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A Study on Labour Management Relationship in Selected Industries of Kachchh District of Gujarat: A Pilot Study

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Abstract

Industrial relations as a concept, emerged in the eighteenth century explains the relationship between employees and management, particularly a group of employees and management within the organizational setup. The quality of relationship between management and workforce plays a pivotal role in augmenting and enhancing workers' motivation level, their level of commitment towards work, their loyalty towards the organization and their inclination to pursue organization citizenship behaviour. This paper reports the results of the pilot study conducted to examine the quality of labour management relationship on the dimensions of empathy, bonding, trust, care, support, communication, work environment and transparency. The study is mainly aimed at evaluating the reliability and validity of the various constructs of a survey questionnaire to be used for an exhaustive study. The study is conducted for a sample of 100 respondents selected by non-random convenient sampling method. Analysis of pilot data followed two approaches; exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). The CFA was performed simultaneously while examining the convergent and discriminant validity using SPSS AMOS. This study proposes a model that can evaluate the quality of labour management relationship on various dimensions. The outcomes of the study makes noteworthy contribution in assessing the viability of the model to be used for measuring the quality of labour management relationship.

Keywords: Labour Management relationship, empathy, trust, Industrial relations, reliability, validity.

Introduction

The economic growth of a country depends upon its industrial growth. The growth of industry depends upon the industrial labour force. Labour, along with capital and the technological level, is considered a major factor in the neoclassical models of economic growth. These models are based on applying the Cobb-Douglass production function, which underlies the concept of economic growth. Labour force is an integral part of development process. Labour force is directly related with the principal components of demography i.e., fertility, mortality and, migration.

Industrial relations as a concept, emerged in the eighteenth century explains the relationship between employees and management, particularly a group of employees and management within the organizational setup. It is a multidisciplinary approach, which termed mostly as employment relations since the importance is on employment relations than the industry. Industrial relations, a most delicate and complex problems of modern industrial society which is characterised by rapid change, industrial unrest and conflicting ideologies in national and international spheres. It is a dynamic concept which depends upon the pattern of society, economic system and political set-up of a country and changes with the changing economic and social order. It is an art of living together for the purpose of production, productive efficiency, human well-being and industrial progress.

This employer-employee relationship thus built in order to establish and develop the industrial democracy within the organisation, to promote the discipline and morale of workers, enhance productivity and industrial prosperity, maintain industrial peace by solving employees' problems through mutual negotiations and share the profit of an enterprise achieved by the contribution of the workmen (Suseendar, C. 2016).

Over the last few years, the study of commitment and employee relationship management has advanced in many different directions. A variety of disciplines have adopted the topic as a theme in their research and these have offered fresh and significant insights. These recent advances include new approaches to both the conceptualization of employee relationship and commitment and the particular human resource practices intended to increase it. Emerging theory also suggests that work relationships play a role in meeting our social and developmental needs, and in so doing, affect our attitudes toward our jobs and organizations. Specifically, relational systems theory holds that employees have five different „relational needs, and are more likely to become committed to their organization and engaged in their work when they are embedded in a set of workplace relationships that meet these needs (Vijayakumar, T. A).

The quality of relationship between management and workforce plays a pivotal role in augmenting and enhancing workers' motivation level, their level of commitment towards work, their loyalty towards the organization and their inclination to pursue organization citizenship behavior. Employer can nurture the labor management relationship in multiple ways. The quality of labor management relationship can be evaluated and measured on the parameters of level of empathy between employer and employee, level of bonding in their relationship, the extent to which they trust each other, the way employer cares for employees, the level of support extended by the employer to employees, quality of work environment, level of transparency in their relationship etc.

In this study an attempt has been made to evaluate the quality of labour management relationship between the employer and employees in selected industries of Kachchh district of Gujarat. Kachchh has witnessed heightened industrial development with the establishment of large number of industrial units in Kutch especially after devastating earthquake of shook the district in year 2001. The dramatic industrial makeover of Kachchh is nothing short of a miracle. Kachchh today has become a growing economic and industrial hub in the state. Satija K. (2018) asserts that since 2001, after the massive earthquake in Kachchh district, the labour force participation rate has increased. The sources of this amplified labour force have been widely debated among academicians and policymakers. One of big argument is that the participation rate is augmented due to high demand of labours because of the new establishment of special economic zones, minerals industries and some subsidized benefits by the Gujarat government to the industrialist. Kachchh has a highly technically skilled and mobile labour force that can respond quickly to changing employment needs. This creates research interest to examine and evaluate the nature and quality of labor management relationship between employer and employees in selected industries of Kachchh district.

The pilot test is a crucial step in the scale development process (Churchill, 1979). This study reports the results of the pilot study conducted to examine the quality of labour management relationship on the dimensions of empathy, bonding, trust, care, support, communication, work environment and transparency. The study is mainly aimed at evaluating the reliability and validity of the various constructs of a survey questionnaire to be used for an exhaustive study. The study is conducted for a sample of 100 respondents selected by non-random convenient sampling method. Analysis of pilot data followed two approaches; exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). The CFA was performed simultaneously while examining the convergent and discriminant validity using SPSS AMOS. This study proposes a model that can evaluate the quality of labour management relationship on various dimensions. The outcomes of the study makes noteworthy contribution in assessing the viability of the model to be used for measuring the quality of labour management relationship.

Sources of Data

The two methods of collecting data for quantitative research are experiments and a survey. A survey is used for exploratory and descriptive study. The analysed quantitative data can be used to test and give reasons for specific relationships between variables, and produce models based on these relationships (Saunders et al., 2012). To meet the objectives of the study, a cross-sectional survey design is used to collect data. Cross-sectional design means data is collected from more than one case at a single point in order to collect quantifiable data and examine the patterns of associations with two or more variables (Bryman and Bell, 2011). There are several techniques used to conduct survey, such as structured observations and questionnaires. However, questionnaire is the common technique for survey, as it is suitable for descriptive and analytical research (Saunders et al., 2012). The questionnaire used for data collection consisted of 60 statements measuring the perceived quality of labour management relationship using a five-pint likert scale on the eight dimensions including empathy, bonding, trust, care, support, communication, work environment and transparency. The type of questionnaire can be determined using the method of communication (Churchill, 1995), divided into three types; self-administrated questionnaires, personal interviews, and telephone interviews (Blumberg et al., 2008). This study has used self-administered questionnaire physically filled by the respondents.

Research Methods

This study is mainly aimed at evaluating the reliability and validity of various constructs of the questionnaire to be used for a comprehensive study to be conducted in future. The study is further aimed at designing and assessing the model studying the quality of labour management relationship on various dimensions.

Reliability of research constructs has been evaluated by administering the Cronbach's alpha test. Reliability refers to the degree of consistency between the measurement items of the variable is stable at any point of time, and free of errors (Kline, 2005). Cronbach's alpha is the most widely-used measure to assess the reliability, which tests the internal consistency by applying the consistency to all variables (Hair et al., 2010). The validity of the instrument has been measured by assessing the convergent validity and discriminant validity. Construct validity is evaluated by assessing the convergent validity and the discriminant validity (Hair et al., 2003). The convergent validity means the indicators measuring certain construct share the high proportion of variance in common (Hair et al., 2010). The convergent validity is assessed by factor loading, average variance extracted and composite reliability. Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) are used to identify the factors contributing the labour management relationship and for designing and assessing the model studying labour management relationship.

Conceptual Model

Results and Discussion

• Reliability Assessment

Reliability refers to the degree of consistency between the measurement items of the variable is stable at any point of time, and free of errors (Kline, 2005). There are three ways of measuring reliability: test-retest, measuring the consistency at two different points; split-half; or Cronbach's alpha, examining the consistency of the whole questionnaire. Applying the split-half is easy, but the results depend on the method of splitting the data (Field, 2005); therefore, Cronbach's alpha is the most widely-used measure to assess the reliability, which tests the internal consistency by applying the consistency to all variables (Hair et al., 2010). It is useful at this stage to measure the reliability of the new data collected from the main survey sample using the purified sample items. Thus, eliminating the probability that the results of the pilot test are due to chance and reducing the errors from sampling items and external factors, such as personal factors, to develop content valid measures (Churchill, 1979). Also, testing the reliability of the scale is a preceding step before assessing the validity (Churchill, 1979; Hair et al., 2010).

Table 1: Reliability Assessment

Construct	Items	Mean	Standard Deviation	Minimum Inter-Item Correlation	Corrected Item Correlation	Cronbach's Alpha if item deleted
Empathy Cronbach's Alpha = 0.970	EMP1	3.79	1.122	0.755	0.869	0.966
	EMP2	3.62	1.126	0.807	0.911	0.963
	EMP3	3.58	1.232	0.798	0.891	0.964
	EMP4	3.52	1.275	0.755	0.890	0.964
	EMP5	3.55	1.266	0.793	0.898	0.964
	EMP6	3.7	1.193	0.782	0.893	0.964
	EMP7	3.66	1.157	0.779	0.873	0.965
Bonding Cronbach's Alpha = 0.973	BON1	3.94	1.205	0.662	0.861	0.970
	BON2	3.73	1.238	0.683	0.851	0.971
	BON3	3.76	1.046	0.662	0.747	0.972
	BON4	3.58	1.191	0.702	0.755	0.972
	BON5	3.48	1.141	0.683	0.837	0.971
	BON6	3.49	1.251	0.692	0.851	0.971
	BON7	3.560	1.217	0.686	0.822	0.971
	BON8	3.680	1.136	0.692	0.828	0.971
	BON9	3.670	1.190	0.683	0.827	0.971
	BON10	3.580	1.257	0.676	0.818	0.970
	BON11	3.800	1.223	0.685	0.816	0.971

	BON12	3.690	1.203	0.692	0.813	0.971
Trust Cronbach's Alpha = 0.942	TRU1	3.890	1.188	0.591	0.901	0.919
	TRU2	4.010	1.259	0.620	0.927	0.913
	TRU3	3.770	1.246	0.580	0.892	0.920
	TRU4	3.640	1.259	0.633	0.907	0.917
	TRU5	3.740	1.440	0.580	0.632	0.971
Care Cronbach's Alpha = 0.966	CAR1	4.020	1.163	0.766	0.890	0.960
	CAR2	3.770	1.100	0.792	0.921	0.958
	CAR3	3.580	1.241	0.786	0.912	0.958
	CAR4	3.470	1.123	0.735	0.847	0.963
	CAR5	3.440	1.183	0.722	0.871	0.961
	CAR6	3.650	1.192	0.735	0.869	0.961
	CAR7	3.630	1.186	0.722	0.844	0.963
Support Cronbach's Alpha = 0.961	SUP1	3.830	1.164	0.701	0.868	0.954
	SUP2	3.560	1.200	0.703	0.878	0.954
	SUP3	3.560	1.157	0.666	0.784	0.959
	SUP4	3.450	1.149	0.739	0.861	0.955
	SUP5	3.520	1.227	0.713	0.819	0.957
	SUP6	3.600	1.189	0.671	0.866	0.954
	SUP7	3.560	1.266	0.666	0.864	0.955
	SUP8	3.640	1.291	0.697	0.855	0.955
Communication Cronbach's Alpha = 0.961	COM1	3.140	1.255	0.674	0.874	0.958
	COM2	2.780	1.186	0.642	0.866	0.958
	COM3	2.780	1.284	0.637	0.830	0.960
	COM4	2.610	1.222	0.725	0.874	0.958
	COM5	2.750	1.266	0.605	0.801	0.961
	COM6	2.680	1.278	0.634	0.848	0.959
	COM7	2.720	1.248	0.711	0.870	0.958
	COM8	2.660	1.312	0.690	0.869	0.958
	COM9	2.550	1.329	0.605	0.788	0.962
Work Environment Cronbach's Alpha = 0.920	WOR1	3.420	1.112	0.521	0.812	0.900
	WOR2	3.240	1.074	0.533	0.855	0.894
	WOR3	3.290	1.113	0.494	0.596	0.929
	WOR4	3.030	1.068	0.562	0.794	0.903
	WOR5	3.080	1.061	0.528	0.812	0.901
	WOR6	2.980	1.223	0.494	0.782	0.905
Transparency Cronbach's Alpha = 0.784	TRA1	3.192	3.132	0.150	0.225	0.952
	TRA2	2.667	1.069	0.239	0.777	0.726
	TRA3	2.525	1.223	0.234	0.749	0.720
	TRA4	2.485	1.281	0.251	0.808	0.706
	TRA5	2.495	1.320	0.150	0.736	0.717
	TRA6	2.404	1.384	0.173	0.741	0.713

After collecting the pilot data, the items are purified by assessing their reliability (Churchill, 1979). The reliability is assessed by measuring Cronbach's alpha and item-to-total correlation.

The inter-item correlation measures the correlation among items. The thresholds for minimum inter-item correlation is 0.3 and corrected item correlation is 0.5 (Hair et al., 2010). Therefore, the items are considered reliable with the minimum inter-item correlation of more than 0.3 (Field, 2005), and value of Cronbach's alpha exceeding 0.7 (Hair et al., 2010; Kline, 2005). Therefore, the item is subject to deletion if it does not meet the cut-off point of 0.3 for minimum inter-item correlation or the value of alpha goes below the above specified levels, or if its deletion will increase the value of alpha (Field, 2005).

Accordingly, the results of the reliability test of the scale used in the survey are presented in Table 1. The empathy is measured by 7 items, all of them have minimum inter item correlation of more than threshold of 0.3. All seven items measuring the empathy are highly reliable with the Alpha value of more than 0.970. Bonding is measured by 12 items. All these 12items have minimum inter item correlation of more than threshold of 0.3 indicating high level of internal consistency. All the items measuring bonding are highly reliable with the alpha value of 0.973. The trust dimension of labour management relationship is measured by next five meeting the requirement of minimum inter item correlation of more than 0.3. The alpha value of 0.942 for the five items measuring trust indicates high level of reliability of scale. The next seven items represent care dimension of labour management relationship. All the items have minimum inter item correlation of more than the threshold of 0.3. All the seven items measuring the care are highly reliable with the Alpha value of more than 0.970. The level of perceived support is measured by 8 items; all these items meet the requirement of minimum inter item correlation of more than 0.3. The scale measuring support is highly reliable with the alpha value of 0.961. The next dimension of communication is measured by 9 items, all of them have minimum inter item correlation of more than threshold of 0.3. All seven items measuring the communication are highly reliable with the Alpha value of more than 0.961. Next six items measure the work environment. All these six items have minimum inter item correlation of more than the threshold of 0.3. The scale measuring communication is highly reliable with the alpha value of 0.920. The perceived level of transparency is measured by next six items. All these six items of minimum inter item correlation of less than 0.3, indicating lower-level internal consistency among the items measuring the perceived transparency. The alpha value for perceived level of transparency is 0.784. The results propose elimination of all the items measuring the transparency as the value of minimum inter item correlation for all these items falls below the threshold of 0.3.

• Exploratory Factor Analysis

actor analysis (FA) is a technique used for identifying variables and suggests dimensions (Churchill, 1979; Field, 2005). It identifies the inter-correlation among the measurement items and groups them in sets known as factors; then, by using theory, these factors will correspond to a concept (Hair et al., 2010). It is used to reduce data and classify variables into a set of factors by identifying the underlying structure among variables (Hair et al, 2010; Pallant, 2010). The two main approaches of factor analysis, they are Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) (Pallant, 2010).

Exploratory factor analysis (EFA) is one of a family of multivariate statistical methods that attempts to identify the smallest number of hypothetical constructs (also known as factors, dimensions, latent variables, synthetic variables, or internal attributes) that can parsimoniously explain the covariation observed among a set of measured variables (also called observed variables, manifest variables, effect indicators, reflective indicators, or surface attributes). That is, to identify the common factors that explain the order and structure among measured variables. In the social and behavioral sciences, factors are assumed to be unobservable characteristics of people, which are manifested in differences in the scores attained by those people on the measured variables (Tucker & MacCallum, 1997). The EFA is conducted in three steps: suitability of data, factor extraction and factor rotation.

The suitability of data is determined by the sample size and the strength of the relationships between items (Pallant, 2010). Tabachnick and Fidell (2006) suggest that the sample size of 300 cases at least is good for factor analysis. Others suggest that it is not the overall sample size but the ratio between participants and items (Pallant, 2010). Field (2005) suggests a ratio of at least 10:1 between the participants and items, while others suggest only five cases for each item (Hair et al, 2010; Palllant, 2010). The factorability of data is measured by two statistical measures: Bartlett's test of sphericity and Kaisr-Meyer-Olkin (KMO) (Pallant, 2010).

Table 2: EFA-KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.930
Bartlett's Test of Sphericity	Approx. Chi-Square	7586.117
	Df	1431
	Sig.	.000

Two statistical tests are used to assess the factorability of the data: Bartlett's test of sphericity and Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (Pallant, 2010, p.183). Bartlett's test of sphericity, a test of significance of the correlation matrix, with significance level of < 0.05, indicates the existence of sufficient correlations among variables. KMO is the ratio between the sum squared of correlations and the summation of sum squared correlations and sum of squared partial correlations. The appropriateness of FA requires a minimum value of 0.6 (Tabachnick and Fidell, 2006). The results of KMO and Bartlett's test are illustrated in above table, indicating the significance of Bartlett's test ($p< 0.05$) and the exceeding of KMO index above the minimum value of 0.6; thereby, suggesting the factorability of data.

The second step is the factor extraction, determining the number of factors that describe the structure of the variables in the analysis (Hair et al, 2010). There are two methods of factor extraction: component analysis and common factor analysis. The component analysis or the principal component analysis (PCA) "considers the total variance and derives factors that contain small proportions of unique variance and in some instances error variance" (Hair et al, 2010. p.107). Whereas, the common analysis "assuming that both the unique and error variance are not interest in defining the structure of the variables" (Hair et al, 2010, p.107). The current study depends on the principal component analysis, commonly-used method (Pallant, 2010), and appropriate for data reduction (Hair et al, 2010).

Table 3: EFA Total Variance Extracted

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	33.241	61.558	61.558	33.241	61.558	61.558	25.943	48.043	48.043
2	5.937	10.994	72.552	5.937	10.994	72.552	8.789	16.277	64.320
3	1.792	3.318	75.870	1.792	3.318	75.870	4.752	8.800	73.119
4	1.351	2.502	78.372	1.351	2.502	78.372	2.498	4.627	77.746
5	1.112	2.058	80.431	1.112	2.058	80.431	1.450	2.685	80.431

In order to determine the factor extraction method, principle component analysis (PCA) was used; this is most common and considered by the majority to be the most suitable approach for summarising the data (Field, 2005; Hair et al., 2010). The factors are extracted based on Kaiser's criterion or eigenvalue; factors of eigenvalue of one or more should be retained. Scree test, a graphical presentation "plotting the latent roots against the number of factors in their order of extraction" (Hair et al., 2010, p. 110), is also used to identify the number of factors to be extracted. Using scree plot variables above the inflection point should be included for further investigation. Hair et al. (2010) suggest that the factors included should explain at least 60% of the variance. For the current study, five factors are extracted with eigenvalue of more than one and explaining 80% of the total variance, as shown in Table 3.

The third step is that of factor rotation; rotation is usually determined after the method of factor extraction (Tabachnick and Fidell, 2006). The rotation method used is in this study is the orthogonal method; the most commonly-used approach suitable for data reduction (Hair et al., 2010; Tabachnick and Fidell, 2006). The VARIMAX orthogonal technique is proven to be a successful analytic approach to obtain an orthogonal rotation of factors (Hair et al., 2010).

Table 4: EFA Rotated Component Matrix[a]

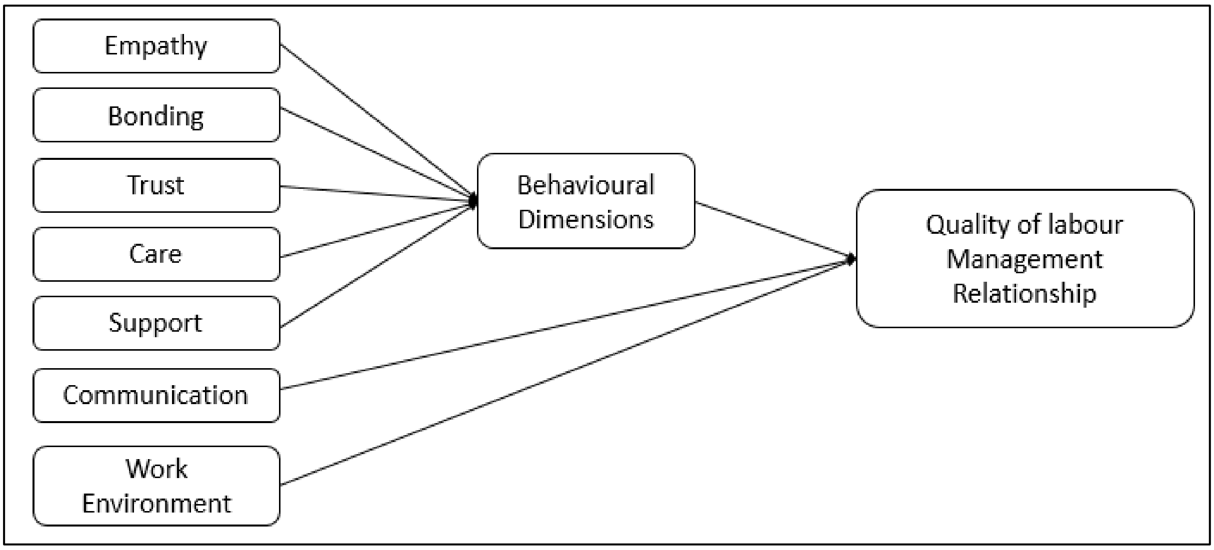
Rotated Component Matrix[a]					
	Component				
	1	2	3	4	5
EMP1	0.861				
EMP2	0.882				
EMP3	0.832				
EMP4	0.831				
EMP5	0.863				
EMP6	0.863				
EMP7	0.810				
BON1	0.846				
BON2	0.825				
BON3	0.645				
BON4	0.772				
BON5	0.796				
BON6	0.767				
BON7	0.816				
BON8	0.821				
BON9	0.770				
BON10	0.849				

BON11	0.718				
BON12	0.748				
TRU1	0.895				
TRU2	0.893				
TRU3	0.877				
TRU4	0.860				
TRU5	0.524			0.689	
CAR1	0.821				
CAR2	0.805				
CAR3	0.795				
CAR4	0.745				
CAR5	0.782				
CAR6	0.784				
CAR7	0.828				
SUP1	0.797				
SUP2	0.787				
SUP3	0.650				
SUP4	0.745				
SUP5	0.658				
SUP6	0.842				
SUP7	0.799				
SUP8	0.778				
COM1		0.863			
COM2		0.861			
COM3		0.844			
COM4		0.884			
COM5		0.818			
COM6		0.801			
COM7		0.829			
COM8		0.847			
COM9		0.767			
WOR1			0.718		
WOR2			0.743		
WOR3			0.512		
WOR4			0.668		
WOR5			0.677		
WOR6			0.671		
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.					
a. Rotation converged in 7 iterations.					

In the assessment of factor loading, that of more than ±0.40 is accepted, given the sample size. The amount of variance accounted for the factor by each variable; communality should exceed the value of 0.5. A variable with communality lower than 0.5 should be omitted as it has insufficient explanation (Hair et al., 2010). Field (2005) accordingly the variables with factor othan one factor (Field, 2005). Accordingly, the only variable to be omitted is TRU5 as it is cross loaded on more than one factor loading of more than 0.5. After the deletion of the TRU5 all the items of the current study are with acceptable communality values, ranging from 0.622 to 0.891. The number of factors extracted is three as indicated in Table 4.

The first five dimensions of labour management relationship i.e. empathy, bonding, trust, care and support are all loaded on first factor which can be named as 'behavioural dimensions. All item's representing communication is loaded on second factor separately and items representing work environment are loaded on third factor separately. Based on the loading of various items on different factor, the relationship existing between various dimensions and quality of labour management relationship can be presented in the form of following conceptual model.

Fig.1: Quality of Labour Management Relationship



• Confirmatory Factor Analysis

Confirmatory factor analysis (CFA) is a multivariate statistical procedure that is used to test how well the measured variables represent the number of constructs. In confirmatory factor analysis (CFA), researchers can specify the number of factors required in the data and which measured variable is related to which latent variable. Confirmatory factor analysis (CFA) is a tool that is used to confirm or reject the measurement theory.

Most uses of confirmatory factor analysis are, in actually, partly exploratory and partly confirmatory in that the resultant model is derived in part from theory and in part from a respecification based on analysis of model fit (Gerbing and Hamilton, 1996). In general, proponents of CFA believes that researchers need to have strong theory underlying their measurement model before analysing the data (Williams, 1995). CFA is often used in in data analysis to examine the expected causal connections between variables. Exploratory Factor Analysis (EFA) is often considered to be more appropriate than CFA in the early stages of scale development because CFA does not show how well your items load on the no hypothesized factors (Kelloway, 1995).

O The measurement Model

The validity of the measurement model depends on the assessment of the model's goodness of fit and the assessment of validity. Therefore, the assessment of measurement-model validity was conducted in two steps: goodness of fit and validity evaluation.

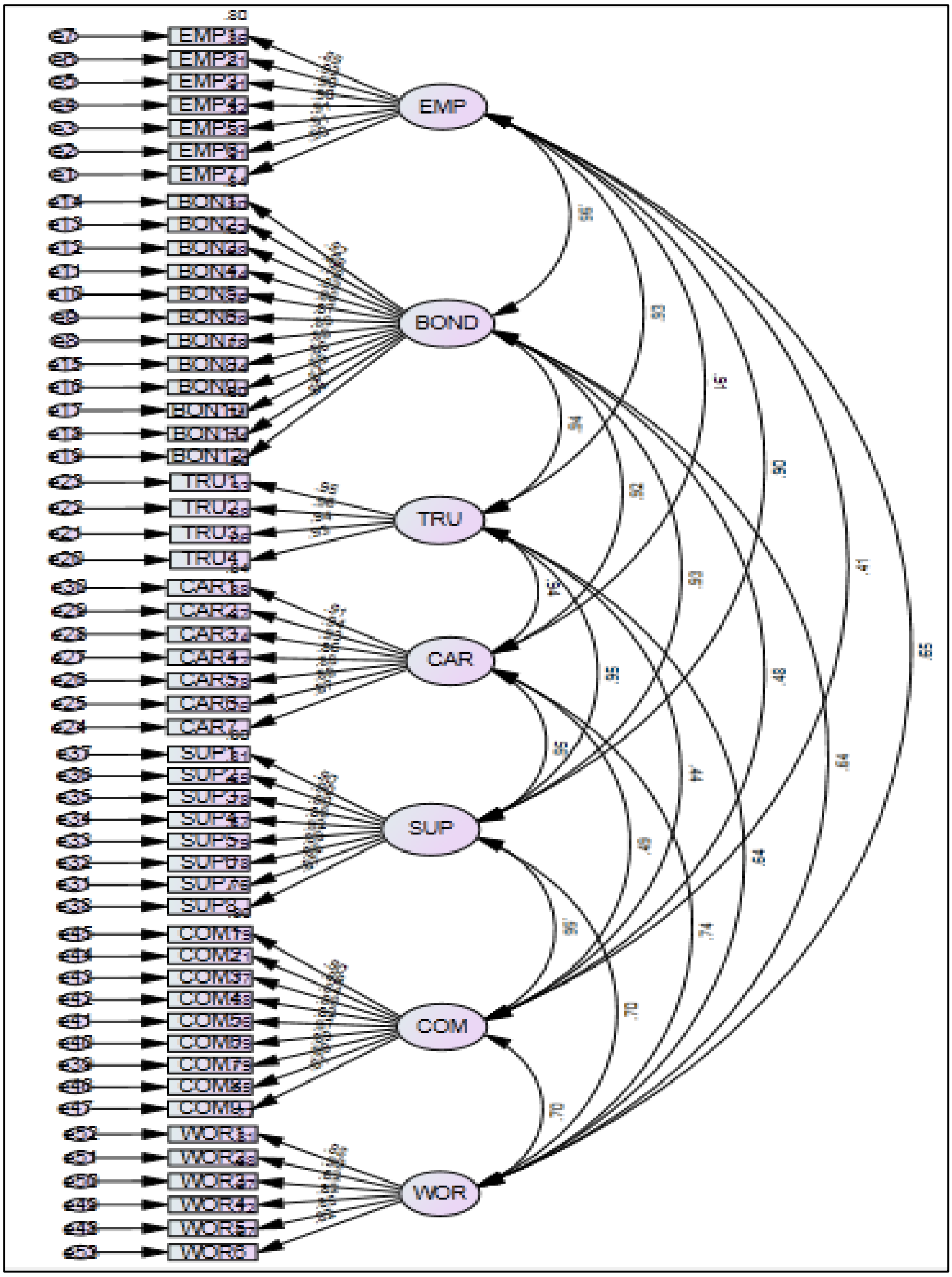


Fig. 2 CFA Measurement Model

The first run of the model consist of 7 latent variables explained by 53 observed variables representing labour management relationship. The model correlates each latent variable with other latent variables.

O **Fitment of the model**

The first run of the measurement is depicted in Figure 2, with initial results yielding acceptable standardised loading of all factors above the threshold of 0.5, as recommended by Bagozzi and Li (1988) and Hair et al. (2010).

Table 5: Model Fitment Indices

Fit Indices	Authors	Recommended Value	Actual Value
X^2	Meyers et al., 2005	P Value > 0.05	2568.844, (P value: 0.000)
CMIN/DF	Marsh & Hocevar, 1985	< 5.0	1.970
	Bentler,1990	< 5.0 Reported if n>200	
	Hair et al., 2009	< 3.0 Good; <5.0 sometimes permissible	
CFI	Bentler,1990	> 0.9	0.838
	Hatcher, 1994	> 0.9	
RMSEA	Byrne,2001	< 0.08	0.099
	Hu & Betler,1999	< 0.05	
	Meyers et al., 2005	< 0.08	
SRMR	Meyers et al., 2005	< 0.08	0.08
NFI	Bentler & Bonett, 1980	> 0.9	0.720
RFI	Meyers et al., 2005	> 0.9	0.704
IFI	Meyers et al., 2005	> 0.9	0.839
PNFI	Meyers et al., 2005	> 0.5	0.682
PCFI	Meyers et al., 2005	> 0.5	0.793

The values of Chi-Square (X2=2568.84), normed chi-square (CMIN/DF=1.970), Comparative fit index (CFI=0.838), root mean square error of approximation (RMSEA=0.099), Normed fit index (NFI=0.720), Relative Fit Index (RFI=0.704), Incremental Fit Index (IFI=0.839), Parsimony Normed Fit Index (PNFI=0.682), Parsimony Comparative Fit Index (PCFI=0.793) Standardized Root Mean Squared Residual (SRMR=0.08) are depicted in above table. It is difficult to achieve the statistical insignificance of the model with a large sample size and large number of observed variables. This potential problem of χ^2-test increases the likelihood of rejecting the model (Bagozzi and Yi, 1988). The values of RMSEA, ranging from 0.05 and 0.08, indicate a good fit (Hair et al., 2010). The CFI is the improved version of normed fit index (NFI); while IFI is the improved version of non-normed fit index (NNFI) overcoming the variability of NNFI with values ranging from 0-1 (Tabachnick and Fidell, 2008). The rule indicates that values of IFI greater than 0.9 indicate good fit (Bagozzi and Yi, 1988; Hair et al., 2010; Kline, 2005). Moreover, Lacobucci (2010) states that if the model IFI (CFI, IFI, or TLI) are greater than 0.9, this is evidence of the acceptable fit of the model. The SRMR is a badness of fit index with lower values that will enhance the fit of the model and the high factor loadings. It is also less sensitive to the violations of normality assumptions and sample size, but places great sensitivity on misspecification of the model. SRMR values close to 0.09 or less represents a reasonable fit. Values SRMR, CMIN/DF, PNFI and PCFI indicates good fit of the model whereas other fit indices indicates relatively poor fit of the model to the data.

O **Validity Assessment**

One of the main objectives of using CFA is to assess the construct validity; the ability of the measurement items to reflect the latent constructs (Hair et al., 2010). Construct validity is evaluated by assessing the convergent validity and the discriminant validity (Hair et al., 2003). The convergent validity means the indicators measuring certain construct share the high proportion of variance in common (Hair et al., 2010). The convergent validity is assessed by factor loading, average variance extracted and composite reliability.

Factor loading – as a rule, the significant factor should not be less than 0.5. The results indicate that all the standardised loading estimates are higher than 0.5, with the lowest value equalling 0.606. All the critical ratios (t-value) were significant above the threshold of ± 1.96 ($p < 0.001$).

Average variance extracted (AVE) is calculated by the mean variance extracted from factor loading using this equation. The AVE represents the average amount of variance that a construct explains in its indicator variables relative to the overall variance of its indicators. The rule of thumb indicates that good AVE starts from the value of 0.5 (Hair et al., 2010).

$$\text{AVE} = \frac{\sum_{i=1}^{n} Li^2}{n}$$

Where,

L: Standardized Factor loadings

i: the number of items

Construct reliability (CR) or composite reliability (Bagozzi and Yi, 1988) measure internal consistency. There are many alternatives to compute the construct reliability; there are slight differences between different reliability coefficients. The CR is computed using SEM from the squared sum of factor loadings per construct and the sum of the error variance terms for constructs, by using this equation (Hair et al., 2010). Reliability of 0.7 or more is considered good; however, a construct of 0.6 reliability value can also be accepted if the other constructs in the model have good reliability (Hair et al., 2009). Bagozzi and Yi (1988) consider composite reliability to be good, starting from the value of 0.6.

$$\text{CR} = \frac{(\sum_{i=1}^{n} Li)^2}{(\sum_{i=1}^{n} Li)^2 + (\sum_{i=1}^{n} ei)}$$

Where,

L: the standardised factor loading

i: the number of items

e: error variance

Table 6: Construct and Discriminant Validity

Validity Analysis											
	CR	**AVE**	**MSV**	**MaxR(H)**	**EMP**	**BOND**	**TRU**	**CAR**	**SUP**	**COM**	**WOR**
EMP	0.97	0.82	0.895	0.97	**0.906**						
BOND	0.973	0.75	0.895	0.975	0.946***	**0.866**					
TRU	0.971	0.895	0.893	0.973	0.930***	0.941***	**0.946**				
CAR	0.967	0.805	0.91	0.97	0.905***	0.915***	0.940***	**0.897**			
SUP	0.961	0.756	0.91	0.963	0.898***	0.929***	0.945***	0.954***	**0.869**		
COM	0.964	0.748	0.494	0.966	0.406***	0.480***	0.439***	0.488***	0.561***	**0.865**	
WOR	0.924	0.671	0.547	0.937	0.645***	0.637***	0.643***	0.740***	0.703***	0.703***	**0.819**

Reliability: The reliability of each constructs is above 0.7, ranging from 0.96 to 0.97, indicating good reliability. The value of composite reliability indicates higher level of internal consistency among the observed variables measuring the constructs.

Convergent Validity: The results presented in the previous table validate the convergent validity of the constructs in the measurement model. The standardised factor loading is above the minimum of 0.5, with significant t-values. Value of average variance extracted is above 0.5 for all constructs, suggesting good convergence. Also CR value of each construct is more than the AVE value of the construct.

Discriminant Validity: The extent that constructs are distinct and the measures of each construct are not correlated to other constructs measures (Hair et al., 2003). Discriminant Validity has been assessed by comparing AVE value with MSV (Maximum Shared Variance) value and by Fornell Larcker Criterion. In their widely cited article on tests to evaluate structural equation models, Fornell and Larcker (1981) suggest that discriminant validity is established if a latent variable accounts for more variance in its associated indicator variables than it shares with other constructs in the same model. To satisfy this requirement, each construct's average variance extracted (AVE) must be compared with its squared correlations with other constructs in the model. The result in above table indicates relatively poor level of discriminant validity among the latent variables.

• Structural Equation Modelling

SEM is a multivariate technique that combines the aspects of factor analysis and regression to examine the interrelationships among constructs (Hair et al, 2010). It has the ability to the multiple interrelate dependence relationships and examine the impact of several independent variables; with different impacts on a dependent variable. The dependent variable can be independent in another equation; therefore, it examines a series of multiple and interrelated dependence relationships (Hair et al, 2010). In defining the model, SEM tests the theory and the hypotheses (Tabachnick and Fidell, 2006). Therefore, it can investigate the relationships between the set of brand knowledge factors and brand experience, independent variables on brand preference as a dependent. Then, it measures the impact of brand preference as an independent factor on brand repurchases intention.

SEM improves the statistical estimation of relationships between constructs by incorporating latent variables, which reduces the measurement errors (Hair et al, 2010). The statistical software used to perform the structural equation modelling is the AMOS. Therefore, the measurement and the structure are presented using the graphical interface.

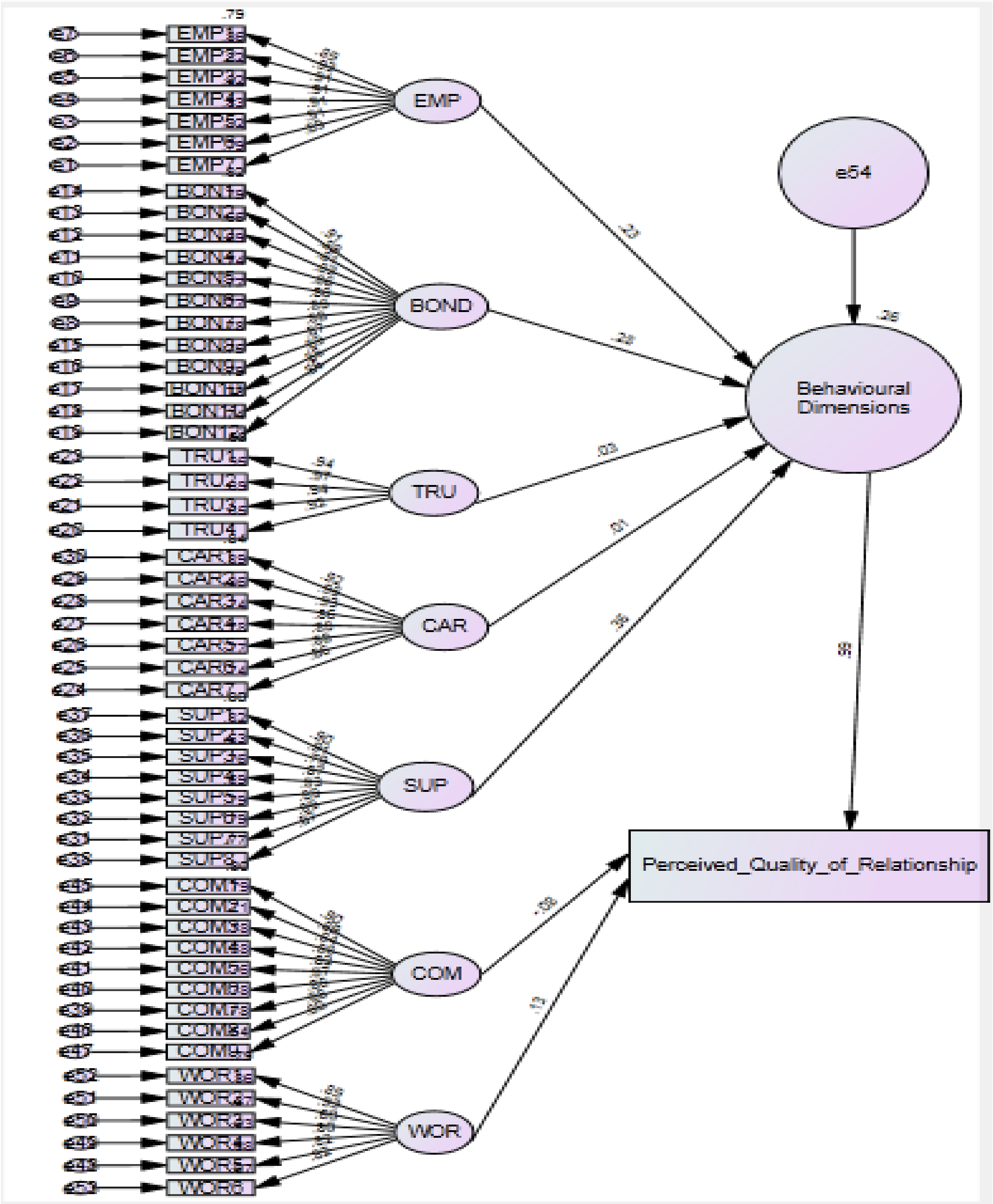


Fig.3 Structural Equation Model

Based on the conceptual model designed earlier on the basis of the result of EFA, Structural Equation Modelling (SEM) is run as indicated in Fig. 3. Empathy, bonding, trust, care and support represents behavioural dimensions, a latent variable. These five dimensions of labour management relationship explain 26% of variance of behavioural dimensions. The behavioural dimensions explain 99% of the variance of perceived quality of labour management relationship. The labour management relationship is mainly influenced by the behavioural aspects.

Conclusion

This study reports the results of the pilot study conducted to examine the quality of labour management relationship on the dimensions of empathy, bonding, trust, care, support, communication, work environment and transparency. The study is mainly aimed at evaluating the reliability and validity of the various constructs of a survey questionnaire to be used for an exhaustive study. The results of the reliability assessment indicated that scale measuring all the constructs of labour management relationship except 'transparency' are highly reliable with high level of internal consistency among the items measuring the constructs. The study suggests to drop all the items measuring transparency. The results of exploratory factor analysis revealed that, the first five constructs of labour management relationship i.e. empathy, bonding, trust, care and support are all loaded on first factor which can be named as 'behavioural dimensions. Communication and work environment are separately loaded. Outcomes of EFA suggest to drop TRU5, as it is cross loaded on more than one factor with high degree of factor loading. The result of validity assessment indicated that all the constructs have high level of convergent validity and poorly acceptable level of discriminant validity. The Confirmatory Factor Analysis (CFA) model is fitting the data well. The study proposes a model explaining the interrelationship among various dimensions of labour management relationship. Variables making up the research model in this study were gathered from related literature. The result of Structural Equation Modelling (SEM) indicated that majority of variance of perceived quality of labour management relationship is explained by behavioural dimensions represented by empathy, bonding, trust, care and support. Overall, the research model has been validated through the examination of reliability and validity of constructs. Some of the items may be discarded in the actual survey while some may be refined to improve the discriminant validity of the final questionnaire.

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