Journal of Research Administration
Society of Research Administrators International

DIMENSIONS OF WORK LIFE BALANCE – MEASUREMENT MODEL TESTING

Dr. Swapna.R

Associate Professor of Commerce, Maharaja's College(Govt.Autonomous), Ernakulam

Abstract

Though work life balance has been an area where serious discussions are happening, due to the multiple roles of women and increase in the number of dual earner families, it is confined to the implications on the society and individual outcomes. Moreover, most of the studies have been conducted in the western scenario where organisations have implemented programmes that promote work life balance way before such studies saw light in India. The problems existing in the sector and the unexplored constructs in the sphere of WLB have prompted this research which is an attempt to identify the dimensions of work life balance of women employees and to develop a model using data from a subset of Kochi's IT companies in order to better understand the dimensions of work-life balance. The results of the study would help the women employed in the IT sector of the metropolitan city of Kochi as well as the industry practitioners the significance of the various dimensions of work life balance and the impact of work and family domain variables on work life imbalance. The study relies on the fundamental concepts drawn from literature relating to previous research works on the antecedents and outcomes work life balance, and understands the concept as a function of demands, Work Involvement(WI), Family Involvement (FI)Work-family conflict(WFC),Family-work conflict(FWC) Quality of work life (QWL) and Quality of family life (QFL) that could lead to Satisfaction with work life balance(SWLB) and Improved effectiveness at work (IEW)

Key words- work life balance, WorkInvolvement, Family Involvement, Work family conflict, Family work conflict,Quality of work life, Quality of Family life, Satisfaction with work life balance, Improved work effectiveness, IT sector.

Introduction

Since the advent of globalization, the job characteristics and employment in general has witnessed remarkable changes. Organizations are operating in an increasingly competitive environment and job has become more demanding, still people in the job are finding new means to connect with the world to be stress free and stay happy. They no longer wish to stay in a job that does not give them space to relate with their family and outside world. Similarly, the trends in the socio-cultural and economic sphere have contributed to significant changes in the demographics of the country witnessed by the number of working women in the work force. The shift in the perception of women roles which were traditionally confined to household chores and child rearing and men as breadwinners to women as experts in multitasking capable of shouldering family responsibilities without compromising the demands on the work front has paved way to serious deliberations and discussions on the topic of work life balance.

© 2024 The Authors

Information and Technology which is considered as the sunshine sector in India is responsible for the increased rate in employment and GDP besides being applauded for its gender inclusivity. Kerala is an emerging destination for IT and ITeS industry with powerful cost advantages. With a dense cluster of Science and Technology personnel in India and the work force having the shortest learning curve, Kerala is a fertile ground for growth of IT sector. Two cities in Kerala – Thiruvananthapuram and Kochi have been ranked as the challenging IT or ITeS destination by NASSCOM. IT hubs at Technopark in Thiruvananthapuram and Infopark in Kochi are the sought after destinations in Kerala which is supported by world class infrastructure backed by synergic research and innovation.

Research Methodology

The study primarily aimed to propose a conceptual model and examine the inter-relationship between the proposed constructs of interest. Hence, the study followed a descriptive research design, where the study collected data through a structured questionnaire. The questionnaire covers questions ranging from various work and family profile characteristics, demographic questions, and also questions covering involvement (work and family), inter-role conflict, quality of life, satisfaction and work effectiveness. To collect the responses, the study conducted a sample survey among 513 women IT professionals in Kochi, in the state of Kerala. During the survey, these women IT professionals were identified and later selected through random sampling technique.

Objectives of the study:-.

1. To propose a conceptual model explaining the relationship of involvement (work and family), quality of life (work and family), inter-role conflict, satisfaction with work life balance and work effectiveness of women employees in the IT sector of Kochi.

2. To empirically validate the proposed conceptual model and examine:

- The intervening effect of quality of life (work and life) between involvement and satisfaction with work life balance.
- The intervening effect of inter-role conflict (work family and family work) between involvement and satisfaction with work life balance.
- To examine the impact of satisfaction with work life balance on improved work effectiveness.

Discussions

Check of Normality : It is recommended that the multivariate normality of the data can be detected by inspecting and confirming univariate normality and linearity of the study variables (Gnanedesikan, 1977). Hence, in this study, as part of assumption checks, the researcher analysed

the statistical test for normality using Kolmogorov-Smirnov test and later analysed the empirical measures that reflected the shape of the sampling distribution by analysing the skewness and kurtosis values of the study variables. As part of this, the study followed the rule of thumb, that if either estimated *Z* value of the study variables exceeds the specified critical value (±4 at 0.05 level of significance), the distribution is considered to be non-normal in terms of that characteristic or that variable (See: Hair et al., 2005). Among all the incorporated metric variables, the check of normality reported that some of the items deviate from normality in the overall normality test (*p*-value <0.001). However, some of the incorporated study variables had shape characteristics significantly comparable to the normal curve (Z-skewness = 3.69 and 3.63 and Z-kurtosis = -0.45 and -1.92, respectively). The overall tests provided no insights into which transformations might be most appropriate, hence, in the study, the Box-Cox transformation was applied to the data to improve or achieve the normality of the sample data. The analysis supported that the tests of normality were significant in some cases it is non-significant, and in some other cases reported or markedly improved to acceptable levels. Although, from the check the researcher found that some variables still have severely non- normal distributions, SEM techniques can be applied to generate generally accurate MLE parameter estimates (Kline, 2004). Mardia test was also performed to check the multivariate normality of the selected study items and the test result was found to be insignificant.(Mardia test value=2.15., p>0.05.) Hence the study inferred that the data followed multivariate normality. Next, the study checked whether there exists sufficient correlation between the study items. From the analysis, it was reported that the variables were sufficiently inter-correlated to produce representative factors with substantial linear associations. The correlation matrix revealed that in all cases the correlations are significant at the 0.05 level.

Check of Reliability : Since in this study the researcher used questionnaire based surveys to collect data with regard to the latent variables considered in the study, it is decided to confirm the reliability and validity of the survey instrument or scales used before the test of hypotheses proposed in the study. This stage of confirmation is required, because in order to adequately measure these variables, associated survey instruments must have sufficient reliability and validity (Hair et al., 2010). This was assured through the selection of instruments demonstrating a solid track record of acceptable reliability and construct level validity. Hence, in the first stage of reliability and validity confirmation, reliability checks using the construct wise Cronbach's alphas and construct wise validity checks using confirmatory factor analysis were computed for this study. This stage of analysis helped the researcher to assure data were repeatable or free from random error and gave a confirmation to the fact that the scales used to measure the latent variables measures the construct that the researcher intended to measure. According to Trochim (2006), reliability of the scale explains or refers the fact that the measuring instrument is free from random error or shows the consistency of measurement if repeated. Trochim (2006) noted that reliability was not measured but estimated. In two ways the researchers can perform reliability of the scale measures, such as test/retest reliability and internal consistency reliability. Test/retest reliability denote that giving the test a second time to the same group under the same conditions should yield the same or consistent measurement scores. In most of the cases, test/retest for the population was

© 2024 The Authors

not feasible, because the survey was given only one time and also testing and retesting is considered to be more time consuming. The second type, internal consistency reliability can be estimated by Cronbach's alpha (also called as coefficient alpha: Cronbach, 1954). It is recommended that the Cronbach's alpha was a type of reliability coefficient that represents the measurement of internal consistency reliability of the scale measure (Kline, 2011). In support with this, Kline (2010) stated that Cronbach's alpha measures internal consistency of the construct items within a group of items. It is also reported that the low level of internal consistency of the scale measures may mean that the total score was not the best unit of measurement for measuring the dimension or the latent construct. In studies, when the number of items increases in relation to the construct measure, internal consistency reliability associated with the same may increase (Kline, 2011). In addition, it is also reported that higher level of average (mean) inter-item correlation scores of the items within the scale also shows better internal consistency reliability (Kline, 2011). In the similar lines, Green and Salkind (2008) reported that the coefficient alpha of the construct or the scale measures should be compulsorily reported to show the internal consistency of the items, because this shows that there exists consistency among the items and hence, these items together measure the same dimensions. A higher level of reported coefficient alpha indicates a greater level of consistency of the scale. If all items are perfectly equivalent or inter-related, the only measurement error was the unreliable error of responding (Green &Salkind, 2008). In this study, the reliability of the study coefficients were estimated for the scales, such as job involvement, family involvement, quality of work life, quality of family life, work family conflict, family work conflict, satisfaction with work life balance, improvement in work effectiveness. In all cases, the internal consistency reliability using Crobach's coefficient alpha values were above the suggested cut-off of 0.50, supported that the scales used to measure these dimensions are free from random error or internally consistent (See Table 5.3).

Table 1: Reliability Coefficients

Dimensions	Cronbach's alpha
Work Involvement	0.80
Family Involvement	0.76
Quality of Work Life	0.79
Quality of Family Life	0.81
Work Family Conflict	0.88
Family Work Conflict	0.70
Satisfaction with Work Life Balance	0.76
Improved Effectiveness at Work	0.81

EFA

© 2024 The Authors

The descriptive statistics presented in the previous section of the present study provided a profile and basic description of the items considered in the study, and a brief description of the data set, which paved the pathway or guidance for conducting the multivariate analyses (Malhotra, 2007). In this section, the researcher details the Exploratory Factor Analyses (EFAs) conducted using the measurement items. Exploratory factor analysis was performed to identify the underlying dimensional structure of the measurement items, and also to test whether the a priori dimensional structure for the selected scales or sub-scales is consistent with the structure obtained with the particular set of measures (Stewart, 1981).

EFA is a useful analytic tool used by the researchers or data analysts to empirically understand the number of constructs that underlie a set of items considered in the study, or to condense information or the study items so that a representative number of variables accounts for the variation in the data, and to define the substantive content or meaning of a set of factors that accounts for the maximum variation in a larger set of items incorporated the proposed study (DeVellis, 1991). The several methods for performing an exploratory factor analysis was proposed, which include principal components, principal axis factoring, alpha factor analysis, maximum likelihood method, etc. (Stewart, 1981). In this, PCA with orthogonal rotation is the most popular and frequently used factoring method. Hence, in the current study, the researcher used series of EFA using PCA.

As part of this EFA, to select the number of factors or to extract the factors the eigenvalue criterion and the scree test are often used as the popular criteria (DeVellis, 1991; Hinkin, 1995). In this, the eigenvalue rule used is that the researcher retains only those factors that explain more variance than the average amount explained by an original item (DeVellis, 1991). The use of the scree plot involves plotting the eigenvalues of the factors in descending order of magnitude against their factor numbers and identifying where the eigenvalues level off. For identifying the number of factors, this method directs the investigator for the visual inspection of the inflection point between a steep slope and the levelling of the eigenvalues, which in turn indicates the number of meaningful factors. Generally, while analysing the number of factors, both eigenvalues and the scree test are based on the magnitude of factors' eigenvalues, which indicates how much variance the extracted factors can explain; however, DeVellis (1991) recommended that the use of these two methods to identify the number of factors during the investigation is far from perfect, and experience of the investigator is an invaluable guide to determine the number of factors. Hence, in the current study, the researcher used the prior literature and the domain understanding to extract and retain the number of factors.

While doing the process of factor extraction, the concept of factor rotation has to be applied to aid interpretation of extracted components by identifying the conceptual relationships among the incorporated items in the analysis. This rotation of factors can also help the investigator to simplify and improve the interpretation of the factor structure generated in the analysis by eliminating ambiguities in the factor loading structure that often accompany initial, confusing, and non-rotated factor solutions (Mitchell, 1994). Among the approaches used in rotating the measurement items,

© 2024 The Authors

varimax rotation is the most commonly used orthogonal rotation approach (DeVellis, 1991; Mitchell, 1994). This method of varimax rotation helps the data analyst or the researcher to understand effects occured in the original data and also facilitates better factor interpretation by minimizing the number of items with higher loadings on any one of the extracted factors. After performing varimax rotation in the EFA process, each original variable used in the analysis tends to be associated with one or a minimum number of factors, and also direct the researcher to get a structure where each factor indicates only a small number of items. Hence, considering the importance of varimax rotation, here in the current study the researcher applied a PCA with varimax rotation method. From the factor structure matrix the magnitude of factor loadings of individual items confirms whether an item should be retained in that factor or removed from it. In general practice, a factor loading of 0.40 or greater is often recommended as the suggested criterion for retaining an item in a component (Hinkin, 1995). Following this, in the present research, the researcher also followed the stated recommendation, where those measurement items with factor loadings lower than the cut-off point of 0.40 were eliminated from the factor structure.

DeVellis (1991) recommend that this stage of EFA helps the investigator to explore latent variables and its underlying representative measurements with a set of items, but not necessarily the concept assumed to be operationalized in the study; hence, the results of EFA sometimes merely confirms empirical relationships or interdependence among measurements with a specific set of measures. This mode of EFA indicates the operationalization of the latent construct but not necessarily in all cases the construct itself (DeVellis, 1991, p. 107). For doing this, Confirmatory factor analysis is another technique or factor analytic strategy used by the investigator, and it followed to confirm an expected factor structure of the measurement items rather than to determine or identify the latent structure (DeVellis, 1991). Hence, in a departure from exploratory factor analysis, the desired factor structure undertaken as part of the study needs to be clarified or confirmed in confirmatory factor analysis.

In the current study, four different EFAs were conducted. In the first stage, an EFA was performed using all the items measuring work involvement and family involvement dimensions. In the second EFA, the items covering quality of work life and quality of family life factors were incorporated. In the third EFA, the study incorporated all those items covering the family work conflict and work family conflict. Finally, in the fourth EFA, the study considered all those items measuring satisfaction with work life balance and improved effectiveness at work were incorporated.

EFA One: In this first stage EFA analysis, twelve items of work involvement and nine items of family involvement measures taken together as twenty one items were incorporated in the analysis using the principal component analysis. As reported in Table 5.4, the factor analysis results supported a KMO value of 0.669, and Bartlett's test of Sphericity = 3889.319, $p < 0.01$. This supported that factor analysis was suitable for these two factors. Further the analysis of communality and factor loadings (table 5.5.) revealed that all the items covering the constructs were loaded into respective factors, and these loadings were above the suggested cut-off of 0.50. In addition, the total variance explained by these two factors revealed a total variance of 64.48 %.

© 2024 The Authors

Thus, the study confirmed the uni -dimensional structure of involvement in work and family domain.

Table 5.4: KMO and Bartlett's Test [EFA one]

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.669
Bartlett's Test of Sphericity	Approx. Chi-Square	3889.319
	Df	378
	Sig.	.000

EFA two : In the second stage, the study performed an EFA using all those items covering quality of family life and quality of work life. The factor analysis results supported a KMO value of 0.754, and Bartlett's test of Sphericity = 5797.531, $p< 0.01$. Further, from the analysis, no cases of cross loadings were reported. In addition all these items were loaded highly into the respective factors. However, some of the items reported low loading into its respective factors. Therefore, these items were deleted from further analysis. The examination of total variance explained by these two factors revealed a variance of 78.10%. Thus, the study confirmed that the selected two dimensions are unidimensional in nature. See Tables 5.6 and 5.7 for more details.

Table 2 KMO and Bartlett's Test [EFA ONE]

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.754
	Approx. Chi-Square	5797.531
Bartlett's Test of Sphericity	Df	630
	Sig.	.000

EFA three : As reported in Table 5.8 to 5.9, the study conducted a third EFA incorporating all the items covering the outcome variable dimensions, such as work-family conflict and family work conflict. The factor analysis results supported a KMO = 0.675, and Bartlett's test of Sphericity= 13754.580, $p< 0.01$. The examination of factor loadings of these items indicated that the items were loaded into its respective factors. All these factors explained a total variance of 63.27%. Moreover, the results also confirmed that all these items reported high loadings. Thus, considering all these, the current study confirmed the unidimensional status of these selected set of dimensions (e.g.,work- family conflict and family- work conflict).

Table 3: KMO and Bartlett's Test [EFA THREE]

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.675
Bartlett's Test of Sphericity	Approx. Chi-Square	13754.580
	Df	2080
	Sig.	.000

EFA four: The fourth EFA was performed to analyse the dimensional structure of the dimenions, such as satisfaction with work life balance and improved effectiveness at work. The

KMO and Bartlett's Test (See Table 5.10) supported the adequacy of performing the EFA. Later, the study results supported communality above the recommended threshold of 0.50. However, from the analysis it was found that some of the items reported a low communality and low loadings. Thus, the study decided to keep all the items measuring the dimension and also dropped item with low loading and communality (See Table 5.11 for more details). In addition, the total variance explained by these two factors revealed a total variance of 67%. Thus, the study confirmed the two dimensional structure of satisfaction with work life balance and improved effectiveness at work.

Table 4 KMO and Bartlett's Test [EFA FOUR]

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.910
Bartlett's Test of Sphericity	Approx. Chi-Square	1123.1
	Df	78
	Sig.	.000

Model Tests

In this study, this measurement model testing was conducted through Confirmatory Factor Analysis (CFA). Validity explains the ability of an instrument (here the scales)to measure what the researcher intended to measure. Similarly, reliability of an instrument examines the extent of random error in the scale measures. In this stage, study decided to perform two types of validity. First type validity called as convergent validity. This type of validity explains the extent of convergence among the items covering the respective dimension. Similarly, the discriminant validity explains the extent of divergence between the items covering the different dimensions. In this stage, the study analysed the reliability of the study measurements using a coefficient, called as Composite Reliability (CR). In the following pages, the study provided the measurement model testing and results derived from CFA analysis and also provides its interpretations.

Convergent validity

Convergent validity of the scale measures were tested using three different measures. The first measure used is CFA factor loadings. It was recommended that if the CFA factor loadings are above 0.50 and loaded high, then it indicate the evidence of convergent validity. Further, another measure generally used by researchers to confirm the convergent validity is called as: Average Variance Extracted (AVE). If the AVE values are above 0.50 it also indicate the convergent validity of the scale measures. Finally, it is also suggested that if the CR values are above 0.50 it also informs the evidence of convergent validity. In the current study, the researcher used all these three measures for the purpose of checking the same.

As reported in table 5, the examination factor loading reported that all the items measuring its respective dimensions were loaded highly into that factor. In all the cases, the factor ladings were above the suggested cut-off of 0.50. In addition, the examination of estimated CR values supported that for all dimensions the values were above the suggested cut-off of 0.50. Finally, the examination of AVE values also supported that for all dimensions, the calculated AVE values were

© 2024 The Authors

above the suggested threshold of 0.50. All these confirmed that the scale measures used to capture different dimensions carrying sufficient convergent validity.

Discriminant Validity

To examine the discriminant validity the study followed an important discriminant validity check procedure recommended by Hair et al (2010). In this procedure, it is recommended that if the AVE values of the dimensions are greater that the correlation square between the construct pairs it indicate the discriminant validity. As reported in Table 5.13, the examination of AVE values with the correlation square between the constructs revealed that in all the cases the calculated AVE values were greater than the pair wise correlations. Thus, the study confirmed the fact the scale measures used measure different dimensions are divergent or it carries adequate level of discriminant validity.

In addition to the aforementioned measures, a variety of goodness-of-fit indices are also available for use in confirmatory factor analysis to indicate the adequacy of measured constructs to a model, but there seems to be little consensus on what are the appropriate indices (Hinkin, 1995). Hinkin (1995) noted that significance of Chi-square was reported most frequently, and the smaller the chi-square value, the better the data fit to the model. However, chi-square is very sensitive to sample size, diverse indices have thus been developed for assessing overall goodness of fit. A ratio of the chi-square value to the degrees of freedom of 5 to 1 was a practical rule of thumb (Hinkin, 1995). Although evaluation of fit indices is somewhat subjective, the higher values, the better the model fit to the empirical data. In addition, Hinkin (1995) reported that fit indices above 0.85 were considered acceptable. The details about the model fit indices used in the present study will be discussed in next section of structural model testing. Considering the recommendations, the study also analysed the goodness of fit of the overall measurement model from the correlated CFA model. From the analysis, it was observed that the overall correlated CFA model indicated a good fit ($\chi 2$ = 1234.12, CFI = 0.90, GFI = 0.89, SRMR = 0.040, RMSEA = 0.050, TLI = 0.92). It also confirms the goodness of fit of the measurement model. All these directed the study that the scale used to measure different dimensions are valid and reliable, therefore, proceed for hypotheses testing.

Table 5: AVE, CR and Correlations

	CR	AVE	MSV	JI	FI	QW	QF	WFC	FWC	SWB	IWF
WI	0.846	0.658	0.320	0.811							
FI	0.870	0.430	0.373	0.326	0.656						
QWL	0.890	0.452	0.367	-0.032	0.606	0.672					

© 2024 The Authors

QFL	0.765	0.353	0.291	0.221	0.441	0.297	0.594				
WFC	0.912	0.509	0.108	-0.037	-0.006	-0.112	-0.311	0.713			
FWC	0.841	0.571	0.533	-0.425	-0.611	-0.239	-0.539	0.099	0.756		
SWB	0.790	0.490	0.181	0.148	0.426	0.300	0.326	-0.060	-0.380	0.700	
IEW	0.819	0.480	0.166	0.052	0.223	0.374	0.247	-0.131	-0.123	0.407	0.693

Note: WI = work involvement, FI = family involvement, QWL = quality of work life, QF = quality of family life, WFC = work family conflict FWC = family work conflict, SWB = satisfaction with work life balance, IEW = improved effectiveness at w

Structural Equation Modelling

Structural equation modelling (SEM) technique using Maximum Likelihood Estimation procedure was employed in the current research to test the proposed hypotheses. SEM is a statistical methodology that follow a confirmatory (i.e., hypothesis-testing) approach to the analysis of a structural theory proposed by the researcher bearing on some phenomenon (Byrne, 2001). While performing SEM, it tests simultaneously all proposed relationships in the hypothesized model which confirms the extent to which the model proposed in the study is consistent with the data. In this line, Byrne (2001) summarized a number of advantages of performing SEM over other related multivariate techniques. First, while performing SEM the researcher takes a confirmatory approach to the model testing and analyses data basically for inferential purposes by demanding that the pattern of relationship between the variables within the model framework is specified *a priori.* In contrast to this, many other methods takes the route of descriptive nature, hence SEM is preferred over other related multivariate techniques. Second, the other related traditional multivariate methods are incapable of either assessing or correcting the overall measurement error. In case of SEM analysis, the researcher can avoid inaccuracies caused by ignoring error when it exists in the explanatory variables. The structural model also helps the researcher also see the specification of error term covariances (Golob, 2003). Third, data analysis using SEM technique, in comparison with other related multivariate techniques also allows measurement of the relationship among unobserved and observed variables comprehensively through the examination of covariance among the observable variables proposed in the study. Another important advantage of SEM is that it can handle a large number of endogenous variables (dependent variables) and exogenous variables (independent variables), as well as unobserved variables simultaneously specified as linear combinations of the observed variables (Golob, 2003). Last and more important, no such widely and equally competitive applied methods are currently available in the data analysis

© 2024 The Authors

paradigm alternative to SEM for modelling multivariate relations among the proposed variables or for estimating point and/or interval indirect effects.

Considering the advantages of SEM over other multivariate techniques, the two-stage SEM analytic estimation technique was adopted in to test the simultaneous inter-relationship between the constructs of interest proposed in the current research. In this two stage estimate procedure, the researcher can avoids the interaction of the measurement model and the structural model (Hair, Anderson, Tatham, & Black, 1995). The general SEM model framework and its estimation, one can decompose it into two sub-models: the first model called as measurement model (See the previous section presented in this chapter) and the second model called as the structural model. The first stage of measurement model indicates the relationship between the unobserved latent variables and observable variables (indicator variables). It was performed in this study using CFA. The estimation and confirmation of the measurement model using provides the link between the observed indicator variables and the underlying constructs they are designed to measure (Byrne, 2001; Golob, 2003; Nachtigall, Kroehne, Funke, &Steyer, 2003), or the major objective of this stage is to confirm the validity and reliability of the scales used. The second stage of structural model represents the relationship among the latent variables (constructs) of interest. The structural model specifies the manner by which particular latent variables cause changes in the values of certain other latent variables in the model. In general parlance, estimation of SEM is performed using the covariance analysis method (called as covariance based SEM), in which the researcher estimates the parameters such that the variances and covariances implied by the model are as close as possible to the observed variances and covariances of the sample (Golob, 2003). Among other popular estimation methods, such as unweighted least squares (ULS), maximum likelihood (ML) and generalized least squares (GLS), the most commonly used method for estimating SEM is maximum likelihood (ML) estimation technique. "Nearly all of the major software programs use ML as the default estimator" (Schermelleh-Engel, Moosbrugger, &Miiller, 2003, p. 25).The ML method of estimation maximizes the probability that the observed covariances are generated from a population under consideration that has its variance and covariances generated by the process implied by the model (Golob, 2003). It is also stated that the ML estimation procedure is rather more robust against deviations of the normality assumption for the sample. It is also pointed that the estimation of SEM with ML estimation can be applied in many data analytic situations such as when interval scales (e.g., Likert scales) are used to collect data on feelings and perceptions (Golob, 2003; Schermelleh-Engel et al., 2003). Hence, in support with this, in the present study, ML estimation procedure was used in the SEM technique. In this method of estimation, the goodness-of-fit indices are used to examine if a proposed model of the study is consistent with the pattern of variances and covariances dominant in the data. In this line, many other useful criteria have been developed proposed for confirming the overall goodness-of-fit in SEM methodology and for confirming how well one model does have a fit over another model. According to Schermelleh-Engel et al. (2003), covariance based SEM capable of producing multiple goodness-of-fit indices, such as: (a) descriptive measures of overall model fit or goodness of fit, such as chi-square *($\chi 2$),* root mean square error of approximation (RMSEA), root mean square residual (RMR),

© 2024 The Authors

and standardized root mean square residual (SRMR); (b) descriptive measures based on model comparison. The measures in the second category based on model comparisons are the normed fit index (NFI), the nonnormed fit index (NNFI), the comparative fit index (CFI), the goodness-of-fit index (GFI), and the adjusted goodness-of-fit index (AGFI); and (c) descriptive measures of model parsimony, such as the parsimony goodness-of-fit index (PGFI), and the parsimony normed fit index (PNFI), etc. The concept of parsimony serves as a criterion for choosing between several alternative models proposed in the study. Although in a SEM framework, most of these evaluation criteria or indices are based on the Chi-square statistic. The chi-square value is preferred in a model confirmation perspective over a test statistic as a measure of fit due to its sensitivity to sample size and deviations from multinormality (Golob, 2003). Given the limitations of Chi-square, different researchers have proposed a plethora of newly goodness-of-fit indices in the SEM framework to examine the goodness of fit of the model, and these indices take a more pragmatic approach to the evaluation process (Byrne, 2001). In this, one of the first fit statistics generally used to address this problem was the normed Chi-square, i.e., the ratio of x2/df (Wheaton, Muthen, Alwin, & Summers, 1977). Alternative goodness-of-fit measures of overall model fit have also been developed proposed in the current SEM literature, such as the root mean square error of approximation (RMSEA), root mean square residual (RMR), and standardized root mean square residual (SRMR). In the SEM framework, the root mean square residual (RMR) shows the average residual value derived from the fitting of the variance-covariance matrix for the proposed model to the variance covariance matrix of the sample data collected (Byrne, 2001). However, it has been stated that these residuals are difficult to interpret due to its relation to the sizes of the observed variances and covariances. Considering this limitation, the standardized root mean square residual (SRMR) were proposed, which represent the average value across all standardized residuals. In addition, it is very recently RMSEA been recognized as one of the most useful informative criteria in covariance structure modelling framework (Byrne, 2001). In addition, the other most frequently used goodness-of-fit measures grounded on direct assessment of the variance covariance matrices for the sample and model are the normed fit index (NFI), the non-normed fit index (NNFI), the comparative fit index (CFI), the goodness-of-fit index (GFI), the adjusted goodness-of-fit index (AGFI), the parsimony-adjusted goodnessof- fit index (PGFI) etc. Among the stated direct assessment measures, the normed fit index (NFI) is considered as a practical criterion for evaluation of proposed model fit, however, there exists some limitation of the same , because it has a tendency to underestimate fit in small samples (Byrne, 2001). Bentler and Bonnett (1980) developed the Non-normed Fit Index (NNFI), also known as the Tucker-Lewis Index (TLI) which generally show the disadvantage of the NFI which is affected by sample size. In addition, CFI was also formulated by Bentler (1990) from NFI to take sample size into account. The another measure, goodness-of-fit index (GFI) is a measure of the relative amount of variance and covariance matrix of the sample datathat is jointly explained by the variance and covariance matrix for the hypothesized model (Byrne, 2001). The AGFI has the benefit of adjusting for the number of degrees of freedom contained in the model, which makes the AGFI unique from the GFI. Both GFI and AGFI indices range from zero to 1.00, where the values close to 1.00 being indicative of

© 2024 The Authors

good fit of the model. The measure, parsimony-adjusted goodness-of-fit index (PGFI) takes into account the complexity of the hypothesized model proposedfor the assessment of overall model fit (Byrne, 2001), which was modified later based on GFI and NFI. It is hard to decide which global indices to use for reporting results of model fitting; thus it is necessary to consider multiple criteria in evaluating a model (Bagozzi& Yi, 1998; Schermelleh-Engel et al., 2003). Based on the prior literature, here in this study we designed SEM as the appropriate technique, because it can takes care multiple dependence relationships such as those investigated in the present research. In addition, the technique of SEM was used and preferred in this research to determine if the estimated population covariance matrix of the proposed model was consistent with the observed covariance matrix. To examine the same, we used AMOS software package due to its user friendliness. In addition, AMOS can also link data directly to SPSS platform and provides a very user friendly graphical user interface that allows the researcher to configure path diagrams, calculate the necessary model fit, and estimate required parameters.

Test of Hypotheses The integrated model was developed to test ten hypotheses formulated,

(H_1) Work Involvement of women employees positively impacts their Quality of Work Life

(H_2) Family Involvement of employees has a positive impact on their Quality of Work Life.

(H_3) Work involvement has a negative impact on employees' Quality of Family Life.

(H_4) Family Involvement of employees' has a positive impact on their Quality of Family life.

(H_5): Quality of Work Life of employees' has a negative impact on Work Family Conflict.

(H_6): Quality of Family Life has a negative impact on Family Work Conflict.

(H_7): Work Family Conflict has a negative impact on Improved Effectiveness at Work.

(H_8): Family Work Conflict negatively impacts Improved Effectiveness at Work.

(H_9): Work Involvement has a positive impact on Improved Effectiveness at Work.

(H_{10}): Satisfaction with work life balance positively impacts Improved effectiveness at work.

Table 6: Goodness- of- fit Measures of the Structural Model

Fit indices	Estimated values
χ^2	6960.50(df = 3631, p = .001)
χ^2/df	1.91
CFI	.836
IFI	.838
GFI	.900
TLI	.827

© 2024 The Authors

RMR	.055
SRMR	.058
RMSEA	.049

Note: The model fit indices reported here generated from the SEM model.

Further, the study examined the path coefficients to test the proposed set of study hypotheses. While checking the path coefficients, it was found that that all the estimated path coefficients followed the researchers' expectation with regard to direction and magnitude. Table 6 given below provides the estimated path coefficients derived from the model. In this table, the first and second columns show the relationship between the exogenous and endogenous constructs. The third column reported the unstandardized path coefficients. In the fourth column, the standardized path coefficients are provided. Next, to standardized path estimates, in the fifth column, standard errors are provided. In the sixth column, the table reported the p- value and the final column reports the status of hypotheses testing results (i.e. accepted or rejected).

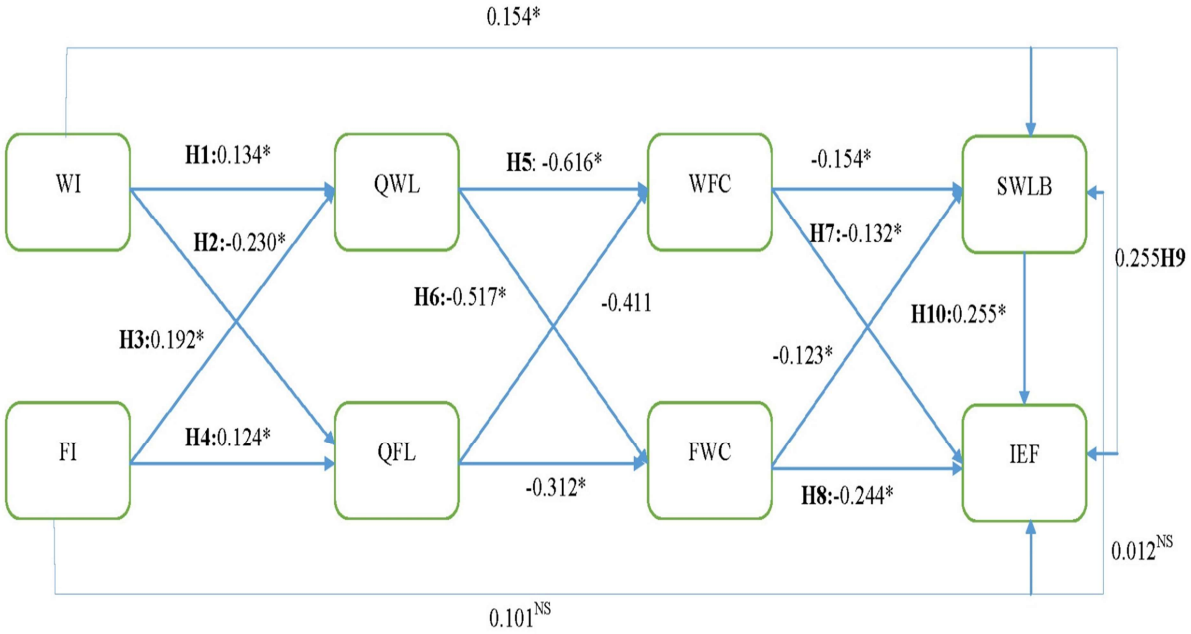
Table 7 Hypotheses Test Results of SEM

Endogenous variable		Exogenous Variables	Unstd. Estimate	Std Estimate	S.E.	P value	Hypothesis Status
WI	→	QWL	0.134	0.059	0.05	0.000	H1 supported
FI	→	QWL	0.192	0.171	0.041	0.000	H2 Supported
WI	→	QWL	-0.230	-0.276	0.062	0.000	H3 Supported
FI	→	QFL	0.124	0.183	0.058	0.000	H4 Supported
QWL	→	WFC	-0.616	-0.585	0.107	0.000	H5 Supported
QFL	→	FWC	-0.312	-0.035	0.112	0.000	H6 Supported
WFC	→	IEW	-0.132	-0.145	0.045	0.000	H7 Supported
FWC	→	IEW	-0.244	-0.402	0.110	0.000	H8 Supported
WI	→	IEW	0.255	0.341	0.082	0.000	H9Supported
SWLB	→	IEW	0.255	0.321	0.100	0.000	H10 Supported

Note: WI = work involvement, FI = family involvement, QWL = quality of work life, QFL = quality of family life, WFC = work family conflict FWC = family work conflict, SWLB = satisfaction with work life balance, IEW = improved effectiveness at work

Hypothesized Model

© 2024 The Authors



Conclusion

The study used eight constructs relevant to work life balance and studied their interrelationship and extent of influence in moderating work life balance. The identified dimensions included involvement in work and family, conflict between the domains of work and family, quality of life, satisfaction due to work life balance and improved effectiveness at work. The effect of resources such as quality of work and family life, presumed to moderate the outcomes of conflict, satisfaction with work life balance and effectiveness at work were analysed. Structural Equation Modelling techniques were used to validate the proposed model explaining the relationship between variables used in the study and subsequently the hypotheses formulated were tested.

Gender equity is witnessed in the IT sector of India where there is a pool of talented and dedicated women, at the same time the sector is also criticized for the erratic work schedules, deadlines and lack of job security inspite of the notion that it offers attractive pay packages. The dimensions studied and relationships tested here would enable the industry in evolving strategies to redesign the work environment such that it enhances work involvement and quality of work life of its employees leading satisfaction with work life balance and consequently improved effectiveness at work.

References

1. Adekola, B. (2010). Interferences between work and family among male and female executives in Nigeria. *African Journal of Business Management*, *Vol. 4(6)*: pgs 1069-1077.

© 2024 The Authors

2. Allad Idrish and Maisuria.H.M (2015) " IT sector in India- Evolution, Growth and a Tool of Economic Development" ;*International Journal for Research in Management and Pharmacy*. Vol. 4(2) pgs 10-13.

3. Allan, C., Loudoun, R., & Peetz, D. (2007). "Influences on work/ non-work conflict." *Journal of Sociology*, Vol.43: pgs 219-239.

4. Annie Owusua Nkulenu Effect of Work-Family Conflict on Quality of Work-Life in Ghana *European Journal of Business and Management* ;www.iiste.org ISSN 2222-1905 (Paper) ISSN 2222-2839 (Online) Vol.7(4).

5. Baruch, G. K., Biener, L., & Barnett, R. C. (1987). Women and gender in research on work and family stress. *American Psychologist, Vol.42*(2): pgs 130-136.

6. Bagozzi, R. and Yi, Y. (1988) On the Evaluation of Structural Equation Models.

Journal of the Academy of Marketing Sciences, Vol.16: pgs 74-94.

7. Byrne, B. M. (2001). Structural Equation Modeling with AMOS: Basic Concepts, Applications, and Programming. Mahwah, NJ: Lawrence Erlbaum Associates

.

8. Bentler, P.M. and Bonnet, D.C. (1980), "Significance Tests and Goodness of Fit in the Analysis of Covariance Structures," Psychological Bulletin, Vol.88 (3): pgs 588-606

9. Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika*, Vol.16: pgs 297–334.

10. De Vellis, R. F. (1991) Scale Development: Theory and Application. London: Sage.

11. Diamantopoulos Adamantios .,& Sigua, Judy A (2000) Introducing LISREL: A Guide for the Uninitiated Sage Publications Ltd. Pg 85.

12. Golob, T.F (2003) Structural equation modelling for travel behaviour research, *Transportation Research* Part B , Vol.13: pgs 1-25.

13. Gnanadesikan, R. (1997). Methods for statistical data analysis of multivariate observations. Wiley Series in Probability and Statistics, 2nd Edition. Wiley Interscience. ISBN 978-0-471-16119-6.

14. Green, Samuel B & Salkind, Neil J (2008). Using SPSS for Windows and Macintosh : analyzing and understanding data (5th ed). Pearson/Prentice Hall, Upper Saddle River, N.J.

15. Hair, J. F., Anderson, R. E., Tatham, R. L., & Black, W. C. (2005). Multivariate data analysis. New Jersey: Prentice-Hall.

16. Hair Jr., J.F., Black, W.C., Babin, B.J. and Anderson, R.E. (2010) Multivariate Data Analysis: A Global Perspective. 7th Edition, Pearson Education, Upper Saddle River.

17. Hooper, D , Joseph Coughlan, J & Mullen, M R (2008)Structural Equation Modelling: Guidelines for Determining Model Fit*" Electronic Journal of Business Research Methods* Vol. 6(1): pgs 53-60.

18. Hu, L. & Bentler, P. (1999). "Cutoff criteria for fit indices in covariance structure analysis: conventional criteria versus new alternatives". *Structural Equation Modeling, A Multidisciplinary Journal , Vol.6*(1): pgs 1-55.

19. Jaccard, J., & Wan, C. K. (1996). Quantitative applications in the social sciences, No. 07-114. LISREL approaches to interaction effects in multiple regression. *Thousand Oaks, CA, US: Sage Publications, Inc*

20. Kanungo, r. n. (1982) Measurement of job and work involvement. *Journal of Applied Psychology*, Vol.67: pgs 341-349.

21. Karasek, R. (1979). Job Demands, Job Decision Latitude, and Mental Strain: Implications for Job Redesign. *Administrative Science Quarterly,* Vol.*24*(2): pgs 285-308.

22. Kline, R. B. (2004). Beyond significance testing: Reforming data analysis methods in behavioral research. Washington, DC, US: American Psychological Association. http://dx.doi.org/10.1037/10693-000.

23. Kline, R. B. (2005). *Methodology in the social sciences. Principles and practice of structural equation modeling (2nd ed.).* New York, NY, US: Guilford Press.

24. Kline, R. B. (2010). Promise and pitfalls of structural equation modeling in gifted research. In B. Thompson & R. F. Subotnik (Eds.), *Methodologies for conducting research on giftedness* (pgs. 147-169). Washington, DC, US: *American Psychological Association.*

25. Kline, R. B. (2011). Principles and practice of structural equation modelling. New York, NY: Guilford Press.

26. MacCallum RC, Browne MW, Sugawara HM (1996). Power Analysis and Determination of Sample Size for Covariance Structure Modeling. *Psychological Methods*. Vol.1:pgs 130–49.

27. Malhotra (2007) Marketing Research :An Applied Approach , *Marketing Research: An Applied Approach*.

28. Mitchell V.W(1994). How to identify psychographic segments: Part *1Marketing Intelligence and Planning,* Vol.12(7): pgs 4-10.

29. Natchigall C., Kroehne U ., Funke, F ., Steyer, R (2003) Should we use SEM?—Pros and cons of Structural Equation Modelling **.**

30. Netemeyer RG, Boles JS, McMurrian R (1996) Development and validation of

© 2024 The Authors

family conflict and family-work conflict scales. *Journal of Applied Psychology.* Vol.81(4): pgs 400-410.

31. Rashida, Banu., Duraipandian. (2014*).* Development of an instrument to measure work life balance of it professionals in Chennai. .*International Journal of Management*Vol. 5(11): pgs 21-33.

32. Revathy, B., Geetha,C (2013) Career Women and Work Life Balance (Book) *APH Publishing* ISBN-13: 978-9331318428

33. Schermelleh-Engel, K., Moosbrugger, H., & Müller, H. (2003). Evaluating the Fit of Structural Equation Models: Tests of Significance and Descriptive Goodness-of-Fit Measures. *Methods of Psychological Research, V0l.8*(2): pgs 23-74.

34. Steiger, J.H (2007) Understanding the limitations of global fit assessment in structural equation modelling ;*Personality and Individual differences* , Vol.42 (5): pgs 893-898.

35. Stewart , D .W (1981) "The Application and Misapplication of Factor Analysis in Marketing Research" *Journal of Marketing Research* 18(1) https://www.researchgate.net/publication/265116319_

36. Swapna R (2019) " A study on work life balance of women employees in the IT sector of Kochi" – *Thesis submitted to MG university , Kottayam*

37. Tabachnick, B. G., & Fidell, L. S. (2007). Using Multivariate Statistics (5th ed.). New York: Allyn and Bacon.

38. Timothy R. Hinkin (1995) .A Review of Scale Development Practices in the Study of Organizations. *Journal of Management* 1995, Vol. 21(5): pgs 967-988.

39. Trochim.,MK (2006) Research Methods Knowledge Base (2006*) Qualitative Measures.*

40. Wheaton, B., Muthen, B., Alwin, D. F., & Summers, G. (1977). "Assessing Reliability and Stability in Panel Models". Sociological Methodology,Vol. 8: pgs 84-136.

© 2024 The Authors