

CONSTRUCT VALIDATION OF A MEASURE OF ENVIRONMENTAL SCANNING FOR THE SOUTH AFRICAN OCCUPATIONAL LEARNING CONTEXT

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Abstract

Environmental scanning is a very critical process which must precede the implementation of occupational learning programmes in South Africa. The process could help organisations to enhance their strategic planning effort for occupational learning by reducing environmental uncertainty and improving their anticipatory management. The current study seeks to examine construct validity of an Environmental Scanning (ES) scale for the South African occupational learning context. Data were collected from 552 participants using a non-experimental cross-sectional survey design. The findings show that the ES scale is a valid and reliable measure, and the data fits the model very well ($\chi^2 = 24.05$; $\chi^2/df = 2.67$; TLI = .97; IFI = .98; NFI = .97; CFI = .98; SRMR = .02 and RMSEA = .05).

Keywords: Environmental Scanning, Occupational Learning Context, South Africa

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1 Introduction

Occupational learning has become a priority for the South African government as it battles with the challenge of developing and sustaining a skilled and competent workforce to meet important social and economic goals. The Skills Development Act 97 of 1998 (as amended in 2008) was enacted to give expression to strategies and interventions that seek to solve the persisting challenge of skills shortage in the country. The Act provides for the establishment of an institutional framework to devise and implement national, sector and workplace strategies to develop and improve the skills of the South African workforce (RSA, 1998). The Act further provides for learning programmes that lead to recognized occupational qualifications. Occupational learning programmes in the form of learnerships and apprenticeships culminate as occupational qualifications. An occupational learning programme is a learnership, an apprenticeship, a skills programme or any other prescribed learning programme that includes structured learning and work experience components (Coetzee et al., 2012; RSA, 2008; Van Rooyen, 2009). Structured learning takes place at a training institution (e.g., Technical College) whereas structured work experience takes place in industries, business or projects (Davies and Farquharson, 2004). Learning programmes in South Africa exist in a highly regulated context (Skills Development Act 97 of 1998; Learning Programme Regulations of July 2012). These programmes are implemented in

multiple stakeholder environments which present significant challenges in terms of effective delivery and achievement of outcomes (Davies and Farquharson, 2004).

According to Marock et al. (2008), learning programmes are inserted into a complex and increasingly bureaucratised qualifications and quality assurance infrastructure. They are administered by the Sector Education and Training Authorities (SETAs), which are in effect, a set of newly created institutions that have yet to develop capacity to drive skills development. The efficacy of learning programmes is reliant on the contribution of all key stakeholders from policy implementation to learner beneficiaries (Tshilongamulenzhe, 2012). Moreover, the environment under which these programmes must be implemented should be supportive of the needs of multiple stakeholders. For effective implementation however, it is often assumed that workplaces conditions are suitable environments for effective learning to take place, and that, work-related practices would play a key role in the development of professional skills and competences of learners and apprentices.

Studies have been conducted which show that working conditions affect the success of occupational learning programmes (Jordan et al., 2010, Lamamra and Masdonati 2009). There is a vast literature that conceptualises workplace learning environment as interdependently influenced by socio-cultural, physical, and material dimensions (Billett, 2010; Fenwick et al., 2012; Nerland and Jensen, 2010, Trede

et al., 2013). However, to ensure a successful implementation of occupational learning programmes in South Africa, environmental scanning has become a critical step in creating an organisational foresight capability. Extensive literature review that was conducted as part of this study revealed no existence of a measure of environmental scanning in the South African occupational learning context, hence the decision by Tshilongamulenzhe (2012) to develop one. This article, therefore, seeks to test construct validity of such a new measure, the Environmental Scanning (ES) scale.

2 Theoretical perspectives regarding environmental scanning

Environmental scanning is recognized in the strategy literature both as a starting point for strategic planning (Hofer and Schendel, 1978; Poter, 1980; Hax and Majluf, 1984) and as one of the principal mechanisms for organisational adaptation process (Pfeffer and Salancik, 1978; Daft and Weick, 1984). This is because organisations that learn faster are able to adapt to change quicker and thus avoid the economic evolutionary “weeding out” process (Schein, 1993). Environmental scanning could help organisations reduce environmental uncertainty and result in more successful anticipatory management (Zhang and Majid, 2009). According to Tshilongamulenzhe (2012), environmental scanning within the South African occupational learning context entails an analysis of an organisation’s external and internal environments in order to draw inputs necessary to plan and organise for the successful delivery of an occupational learning programme. This includes an analysis of the relevant legislation, facilities, relevant equipment and the availability of both the financial and human resources.

Aguilar (1967) defines environmental scanning as scanning for information about events and relationships in an organisation’s outside environment, the knowledge of which would assist top management in its task of charting the organisation’s future course of action. Equally, Hambrick (1981) defines environmental scanning as the managerial activity of learning about events and trends in the organisation’s environment, and conceives it as the first step in the ongoing chain of perceptions and actions leading to an organisation’s adaptation to its environment. Choo (2002) conceptualized environmental scanning as an integrated information management process in order to preserve much of the information which is invariably lost within the organisation, and hence enhance the effectiveness of the scanning effort.

Guided by Choo’s (2002) information management model, Zhang et al. (2010) developed a six-step environmental scanning framework which was considered useful for the current study. The framework starts off with (1) a clear definition of

scanning needs. Organisations then actively (2) collect environmental information through various channels and from various sources. The collected information is either (3) stored for future use or (4) processed and synthesized with the existing organisational knowledge. After filtering (removing the irrelevant parts of the information), repackaging (selecting information from different sources and merging it) or interpreting (analyzing and adding organisational context and meaning to the collected information based on understanding), the processed environmental intelligence may be (5) organised and stored in an organisational knowledge repository for future use or (6) may be disseminated directly to target users. This framework underscores the importance of information intelligence during environmental scanning prior to the implementation of occupational learning programmes. According to Davies and Farquharson (2004), learning programmes provide an alternative model of vocational education and training that is particularly appropriate for a high unemployment and low skills context. However, these programmes require intensive coordination and planning in order to manage a range of stakeholder inputs required for effective implementation.

In the South African skills development context, the Quality Council for Trades and Occupations (QCTO) model of quality management emphasizes that workplace approval as learning sites for occupational learning programmes will be granted after evidence is produced that such workplaces have the ability to provide work experience component (DHET, 2010). Hence environmental considerations are vital for the successful delivery of occupational learning programmes. It is imperative for skills development providers, who are the key players in the occupational learning context in South Africa, to define the scope of an occupational learning programme. The process of scoping could be done successfully once the environment in which these programmes are to be implemented is carefully scanned. The scope will identify the inputs, range, criteria, stakeholders and outcomes of the programme. Once the scope has been defined, the programme should be scheduled according to relevant times, dates and the needs of multiple stakeholders (Bisschoff and Govender, 2004).

2.1 Scale development theory

According to Karlsson (2009), developing a valid and reliable scale is a process parallel to that aimed at constructing and testing a theory. As a result, scales go through a process of developing and testing. The aim is not only to develop a scale to allow theory testing but also to have a scale that is valid, reliable and reusable for other theories as well as for application purposes. According to Tshilongamulenzhe (2012) and Tshilongamulenzhe et al. (2013), the development of a measure of

environmental scanning (ES) for the South African occupational learning context was guided by a framework proposed by DeVellis (2012) as the most recent source. DeVellis (2012) proposes that it is essential that there be at least a theoretical model to guide scale development in order for scales to be valid, and he recommends the following steps in constructing new scales: (a) determine clearly what you want to measure, (b) generate an item pool, (c) determine the format of the measure, (d) have experts review the initial item pool, (e) consider inclusion of validation items, (f) administer items to a development sample, (g) evaluate the items, and (h) optimize scale length. Tshilongamulenzhe (2012) followed these steps in the development of the ES scale.

3 Methodology

3.1 Research approach

A quantitative, non-experimental, cross-sectional survey design was applied in this study and primary data were collected from five Sector Education and Training Authorities (SETAs) and a human resource (HR) professional body in South Africa.

3.2 Research participants

Participants in this study were 552 individuals drawn from six organisations (five SETAs and a human resource professional body) in South Africa using a probabilistic simple random sampling technique. These participants were diverse in their occupational status and included learning or training managers/employers, mentors/supervisors of learners/apprentices, skills development officers/providers, learning assessors/moderators as well as learners/apprentices. All sampled participants had to have some knowledge and understanding of the South African skills development context, including the new occupational learning system. Young people represented the majority of the participants. About 76.7% of the participants were aged 35 years and below. Females constituted about 51.3% of the participants. In terms of educational achievement, 55.4% of the participants had acquired a senior certificate (matriculation/N3) as their highest qualification, with only 14% who had achieved a professional (4 years)/honours degree and higher. About 78% of the participants were involved in learnerships, with 12.5% who reported involvement in apprenticeships. In terms of current occupational commitments, over 60.7% of the participants were learners/apprentices, with 9% comprising employers/managers. The remaining percentage was spread between supervisors, skills development providers and assessors/facilitators.

3.3 Measuring instrument

A six-item Environmental Scanning (ES) scale developed by Tshilongamulenzhe (2012) was used for data collection. Responses were measured on a 6-point likert scale ranging from (1) 'Strongly agree' to (6) 'Strongly disagree'. Sample items included 'An organisation must have qualified professionals to train in a particular profession or occupation in which learners require training', 'The workplace conditions with regard to health and safety must promote effective learning', and 'Formal training infrastructure and resources must be available and in good condition (these include sites, library, internet, office, classroom, computer and facilitators)'.

3.4 Research procedure

Permission was sought from the target organisations. Five SETAs and an HR professional body gave permission for the research to be undertaken within their jurisdictions. Once permission to undertake the research had been granted, the researcher started the process of planning for sampling and data collection with the respective organisations. The data collection process was carried out in the provinces of Gauteng, North West and Mpumalanga in South Africa.

3.5 Statistical analysis

Data for this study were analysed using the Statistical Package for Social Sciences (SPSS, Version 23) and Analysis of Moment Structures (AMOS, Version 23) (IBM, 2015). Both the exploratory and confirmatory factor analyses were computed. Exploratory factor analysis (EFA) was executed using SPSS and structural equation modeling was executed using AMOS as part of confirmatory factor analysis (CFA). Exploratory factor analysis focuses on whether the covariance or correlations between a set of observed variables can be explained in terms of a smaller number of unobserved constructs known either as latent variables or common factors (Landau and Everitt, 2004). The analysis is often used to gather information about inter-relationship among the set variables.

First, factor analysis was computed in the current study to test the suitability of data for further analysis. An inspection of a correlation for a coefficient above .30 was done followed by the calculation of sample adequacy (Kaiser-Meyer-Olkin [KMO] and Bartlett's test for sphericity). Suitability of KMO sampling is connected with the suitability of the correlations among the scale items. A KMO value over .60 is an acceptable value (Ntoumanis, 2001). If KMO value is high, Bartlett's test becomes statistically significant. Secondly, the factorial structure of the ES scale was tested through the execution of principal components analysis. A principal components analysis is essentially a method of data reduction that aims to

produce a small number of derived variables that can be used in place of the larger number of original variables to simplify subsequent analyses of data (Landau and Everitt, 2004). Construct validity was tested using structural equation modelling, a CFA technique that is applied to estimate, analyse and test models which specify relationships among variables (Bruce, 2003). A model is established at the beginning and thereafter tested to ascertain whether it is supported by the data obtained. The factor structure obtained during EFA was tested through CFA.

4 Results

4.1 Sample adequacy

The KMO Measure of Sampling Adequacy value for the Environmental Scanning (ES) scale was found to be .87 and the Bartlett’s test value was found to be 1084.944 ($p < .000$). As a result of the higher KMO and Bartlett’s test values as depicted in Table 1, a factor analysis became applicable and the correlation among the scale items was deemed to be high.

Table 1. KMO and Bartlett’s Test values

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.873
Bartlett's Test of Sphericity	Approx. Chi-Square	1084.944
	Df	15
	Sig.	.000

4.2 Exploratory factor analysis

Exploratory factor analysis was computed in order to investigate the factor structure of the ES scale by analyzing relationship between items. It is clear in

Table 2 that all six items of the ES scale had achieved excellent loading after the principal components analysis.

Table 2. Item factor load

Item	Factor load
1. An organisation must have qualified professionals to train in a particular profession or occupation in which learners require training.	.675
2. The equipment for training must be in good working condition.	.811
3. The workplace conditions with regard to health and safety must promote effective learning.	.709
4. Formal training infrastructure and resources must be available and in good condition (these include sites, library, internet, office, classroom, computer and facilitators).	.785
5. A suitable workplace must be available (A workplace is a place which provides an opportunity for learners to acquire practical training and work experience).	.746
6. The employer must provide appropriate facilities to train the learner.	.712

Note: Extraction Method: Principal Component Analysis. 1 component extracted.

Only one component was extracted after a varimax rotation and this supports the unidimensionality of the ES scale. As depicted in Table 2, the pattern of communality values for ES scale items ranged from .675 to .811. These results support the validity of a single factor ES scale. All items had high eigenvalue units ranging from .406 to 3.296 with the first item accounting for 54.92% of the variance as depicted in Figure 1.

4.2 Scale reliability

The ES scale was tested for its reliability and the results are depicted in Table 3. The item mean values ranged from 1.29 to 1.41 and that of the total scale

was 8.15. The ES scale has yielded a high reliability coefficient of .83 as shown in Table 3.

4.3 Structural equation modeling

Structural equation modeling was computed to test multiple relationships in the current study as well as the construct validity of the ES scale. First, the standardized regression estimates were computed as depicted in Table 4. The standardised regression estimates for the model tested in this study ranged between .595 and .779, while the standard error coefficients ranged between .074 and .097 as depicted in Table 4. All six items were found to be significant predictors of the environmental scanning construct ($p \leq .001$).

Figure 1. Scree plot for items of ES scale

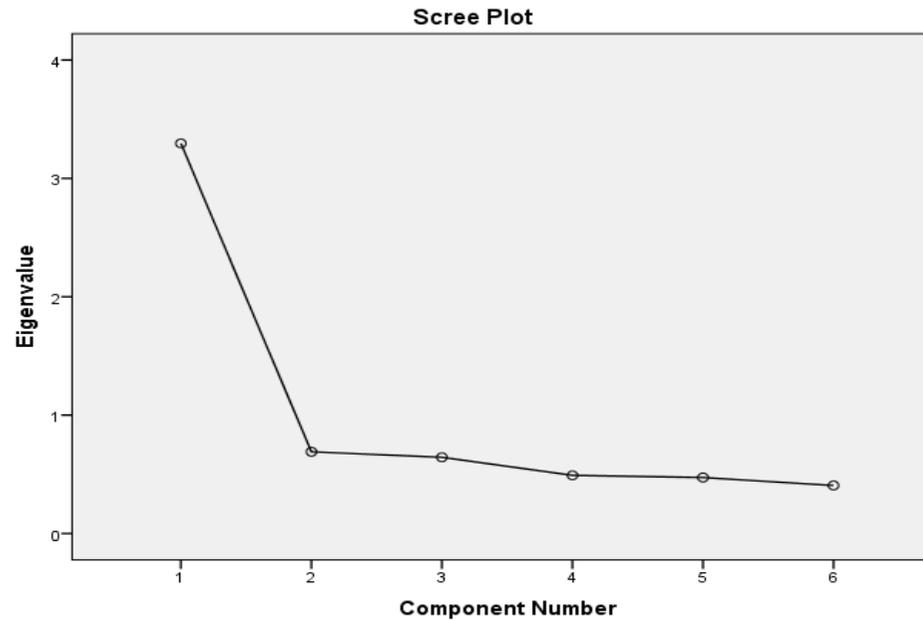


Table 3. Item statistics and reliability coefficients for the ES scale ($n = 552$)

Items	Mean	Std. Dev	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
1. An organisation must have qualified professionals to train in a particular profession or occupation in which learners require training.	1.38	.736	6.77	6.534	.534	.299	.821
2. The equipment for training must be in good working condition.	1.29	.621	6.86	6.497	.695	.489	.788
3. The workplace conditions with regard to health and safety must promote effective learning.	1.32	.591	6.83	6.956	.570	.346	.812
4. Formal training infrastructure and resources must be available and in good condition (these include sites, library, internet, office, classroom, computer and facilitators).	1.41	.740	6.74	6.132	.655	.447	.794
5. A suitable workplace must be available (A workplace is a place which provides an opportunity for learners to acquire practical training and work experience).	1.37	.699	6.78	6.419	.615	.395	.803
6. The employer must provide appropriate facilities to train the learner.	1.37	.687	6.78	6.577	.577	.351	.811
Total scale	8.15	3.014					.832

Table 4. Regression weights for the items of ES scale

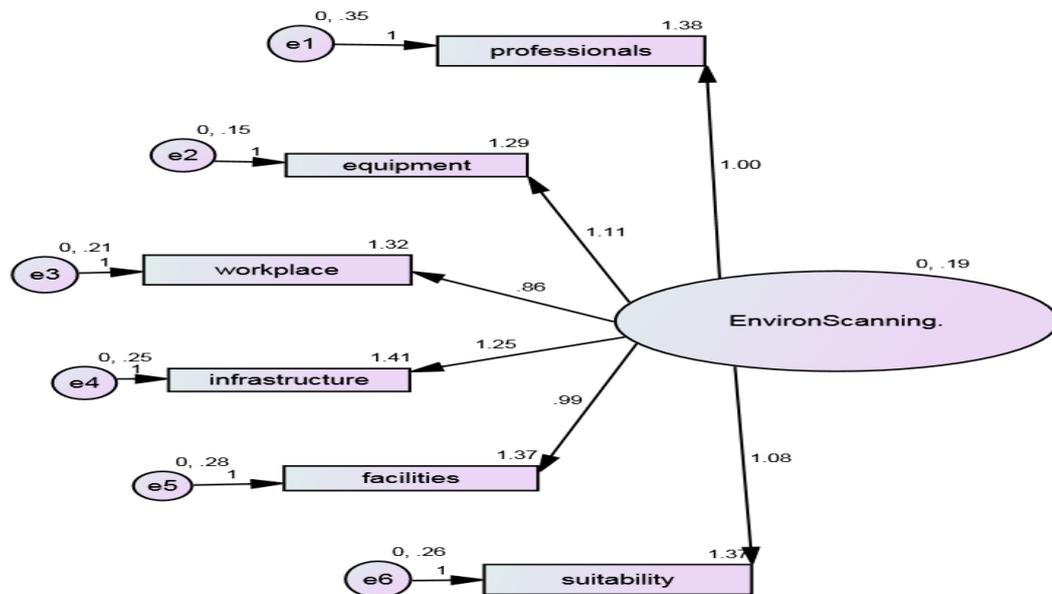
			Estimate	S.E.	Std. Regression Estimate	C.R.	P
professionals	<---	EnvironScanning.	1.000		.595		
equipment	<---	EnvironScanning.	1.105	.084	.779	13.224	***
suitability	<---	EnvironScanning.	1.081	.089	.677	12.140	***
workplace	<---	EnvironScanning.	.864	.074	.639	11.673	***
infrastructure	<---	EnvironScanning.	1.250	.097	.739	12.838	***
facilities	<---	EnvironScanning.	.993	.086	.632	11.578	***

Note: *** = $p \leq .001$

A single factor six-item model depicting the ES scale was established as part of CFA and is shown in Figure 2 with calculated item-factor correlations. Path coefficients in this model ranged from .86 to 1.25. Kline (2005) indicated that path coefficients with absolute values less than .10 could indicate a ‘small’

effect, values around .30 could suggest a ‘typical’ or ‘medium’ effect, and a ‘large’ effect could be indicated by coefficients with absolute values $\geq .50$. In the current study, all the values were higher than .80, thus supporting large effect.

Figure 2. Structural equation model for the ES scale



Several fit indices were computed in the current study to test the structural equation model against the data. The most widely used indices are the absolute fit indices (e.g., Chi-Square (χ^2), Standardized Root Mean Square Residual (SRMR)), relative fit indices (e.g., Normed Fit Index (NFI), Tucker Lewis Index (TLI) and Incremental Fit Index (IFI)) and noncentrality-based indices (e.g., Comparative Fit Index (CFI) and Root Mean Square Error of Approximation (RMSEA)). The current study tested the data against all these fit indices and the results are depicted in Table 5.

4.3.1 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 matrices (Hu and Bentler, 1999). A good model fit would provide an insignificant χ^2 result at $p > .05$ threshold (Barret, 2007; Hooper et al., 2008). A general rule for acceptable model fit is that the ratio of the χ^2 to df (CMIN/DF) should be ≤ 3 (Kline, 2005). The results depicted in Table 5 show a χ^2 value of 24.05 and a χ^2/df ratio of 2.67 which suggest an acceptable model fit.

Table 5. Fit indices for the structural equation model

Model	χ^2	χ^2/df	TLI	IFI	NFI	CFI	SRMR	RMSEA
Criteria for a good fit	>.05	≤ 3	$\geq .95$	$\geq .95$	$\geq .95$	$\geq .95$	$\leq .08$	$\leq .06$
Initial model	24.05	2.67	.97	.98	.97	.98	.02	.05

4.3.2 Standardized Root Mean Square Residual (SRMR)

A Standardized Root Mean Square Residual (SRMR) was computed in the current study. It is the square root of the difference between the residuals of the sample covariance matrix and the hypothesized covariance model (Hooper et al., 2008). Values of the SRMR range from zero to 1.0, with well-fitting models obtaining values less than .05 (Byrne, 1998; Diamantopoulos and Siguaw, 2000). The smaller the SRMR, the better fit of the model. Values as high as .08 are deemed acceptable (Hu and Bentler, 1999; Schreiber et al., 2006). An SRMR of 0 indicates perfect fit. The results depicted in Table 5 show a SRMR value of .02 in the current study which is less than the $\leq .05$ threshold and this supports an excellent model fit.

4.3.3 The Normed Fit Index (NFI)

The NFI assesses the model by comparing the χ^2 value of the model to the χ^2 of the null model (Hooper et al., 2008). The null/independence model is the worst case scenario as it specifies that all measured variables are uncorrelated. Values of this statistic range between 0 and 1. Bentler and Bonnet (1980) recommend that values greater than .90 indicate a good fit. According to Schumacker and Lomax (2004), by convention, NFI values above .95 are good, between .90 and .95 are acceptable, and below .90 indicate a need to respecify the model. A suggestion by Hu and Bentler (1999) is that the cut-off criterion should be $NFI \geq .95$. The results of this study as depicted in Table 5 show a NFI value of .97 which is in excess of the threshold for a good fit.

4.3.4 Tucker-Lewis Index (TLI)

This index is similar to NFI, but penalizes for model complexity. Marsh et al. (1988) and Marsh et al. (1996) found TLI to be relatively independent of sample size. TLI values range from 0 to 1, and values close to 1 indicate a good fit. Hu and Bentler (1999) have suggested $TLI \geq .95$ as the cut-off for a good model fit and this is widely accepted. TLI values below .90 indicate a need to respecify the model. In the current study, a TLI value of .97 was obtained indicating a good fitting model as shown in Table 5.

4.3.5 Incremental Fit Index (IFI)

This index is also known as the DELTA2: IFI (χ^2 for the null model - χ^2 for the default model). By convention, IFI should be equal to or greater than .90 to accept the model. However, a suggestion by Schreiber et al. (2006) is that the cut-off criterion should be $IFI \geq .95$. In the current study, the IFI value was .98 and thus supports a good model fit.

4.3.6 Comparative Fit Index

The CFI is a revised form of NFI which takes into account the sample size (Byrne, 1998) and performs well even when the sample size is small (Tabachnick and Fidell, 2007). This index was first introduced by

Bentler (1990). 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 and 1, with values closer to 1 indicating a good fit. A cut-off criterion of $CFI \geq .90$ was initially advanced (Hooper et al., 2008). However, 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). Schreiber et al. (2006) have suggested $TLI \geq .95$ as the cut-off for a good model fit. The CFI is the most popular index in the recent period to be reported and included in structural equation modeling because it is one of the measures least affected by sample size (Fan et al., 1999). The results depicted in Table 5 show that a CFI value of .98 was obtained in the current study and this supports a best fitting model.

4.3.7 Root Mean Square Error of Approximation (RMSEA)

This fit statistic was first developed by Steiger and Lind (1980). The RMSEA tells of how well the model, with unknown but optimally chosen parameter estimates would fit the population covariance matrix (Byrne, 1998). In recent times, this statistic has become one of the most informative fit indices (Diamantopoulos and Siguaw, 2000) due to its sensitivity to the number of estimated parameters in the model. DiStefano and Hess (2005) indicate that researchers are increasingly using RMSEA as a key CFA index.

Recommendations for RMSEA cut-off points have been reduced considerably. Up until the early nineties, an RMSEA in the range of .05 and .10 was considered an indication of fair fit and values above .10 indicated poor fit (MacCallum et al., 1996). While Hooper et al. (2008) and MacCallum et al. (1996) indicate that the RMSEA value of between 0 and .08 shows a good fit, other researchers suggest that when interpreting the values of RMSEA: values $\leq .05$ indicate a good fit; values between .05 and .08 indicate a reasonable fit; values between .08 and .10 indicate mediocre fit; and values $\geq .10$ indicate a poor fit (Browne and Cudeck, 1993; Browne and Mels, 1990; Steiger, 1989; Thompson, 2004). However, in recent times, a cut-off value of .06 or less seems to be the general consensus amongst authorities in this area (Schreiber et al., 2006). As depicted in Table 5, the RMSEA value obtained in this study was .05 which indicates a good fit. Overall, these results show that the single factor structure of the ES scale was acceptable, yielded valid results and fitted well to the model.

5 Conclusion

The purpose of this study was to examine the construct validity of the Environmental Scanning (ES) scale for the South African occupational learning context. There has been no literature evidence of existence of a similar study which was conducted in

the South African occupational learning context, thus making the current study profound. This study has opened a new avenue for scholarly research and has also broadened the research base for establishing an empirically tested measure of environmental scanning which is a key aspect that should precede the implementation of occupational learning programmes. Occupational learning programmes are pivotal in South Africa as they offer a critical pathway for skills development at intermediate level. The development process of the ES scale has already been reported by Tshilongamulenzhe (2012) and Tshilongamulenzhe et al. (2013). This study sought to capture and examine an important aspect of construct validity which is associated with good scientific practice in the scale development literature. The sample of this study was found to be adequate for further statistical analysis as the KMO value yield was in excess of the threshold of .60 as suggested by Kline (2005). The findings of exploratory factor analysis in this study show a single factorial structure for the ES scale which supports the unidimensionality of this new measure. All items of the ES scale loaded above the threshold of .50 during the principal components analysis as suggested by Walker and Fraser (2005).

The ES scale was tested for internal consistency. Generally, Cronbach's alpha $\geq .70$ is considered acceptable (Kline, 2005; Polit and Beck, 2004). A reliability coefficient of .70 marks a threshold evidencing high degree of internal consistency (Nunnally, 1978). The findings of this study show that the ES scale has achieved a very good reliability score at .83. In terms of model fitness, the results of this study show that the single factor structure of the ES scale fits the data and the model very well ($\chi^2 = 24.05$; $\chi^2/df = 2.67$; TLI = .97; IFI = .98; NFI = .97; CFI = .98; SRMR = .02 and RMSEA = .05). All fit indices computed yielded a better fit between for the data to the model, thus exceeding the threshold values suggested by researcher such as Hu and Bentler (1999), Kline (2005), Byrne (1998), Marsh et al. (1996), Schreiber et al. (2006) and MacCallum et al. (1996). A conclusion that can be drawn from the findings of this study is that the ES scale is a valid and reliable measure that can be used to assess the environment within which occupational learning programmes should be implemented in the South African context. The scale has been empirically tested and the findings support its validity and reliability.

The only limitation is that this study focused on two types of occupational learning programmes, that is, learnerships and apprenticeships. Consequently, the findings of this study should be interpreted within the context of these two programmes and nothing else. It is recommended that a further study be conducted to validate the ES scale on a different sample and where possible, a further investigation of the invariance of this scale across population sub-groups should be conducted.

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