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Using path analysis methodology to explain the impact of the relationship between job suitability and performance suitability

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Abstract

The research aims to identify the relationship between employee training, person-job fit and performance. The correlation between training and Job suitability has been the main concern of scholars and practitioners over the times. This paper presents a review of the relationship between training and performance and also examines the mediating role that quality of training may play in the relationship between these two. Literature suggests that training to a big extent is a determinant of employee performance. The review has also revealed the importance and purpose of training in organizations, and how it contributes to performance. The review so far, reveals a seeming consensus in the belief that there is a positive relationship between training and employee performance and also that training develops the skills, knowledge, abilities and competencies of the employees. In addition, Quality of training mediates the relationship between job fit and performance fit. Based on the review of past studies, this paper proposes the mediating role of person job fit in determining the indirect relationship that may exist between training and performance.

Keywords: Training, Person-Job Fit, Performance Mediation

1. INTRODUCTION

In the global age of today, organizations looking to improve their productivity and efficiency with regard to providing goods and services are gradually looking for ways and means to increase employee performance and efficiency. Training programmers and skills development courses, often a target of financial constraints, may help organizations achieve their premeditated goals and objectives. The constant need for both individual and organizational development can be drawn to many demands, including upholding dominance in the marketplace, increasing employee knowledge and skills, and increasing both efficiency and productivity. A new employee faces little difficulty in his office assignments initially and also existing employees experience difficulties in their tasks due to changing times. So, the new employee requires a roadmap from the senior experienced employees and also from an outsider who is expert on those specific areas. Thus, organizations conduct training programmers to update and improve employees' knowledge, skills and abilities demanded by the job (Diamantidis & Chatzoglou, 2012).

2. Model chi-square (χ^2)

The Chi-Square value is the traditional measure for evaluating overall model fit and, 'assesses the magnitude of discrepancy between the sample and fitted covariance's matrices' (Hu and Bentler, 1999: 2). A good model fit would provide an insignificant result at a 0.05 threshold (Barrett, 2007), thus the Chi-Square statistic is often referred to as either a 'badness of fit' (Kline, 2005) or a 'lack of fit' (Mulaik et al, 1989) measure. While the Chi-Squared test retains its popularity as a fit statistic, there exist a number of severe limitations in its use. Firstly, this test assumes multivariate normality and severe deviations from normality may result in model rejections even when the model is properly specified (McIntosh, 2006). Secondly, because the Chi-Square statistic is in essence a statistical significance test it is sensitive to sample size which means that the Chi-Square statistic nearly always rejects the model when large samples are used (Bentler and Bonnet, 1980; Jöreskog and Sörbom, 1993). On the other hand, where small samples are used, the Chi-Square statistic lacks power and because of this may not discriminate between good fitting models and poor fitting models (Kenny and McCoach, 2003).

3. Root mean square error of approximation (RMSEA)

The RMSEA is the second fit statistic reported in the LISREL program and was first developed by Steiger and Lind (1980, cited in Steiger, 1990). The RMSEA tells us how well the model, with unknown but optimally chosen parameter estimates would fit the populations covariance matrix (Byrne, 1998). In recent years it has become regarded as 'one of the most informative fit indices' (Diamantopoulos and Siguaw, 2000: 85) due to its sensitivity to the number of estimated parameters in the model. In other words, the RMSEA favors parsimony in that it will choose the model with the lesser number of parameters. Recommendations for RMSEA cut-off points have been reduced considerably in the last fifteen years. Up until the early nineties, an RMSEA in the range of 0.05 to 0.10 was considered an indication of fair fit and values above 0.10 indicated poor fit (MacCallum et al, 1996). It was then thought that an RMSEA of between 0.08 to 0.10 provides a mediocre fit and below 0.08 shows a good fit (MacCallum et al, 1996). However, more recently, a cut-off value close to .06 (Hu and Bentler, 1999) or a stringent upper limit of 0.07 (Steiger, 2007) seems to be the general consensus amongst authorities in this area.

4. Goodness-of-fit statistic (GFI) and the adjusted goodness-of-fit statistic (AGFI)

The Goodness-of-Fit statistic (GFI) was created by Jöreskog and Sorbom as an alternative to the Chi-Square test and calculates the proportion of variance that is accounted for by the estimated population covariance (Tabachnick and Fidell, 2007). By looking at the variances and covariances accounted for by the model it shows how closely the model comes to replicating the observed covariance matrix (Diamantopoulos and Siguaw, 2000). This statistic ranges from 0 to 1 with larger samples increasing its value. When there are a large number of degrees of freedom in comparison to sample size, the GFI has a downward bias (Sharma et al, 2005). In addition, it has also been found that the GFI increases as the number of parameters increases (MacCallum and Hong, 1997) and also has an upward bias with large samples (Bollen, 1990; Miles and Shevlin, 1998). Traditionally an omnibus cut-off point of 0.90 has been recommended for the GFI however, simulation studies have shown that when factor loadings and sample sizes are low a higher cut-off of 0.95 is more appropriate (Miles and Shevlin, 1998). Given the sensitivity of this index, it has become less popular in recent years and it has even been recommended that this index should not be used (Sharma et al, 2005). Related to the GFI is the AGFI which adjusts the GFI based upon degrees of freedom, with more saturated models reducing fit (Tabachnick and Fidell, 2007).

5. Root mean square residual (RMR) and standardized root mean square residual (SRMR)

The RMR and the SRMR are the square root of the difference between the residuals of the sample covariance matrix and the hypothesized covariance model. The range of the RMR is calculated based upon the scales of each indicator, therefore, if a questionnaire contains items with varying levels (some items may range from 1 – 5 while others range from 1 – 7) the RMR becomes difficult to interpret (Kline, 2005).

6. Normed-fit index (NFI)

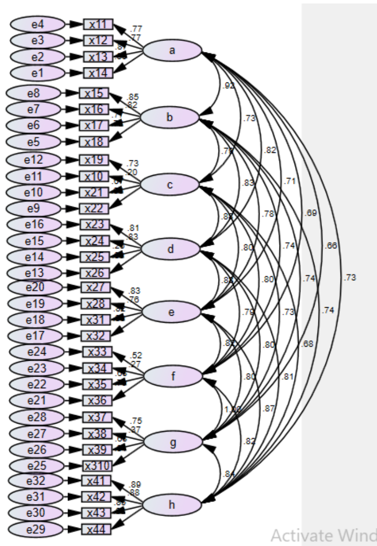
The first of these indices to appear in LISREL output is the Normed Fit Index (NFI: Bentler and Bonnet, 1980). This statistic assesses the model by comparing the $\chi 2$ value of the model to the $\chi 2$ of the null model. The null/independence model is the worst case scenario as it specifies that all measured variables are uncorrelated. Values for this statistic range between 0 and 1 with Bentler and Bonnet (1980) recommending values greater than 0.90 indicating a good fit. More recent suggestions state that the cut-off criteria should be NFI $\geq$ .95 (Hu and Bentler, 1999). A major drawback to this index is that it is sensitive to sample size, underestimating fit for samples less than 200 (Mulaik et al, 1989; Bentler, 1990), and is thus not recommended to be solely relied on (Kline, 2005).

7. CFI (Comparative fit index)

The Comparative Fit Index (CFI: Bentler, 1990) is a revised form of the NFI which takes into account sample size (Byrne, 1998) that performs well even when sample size is small (Tabachnick and Fidell, 2007). This index was first introduced by Bentler (1990) and subsequently included as part of the fit indices in his EQS program (Kline, 2005). Like the NFI, this statistic assumes that all latent variables are uncorrelated (null/independence model) and compares the sample covariance matrix with this null model. As with the NFI, values for this statistic range between 0.0 and 1.0 with values closer to 1.0 indicating good fit. A cut-off criterion of CFI $\geq$ 0.90 was initially advanced however, recent studies have shown that a value greater than 0.90 is needed in order to ensure that misspecified models are not accepted (Hu and Bentler, 1999). From this, a value of CFI $\geq$ 0.95 is presently recognized as indicative of good fit (Hu and Bentler, 1999). Today this index is included in all SEM programs and is one of the most popularly reported fit indices due to being one of the measures least effected by sample size (Fan et al, 1999).

8. Data analysis:

8.1 The first hypothesis: There is a relationship between job suitability and performance suitability



Result (default model)
Minimum was achieved
Chi-square = 832.698
Degrees of freedom = 463
Probability level = 0.000

The parameter estimates, both standardized and unstandardized, are shown next. As you would expect, the regression weights are positive, as is the correlation between all variable.

Table (1) Illustrates Quality model:

Measure	Estimate	Threshold	Interpretation
CMIN	832.698	-	-
DF	436	-	-
CMIN/DF	1.910	Between 1 and 3	Excellent
CFI	.8200	>0.95	Acceptable
SRMR	0.58	<0.08	Excellent
RMSEA	.0920	<0.06	Acceptable
PClose	.0000	>0.05	Terrible

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Table (2) Illustrates Goodness-of-fit:

Measure	Terrible	Acceptable	Excellent
CMIN/DF	> 5	> 3	> 1
CFI	<0.90	>0.95	>0.95
SRMR	>0.10	<0.08	<0.08
RMSEA	>0.08	<0.06	<0.06
PClose	<0.01	>0.05	>0.05

IBM Amos 25

The goodness of fit of a statistical model describes how well it fits a set of observations. Measures of goodness of fit typically summarize the discrepancy between observed values and the values expected under the model in question the CFI index, is 0.82 indicate a good model fit since it is close to 1

Table (3) Illustrates Correlation:

relation		Estimate	S.E.	C.R.	P
Routing	control(e)	0.97	0.116	8.368	0.000
Routing	Reduce waste (f)	0.77	0.120	3.999	0.000
Routing	Efficiency(g)	0.65	0.099	10.803	0.000
Routing	Effectiveness (h)	0.78	0.114	11.333	0.000
Proactive personality	control(e)	0.90	0.106	11.548	0.000
Proactive personality	Reduce waste (f)	0.86	0.102	12.295	0.000
Proactive personality	Efficiency(g)	0.88	0.106	12.161	0.000
Proactive personality	Effectiveness (h)	0.71	0.096	10.452	0.000
Functional involvement	control(e)	0.71	0.094	7.592	0.000
Functional involvement	Reduce waste (f)	0.78	0.120	3.999	0.000
Functional involvement	Efficiency(g)	0.84	0.095	8.890	0.000
Functional involvement	Effectiveness (h)	0.85	0.090	9.409	0.000
Career optimism	control(e)	0.80	0.099	8.049	0.000
Career optimism	Reduce waste (f)	0.73	0.119	3.114	0.000
Career optimism	Efficiency(g)	0.65	0.100	6.053	0.000
Career optimism	Effectiveness (h)	0.66	0.100	10.246	0.000

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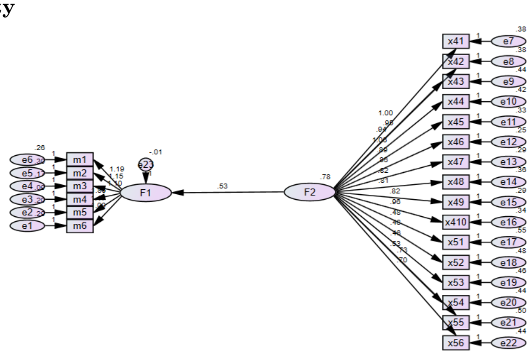
Notice that the estimated regression weights vary little across groups. It seems plausible that the two populations have the same regression weights—a hypothesis that we will test in Model.

8.2 Second hypothesis: There is a relationship between job suitability and training quality



Result (default model)
Minimum was achieved
Chi-square = 830.609
Degrees of freedom = 208
Probability level = 0.000

The parameter estimates, both standardized and unstandardized, are shown next. As you would expect, the regression weights are positive, as is the correlation between all variable.

Table (4) Illustrates goodness of fit

Measure	Estimate	Threshold	Interpretation
CMIN	830.609	-	-
DF	208	-	-
CMIN/DF	1.993	Between 1 and 3	Excellent
CFI	0.79	>0.95	Acceptable
SRMR	0.58	<0.08	Excellent
RMSEA	0.014	<0.06	Acceptable
PClose	0.000	>0.05	Terrible

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Table (5) Illustrates quality model

Measure	Terrible	Acceptable	Excellent
CMIN/DF	> 5	> 3	> 1
CFI	<0.90	>0.95	>0.95
SRMR	>0.10	<0.08	<0.08
RMSEA	>0.08	<0.06	<0.06
PClose	<0.01	>0.05	>0.05

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The goodness of fit of a statistical model describes how well it fits a set of observations. Measures of goodness of fit typically summarize the discrepancy between observed values and the values expected under the model in question the CFI index, is 0.79 indicate a good model fit since it is close to 1.

Table (6) Illustrates Correlation:

Relation		Estimate	S.E.	C.R.	P
Routing	Training	0.988	0.097	10.140	0.000
Proactive personality	Training	1.403	0.138	10.177	0.000
Functional involvement	Training	1.002	0.118	8.480	0.000
Career optimism	Training	1.452	0.145	9.987	0.000

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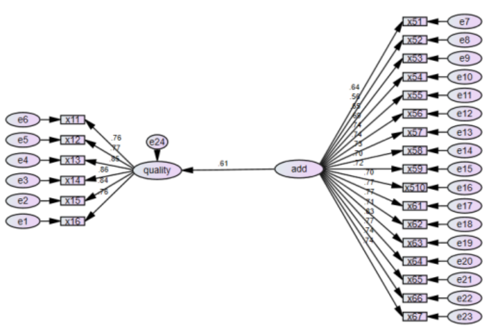
8.3 Third hypothesis: There is a relationship between training quality and performance suitability



Result (default model)
Minimum was achieved
Chi-square = 631.225
Degrees of freedom = 229
Probability level = 0.000
The parameter estimates, both standardized and unstandardized, are shown next. As you would expect, the regression weights are positive, as is the correlation between all variable.

Table (7) Illustrates goodness of fit

Measure	Estimate	Threshold	Interpretation
CMIN	631.225	-	-
DF	229	-	-
CMIN/DF	2.756	Between 1 and 3	Excellent
CFI	.8370	>0.95	Acceptable
SRMR	0.58	<0.08	Excellent
RMSEA	0.010	<0.06	Acceptable
PClose	0.000	>0.05	Terrible

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Table (8) Illustrates quality model

Measure	Terrible	Acceptable	Excellent
CMIN/DF	> 5	> 3	> 1
CFI	<0.90	>0.95	>0.95
SRMR	>0.10	<0.08	<0.08
RMSEA	>0.08	<0.06	<0.06
PClose	<0.01	>0.05	>0.05

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The goodness of fit of a statistical model describes how well it fits a set of observations. Measures of goodness of fit typically summarize the discrepancy between observed values and the values expected under the model in question the CFI index, is 0.837 indicate a good model fit since it is close to 1.

Table (9) Illustrates Correlation:

Relation		Estimate	S.E.	C.R.	P
the control	Training	0.988	0.097	10.140	0.000
Reduce waste	Training	1.403	0.138	10.177	0.000
Efficiency	Training	1.002	0.118	8.480	0.000
Effectiveness	Training	1.452	0.145	9.987	0.000

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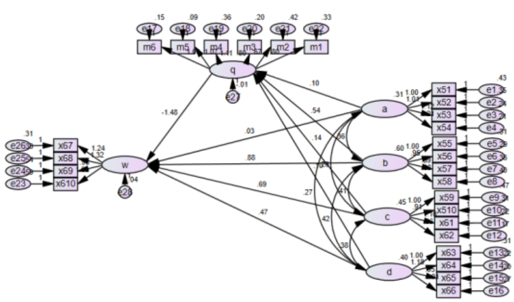
8.4 Fourth hypothesis: Training quality mediates the relationship between job fit and performance fit



Result (Default model)
Minimum was achieved
Chi-square = 1350.262
Degrees of freedom = 662
Probability level = 0.000
The parameter estimates, both standardized and unstandardized, are shown next. As you would expect, the regression weights are positive, as is the correlation between all variable.

Table (10) Illustrates goodness of fit

Measure	Estimate	Threshold	Interpretation
CMIN	1350.262	-	-
DF	662	-	-
CMIN/DF	2.04	Between 1 and 3	Excellent
CFI	0.817	>0.95	Acceptable
SRMR	0.58	<0.08	Excellent
RMSEA	0.084	<0.06	Acceptable
PClose	0.000	>0.05	Terrible

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The goodness of fit of a statistical model describes how well it fits a set of observations. Measures of goodness of fit typically summarize the discrepancy between observed values and the values expected under the model in question the CFI index, is 0.817 indicate a good model fit since it is close to 1.

Table (11) Illustrates quality model

Measure	Terrible	Acceptable	Excellent
CMIN/DF	> 5	> 3	> 1
CFI	<0.90	>0.95	>0.95
SRMR	>0.10	<0.08	<0.08
RMSEA	>0.08	<0.06	<0.06
PClose	<0.01	>0.05	>0.05

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Table (12) Illustrates Direct and Indirect effect

No	Hypothesis	Indirect effect	Direct effect	Result
1	Job suitability → quality of training → control	0.10	0.03	mediates
2	Job suitability → quality of training → reducing waste	0.36	0.88	No
3	Job suitability → quality of training → efficiency	1.38	0.69	No
4	Job suitability → quality of training → effectiveness	2.02	0.47	no

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RESULT:

1. Quality of training mediates the relationship between job fit and performance fit
2. There is a relationship between the quality of training and the suitability of performance
3. There is a relationship between job suitability and quality of training
4. There is a relationship between job suitability and performance suitability
5. demonstrated the positive impact of job suitability and performance suitability
6. demonstrated the positive impact of job suitability and quality of training

RECOMMENDATIONS AND CONCLUSION:

1. For public servants who have clarified work roles and contributions, there should be more evidence supporting the affect-based attribute of role clarity on job contributions.
2. The affect-based mediation model suggests that there can be self-internalization of work values and roles developed through efficiency and Job suitability.
3. As such, our research helps us to understand how and why the value congruence and job satisfaction relationship is driven by the joint effects of transformational effectiveness and quality of training.
4. Our model development also uncovered important managerial practices and considerations concerning particular affect-based work environments. Future

research should continue to fill the conceptual and analytical gaps in this area by refining both theory and practice

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