for outliers is crucial as they can significantly impact the normality of the data, leading to distorted statistical results (Hair et al., 1998; Tabachnick and Fidell, 2011).

Univariate Outliers

To detect univariate outliers, the standardized (z) score was examined in addition to histograms and box plots for each variable. According to Hair (1998), an extreme observation is indicated by an absolute (z) score greater than 4, but for large sample sizes over 200, this threshold may be more conservative. The analysis showed that the standardized (z) scores of the observations for the research variables ranged from -2.862 to 1.969, suggesting that none of the variables exceeded the threshold of ±4. Therefore, it can be concluded that there were no univariate outliers among the observations.

Multivariate Outliers

To ensure the accuracy of the data, multivariate detection was also performed by applying Mahalanobis distance. This approach successfully identified any multivariate outliers in the data set. To determine if a case was a potential outlier, the Mahalanobis D-squared distances were calculated using AMOS regression. A D2/df value greater than 3.5 was considered to indicate a potential multivariate outlier (Hair et al., 1998). The results showed that the largest D2 value was 78.941, which belonged to observation number 74. However, upon examining the 106 exogenous and endogenous variables in the study and their relative estimation errors, the maximum D2/df was found to be 0.745 (78.941/106), which was well below the cut-off of 3.5. Therefore, it can be concluded that there were no multivariate outliers in the data, and all observations were retained for analysis.

Common Method Bias (Harman's single-factor test)

Podsakoff, MacKenzie, Lee, & Podsakoff (2003) stated that common method bias refers to the variance that arises due to the measurement method, rather than the constructs being measured, which can pose a problem. Essentially, this bias occurs because external factors may have influenced the response given, which affects the dataset. In this study, the data was collected using a manual questionnaire survey, which could lead to systematic response bias and either inflate or deflate responses.

To determine whether common method variance was a significant issue in this study, Harman's single-factor test (Hoyle, 1995) was used. Since this study employed a one-wave self-reported design, where all variables were measured at the same point in time, this test was appropriate. According to the results of the test, the one-factor model explained only 47.343% of the total variance, which is less than 50%. Thus, it was concluded that common method variance was not a serious concern (Hoyle, 1995).

Measurement Model (CFA) – Stage 1 of SEM

The CFA model was used as the first stage of the SEM analysis in this study. In the next sections, the development of the measurement model was discussed. AMOS 20.0 was used as a tool for the uni-dimensionality of each construct. The measurement model includes 3 single variables and 49 items to measure 5 latent constructs. The initial CFA model with all 49 items was portrayed in Figure 2.

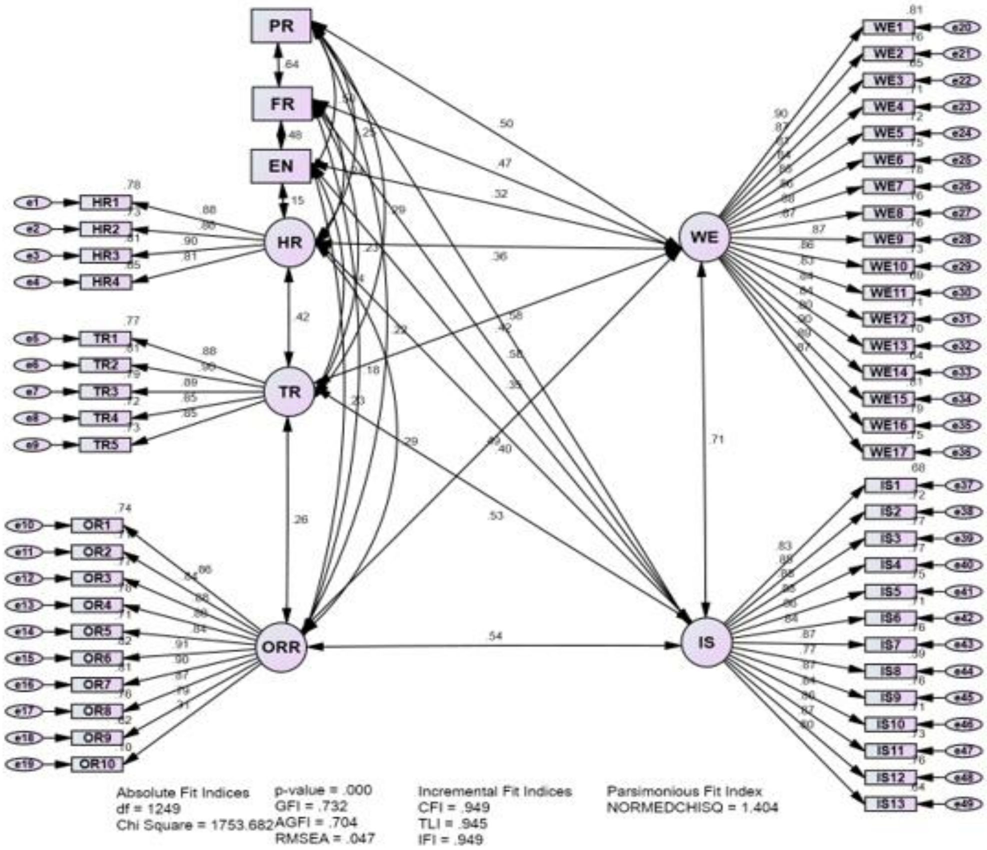

Fig 2. Exogenous and Endogenous Variable with Estimated Error

Standardized Loadings of the Model's Items

The factor loading analysis of each item revealed that OR10 had a factor loading of 0.308, which is lower than the minimum acceptable value of 0.5. As a result, this item was eliminated from the model. After this adjustment, the revised model was tested again to confirm the stability of the factor structure. The outcome indicated that the second standardized factor loadings for the remaining 48 items were all greater than 0.5, ranging from 0.766 to 0.906, as demonstrated in Figure 3. Consequently, no other item needed to be removed due to inadequate factor loading.

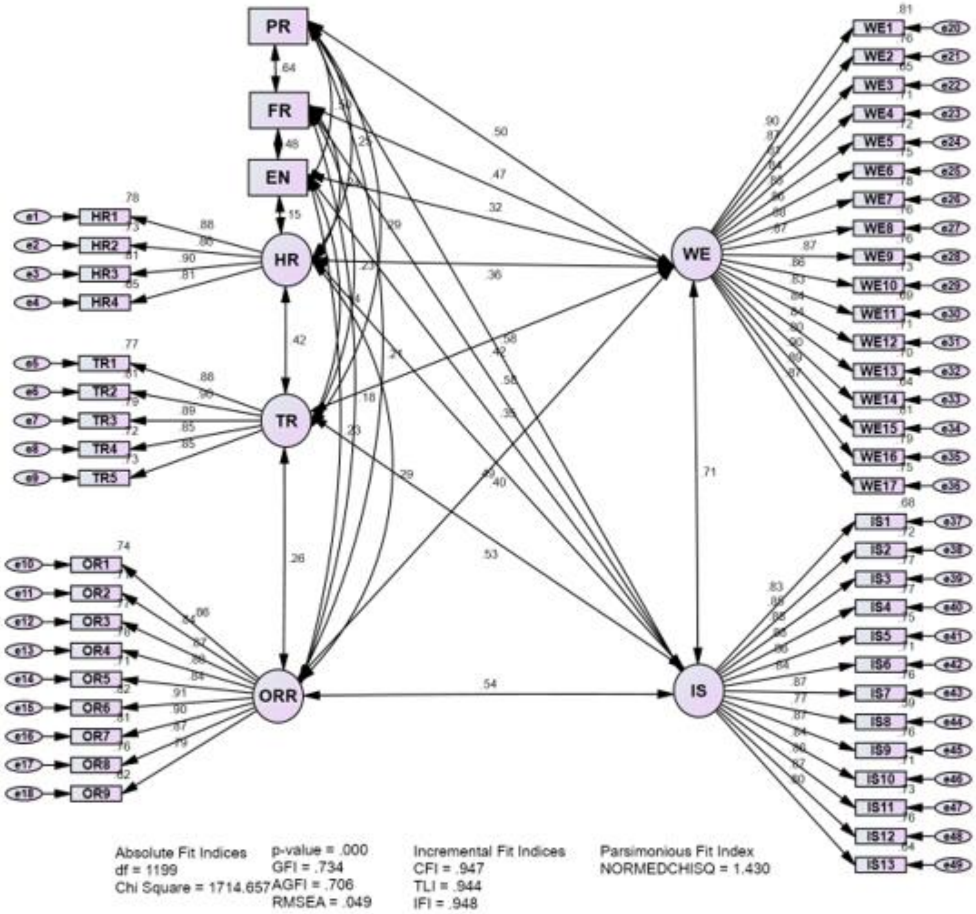

Fig 3. Harman`s Single Factor Test

The goodness of Fit Indices

The goodness of fit analysis revealed that the GFI score was 0.734, which falls below the recommended minimum level of 0.8 suggested by Hoyle (1995). As a result, a more thorough investigation was conducted by examining the modification indices (Hair et al., 2006; Kline, 2010). This analysis revealed that some items had a high discrepancy of covariance between their related errors, with modification indices (M.I.) above 15, indicating redundant items in the model. For instance, the M.I. value of covariance between the errors of WE4 and WE8 was 25.905, meaning that treating the covariance between the error of these two items as a free parameter would reduce the discrepancy by at least 25.905. Since both items are loaded on the same construct (i.e., Work Engagement), the covariance between their errors represents within-construct error covariance. Four other within-construct error covariance terms were found between the pairs of items WE1-WE7, WE2-WE14, WE15-WE17, and OR6-OR7. These within-construct error covariance terms are a threat to construct validity (DeVellis, 2011), and drawing correlation paths between these errors and allowing these paths to be estimated (freeing them) would decrease the $\chi 2$ and enhance the model fit (Hair et al., 1995). Therefore, the model was modified by drawing correlation paths between the errors of these items.

The model also revealed covariance between the error terms of indicator variables loading on different constructs. The high M.I. covariance values of the errors of OR4, WE6, and IS8 with the items' errors of other constructs indicated between-construct error covariance. Significant between-construct error covariance implies that the items associated with this error term are more strongly related to each other than the original measurement model predicts. Bentler (1980) argues that this suggests a significant cross-loading in the model that can lead to a lack of discriminant validity. Thus, the decision was made to remove these items from the model (Awang, 2012).

Moreover, examination of the standardized residual covariance revealed that OR9, WE3, WE5, and WE13 had absolute standardized residual covariance values beyond the threshold of 2.58 with other items in the model. Therefore, these items were deleted from the model.

After iteratively drawing these correlation paths and deleting the items having high between-construct error covariance and standardized residual covariance, the overall measurement model was performed once again. The findings showed that the revised measurement model, consisting of 41 items, was a good fit for the data.

Reliability and Convergent Validity

The reliability and validity of each construct were evaluated after achieving uni-dimensionality. Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) were used to assess reliability, while construct validity was assessed through convergent and discriminant methods.

Table 3. Results of Convergent Validity and Cronbach Alpha

Variable	Item	Factor Loading	Average Variance Extracted (AVE)[a]	Composite Reliability (CR)[b]	Internal Reliability Cronbach Alpha
Human Resources (HR)	HR1	0.88	0.743	0.920	0.919
	HR2	0.856			
	HR3	0.902			
	HR4	0.808			
Technological Resource (TR)	TR1	0.879	0.764	0.942	0.942
	TR2	0.9			
	TR3	0.887			
	TR4	0.849			
	TR5	0.854			
Organizational Resource (OR)	OR1	0.864	0.755	0.956	0.956
	OR2	0.844			
	OR3	0.88			

	OR4[d]	~~0.881~~			
	OR5	0.83			
	OR6	0.891			
	OR7	0.893			
	OR8	0.877			
	OR9[e]	~~0.789~~			
	OR10[c]	~~0.308~~			
Work Engagement (WE)	WE1	0.889	0.747	0.975	0.974
	WE2	0.88			
	WE3[e]	~~0.809~~			
	WE4	0.832			
	WE5[e]	~~0.851~~			
	WE6[d]	~~0.865~~			
	WE7	0.869			
	WE8	0.89			
	WE9	0.872			
	WE10	0.865			
	WE11	0.841			
	WE12	0.827			
	WE13[e]	~~0.837~~			
	WE14	0.804			
	WE15	0.903			
	WE16	0.893			
	WE17	0.868			
Industry Success (IS)	IS1	0.83	0.730	0.970	0.969
	IS2	0.846			
	IS3	0.875			
	IS4	0.879			
	IS5	0.865			
	IS6	0.842			
	IS7	0.874			
	IS8[d]	~~0.766~~			
	IS9	0.874			
	IS10	0.843			
	IS11	0.853			
	IS12	0.87			
	IS13	0.799			

[a]: Average Variance Extracted = (summation of the square of the factor loadings)/{(summation of the square of the factor loadings) + (summation of the error variances)}.

[b]: Composite reliability = (square of the summation of the factor loadings)/{(square of the summation of the factor loadings) + (square of the summation of the error variances)}.
[c]: denotes a discarded item due to insufficient factor loading below cut-off 0.5.
[d]: denotes a discarded item due to high between-construct error covariance.
[e]: denotes a discarded item due to high standardized residual covariance.

Table 3 presents the results of evaluating the standardized loadings of the model's items. It was found that all 41 remaining items had factor loadings greater than 0.5 and ranged between 0.799 and 0.903. This suggests that these indicators effectively preserve the meaning of the factors they represent.

Additionally, Table 3 shows that the AVE, which represents the amount of variance in the indicators accounted for by the latent construct, exceeded the recommended cut-off of 0.5 proposed by Nunnally & Bernstein (1994), ranging between 0.730 and 0.764. The composite reliability value, which indicates how well the construct indicators represent the latent construct, also exceeded the suggested value of 0.6 recommended by Bagozzi and Yi (1988), ranging between 0.920 and 0.975. The Cronbach's Alpha value, which measures the degree to which the measure is error-free, was also above the threshold of 0.7 suggested by Nunnally and Bernstein (1994), ranging between 0.919 and 0.974. Therefore, Cronbach's Alpha achieved for all constructs was considered to be sufficiently error-free.

Discriminant Validity

To evaluate how distinct a construct is from other constructs, discriminant validity was utilized. As suggested by Kline (2005), the correlations between factors in the measurement model should not exceed 0.85. To test discriminant validity, the correlations between constructs and the square root of the average variance extracted for a construct (as proposed by Fornell and Larcker in 1981) were examined. The measurement model's discriminant validity is shown in Table 4.

Table 4. Discriminant validity of the Measurement Model

	EN	PR	FR	HR	TR	OR	WE	IS
Employee Number (EN)	**1**							
Physical Resource (PR)	0.499	**1**						
Financial Resource (FR)	0.477	0.635	**1**					
Human Resource (HR)	0.147	0.254	0.238	**0.862**				
Technological Resource (TR)	0.144	0.292	0.231	0.42	**0.874**			
Organizational Resource (OR)	0.222	0.213	0.176	0.297	0.267	**0.869**		
Work Engagement (WE)	0.313	0.496	0.462	0.364	0.427	0.405	**0.864**	
Industry Success (IS)	0.351	0.581	0.584	0.495	0.526	0.537	0.703	**0.854**

The ten variables were found to have inter-correlations that fell between 0.144 and 0.703, which is below the recommended threshold of 0.85 according to Kline's (2005) suggestion. Additionally, Table 4 demonstrates good discriminant validity among these factors. After analyzing the goodness of fit of the data, convergent validity, and discriminant validity, the results indicate that the constructs and their respective items were both reliable and valid. The measurement model with standardized factor loadings for the remaining 41 items is presented in Figure 4.

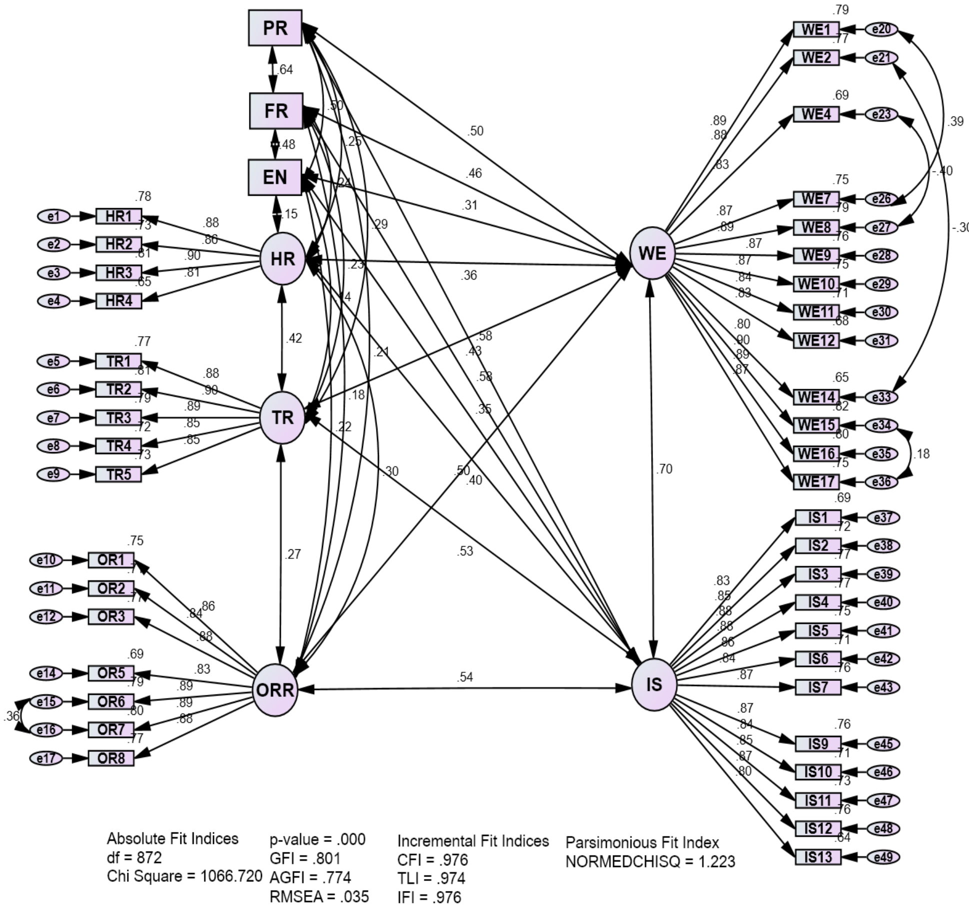

Fig 4. Measurement Model with Remaining 41 Items

Descriptive Analysis

The study conducted a descriptive analysis using the covariance matrix method, which involved examining all the variables related to the constructs. To calculate composite scores for the variables, the original measurement item scores were grouped into parcels based on their factor loadings on the construct. Parcels are computed by taking the sum or average of several individual indicators or items

(Coffman & Maccallum, 2005; Hair, et al., 2006). The study's findings, including the means and standard deviations of the variables, are presented in Table 5.

Table 5. Results of Descriptive Statistic for Variables

Variables	Number of Items	Measurement Scale	Mid-Point	Mean	Standard Deviation	Minimum	Maximum
Employee Number (EN)	1	7 Ordinal	4	3.750	1.851	1	7
Physical Resource (PR)	1	9 Ordinal	5	4.870	2.275	1	9
Financial Resource (FR)	1	9 Ordinal	5	4.860	2.548	1	9
Human Resource (HR)	4	5-Point Likert	3	3.615	0.962	1.25	5
Technological Resource	5	5-Point Likert	3	3.547	0.959	1.2	4.8
Organizational Resource	10	5-Point Likert	3	3.358	1.023	1.222	4.778
Work Engagement (WE)	17	7-Point Likert	4	4.148	1.431	1.647	6.588
Industry Success (IS)	13	5-Point Likert	3	3.459	0.966	1.308	4.769

The study used the mean as a measure of central tendency to assess the respondents' perception of various variables. The mean values of Employee Number (EN), Physical Resource (PR), and Financial Resource (FR) were below the mid-point level, indicating that the respondents' perception of these variables was below average. On the other hand, the mean values of Human Resources (HR), Technological Resources (TR), Organizational Resources (OR), Work Engagement (WE), and Industry Success (IS) were above the mid-point level, suggesting that the respondents' perception of these variables was above average. To measure the degree to which individuals within each variable differ from the variable mean, the study used the standard deviation as a dispersion index. For instance, the standard deviation of 0.962 for Human Resources (HR) indicated that there was significant variation among the survey participants in their perception of this variable. Figure 5 provides a visual representation of the means and standard deviations for all the variables.

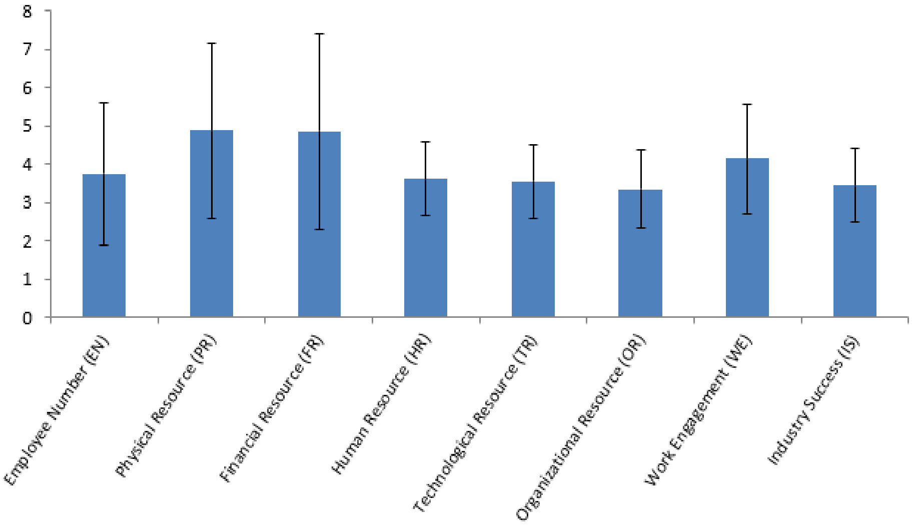

Fig 5. Means and Standard Variations of All Variables

III. Results and Discussions – Stage 2 of SEM

The study employed a structural equation model, which involved conducting SEM analysis as the second stage of the process. Once the measurement model was validated, the structural model could be formulated by defining the connections between the constructs. The structural model indicates how the variables are interrelated.

Causal Effects Hypotheses

The study analyzed the causal impacts of Physical Resources (PR), Financial Resources (FR), Human Resources (HR), Technological Resources (TR), and Organizational Resources (OR) on both Work Engagement (WE) and Industry Success (IS) in the structural model, referred to as H1 through H10. The causal relationship between Work Engagement (WE) and Industry Success (IS), also known as H11, was also examined. Additionally, the study considered Employee Number (EN) as a control variable that influences both Work Engagement (WE) and Industry Success (IS). Figure 6 depicts the AMOS graph of the structural model, illustrating the standardized regression weights and the causal effects of the constructs.

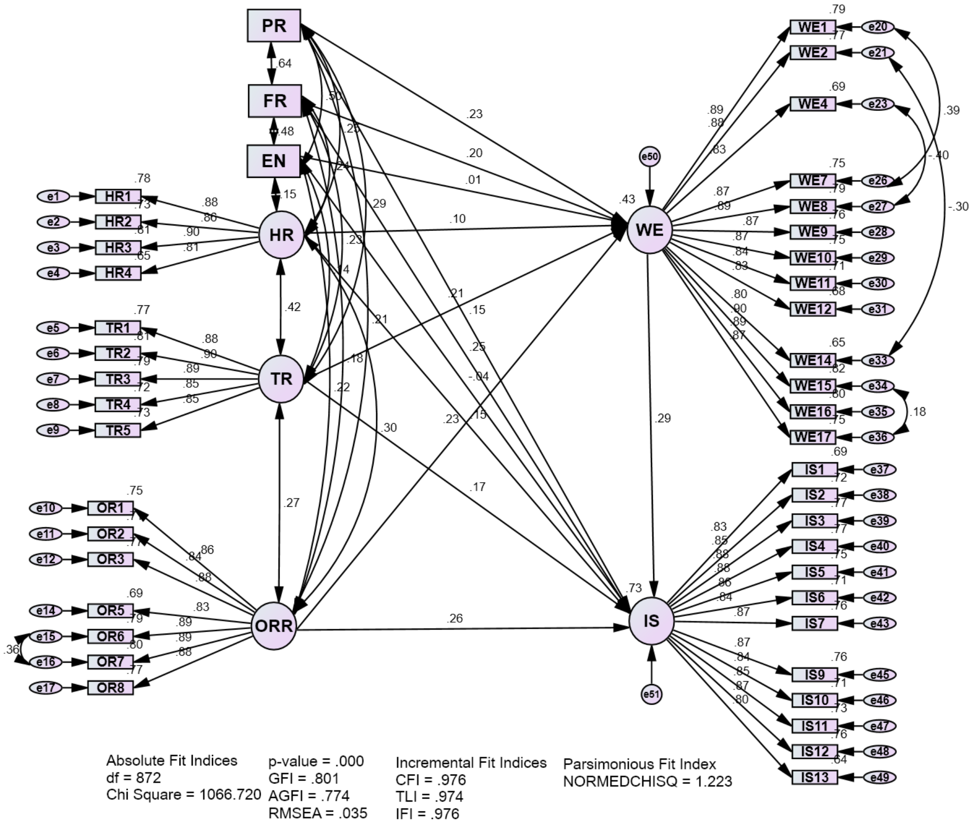

Fig 6. AMOS Graph of Structural Model

The analysis of goodness-of-fit indices suggests that the data fits adequately, as indicated by $\chi 2$ = 1066.720, df = 872, p-value = 0.000, GFI = 0.801, CFI = 0.976, TLI = 0.974, IFI = 0.976, RMSEA =0.035, and $\chi 2$/df= 1.223. Although the chi-square statistic is statistically significant, this is not considered unusual due to the large sample size (Bagozzi, Yi, and Phillips 1991).

The R2 values for Work Engagement (WE) and Industry Success (IS) were 0.43 and 0.73, respectively. This indicates that, for instance, 73 percent of the variations in Industry Success (IS) are explained by its predictors. The R^2 values meet the requirement for the 0.10 cut-off value (Quaddus and Hofmeyer 2007), indicating satisfactory results.

To test the hypothesized causal effects of the variables, the coefficient parameter estimates are examined, and the results of analyzing the hypothesized causal effects are presented in Table 6, which includes the path coefficients.

Table 6. Examining Results of Hypothesized Causal Effects

Path	Unstandardized Estimate		Standardised Estimate Beta (β)	critical ratio (c.r.)	P-value	Hypothesis Result
	Estimate	S.E.				
EN → WE	0.006	0.057	0.007	0.097	0.923	
PR → WE	0.154	0.054	0.230**	2.868	0.004	H1+) Supported
FR → WE	0.119	0.047	0.199*	2.565	0.01	H2+) Supported
HR → WE	0.15	0.105	0.1	1.435	0.151	H3+) Rejected
TR → WE	0.335	0.111	0.209**	3.01	0.003	H4+) Supported
OR → WE	0.352	0.099	0.234***	3.569	0.000	H5+) Supported
EN → IS	-0.023	0.028	-0.041	-0.818	0.413	
PR → IS	0.071	0.027	0.155**	2.624	0.009	H6+) Supported
FR → IS	0.101	0.023	0.25***	4.325	0.000	H7+) Supported
HR → IS	0.149	0.052	0.146**	2.871	0.004	H8+) Supported
TR → IS	0.189	0.056	0.174***	3.353	0.000	H9+) Supported
OR → IS	0.267	0.052	0.262***	5.15	0.000	H10+) Supported
WE → IS	0.197	0.04	0.29***	4.938	0.000	H11+) Supported

*p< 0.05 , **p< 0.01, ***p< 0.001; SE = Standardized Error

Table 15 indicates that, with the exception of one path from Human Resources (HR) to Work Engagement (WE) and two paths from the control variable Employee Number (EN) to Work Engagement (WE) and Industry Success (IS), all other paths were statistically significant with p-values less than the standardized level of 0.05. This suggests that hypotheses H1, H2, H4, H5, H6, H7, H8, H9, H10, and H11 were supported. However, the p-value for the effect of Human Resources (HR) on Work Engagement (WE) was above the standardized significant level of 0.05, indicating that hypothesis H3 was not supported.

Causal Effects Hypotheses

The standardized coefficients of the causal and mediation hypothesized effects in the structural model were illustrated in Figure 7.

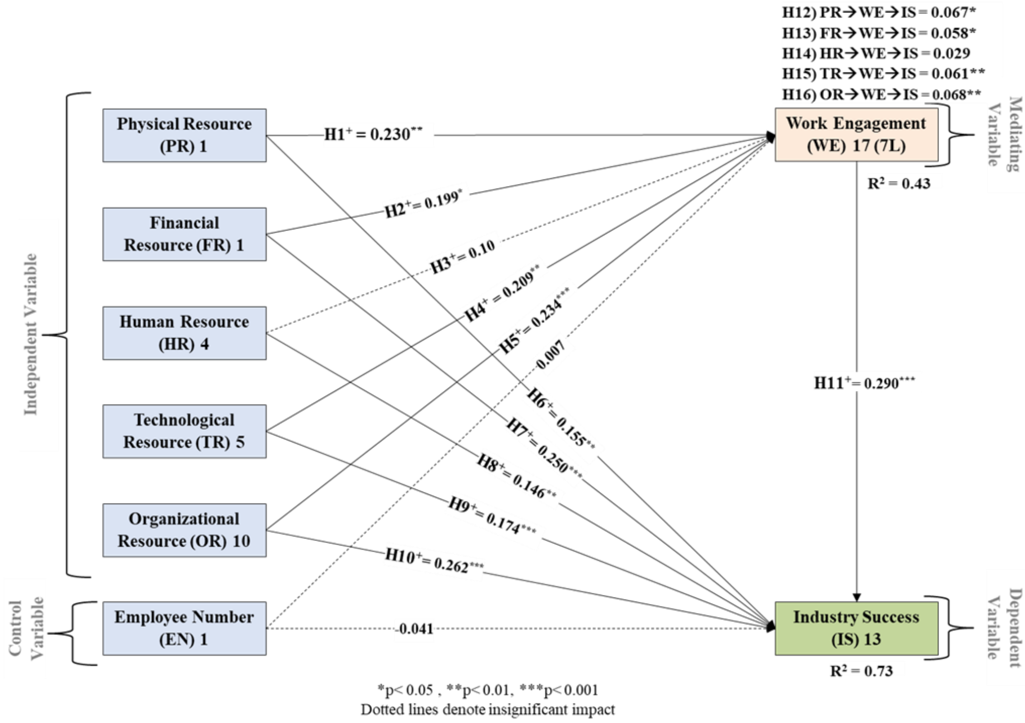

Fig 7. Results of the Examined Causal and Mediation Affects Hypotheses

The results of examining causal effect hypotheses indicated that Physical Resources (PR), Financial Resources (FR), Technological resources (TR), and Organizational Resources (OR) had significant positive effects on Work Engagement (WE). Furthermore, Physical Resources (PR), Financial Resources (FR), Human Resources (HR), Technological Resources (TR), Organizational Resources (OR) and Work Engagement (WE) had significant positive effects on Industry Success (IS). Therefore, hypothesis H1, H2, H4, H5, H6, H7, H8, H9, H10 and H11 were supported while hypothesis H3 was not supported.

The results of examining the mediation hypothesis indicated that Work Engagement (WE) partially mediates the effects of Physical Resources (PR), Financial Resources (FR), Technological Resources (TR), and Organizational Resources (OR) on Industry 4.0 Success (IS). Therefore, hypotheses H12, H13, H15, and H16 were supported while hypothesis H14 was not supported.

V. Conclusion

The study showed that business resources such as Physical Resources, Financial Resources, Human Resources Technological Resources, and Organizational Resources had a significant effect on the success of integrating and adapting Industry 4.0 in the Supply Chain Industry. The finding signifies the need to evaluate and improve an organization's existing tangible and intangible resources. Supply Chain organizations regardless of size should focus on evaluating and improving these resources to support their operation which promote performance excellence to become competitive in the industry and improve quality services for both suppliers and customers. The present study confirmed the role of business resources as critical success factors to the success of Industry 4.0 integration in Supply Chain Management organizations.

The study also shows how employees` work engagement plays a significant role in the success of adapting changes to improve operational excellence by integrating Industry 4.0 with the support of business resources, especially organizational and financial aspects. These results highlight the responsibilities of the upper management on strategical decision-making and goal settings as well as monetary support for the critical projects that enhance existing operations in terms of technology.

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Conflict of Interest:

The author declares that there was no relevant conflict of interest regarding this article.

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