

WORKPLACE INNOVATION: EXPLORATORY AND CONFIRMATORY FACTOR ANALYSIS FOR CONSTRUCT VALIDATION

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ABSTRACT

Workplace innovation enables the development and improvement of products, processes and services leading simultaneously to improvement in organisational performance. This study has the purpose of examining the factor structure of workplace innovation. Survey data, extracted from the 2014 APS employee census, comprising 3,125 engineering professionals in the Commonwealth of Australia's departments were analysed using exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). EFA returned a two-factor structure explaining 69.1% of the variance of the construct. CFA revealed that a two-factor structure was indicated as a validated model (GFI = 0.98, AGFI = 0.95, RMSEA = 0.08, RMR = 0.02, IFI = 0.98, NFI = 0.98, CFI = 0.98, and TLI = 0.96). Both factors showed good reliability of the scale (Individual creativity: $\alpha = 0.83$, CR = 0.86, and AVE = 0.62; Team Innovation: $\alpha = 0.82$, CR = 0.88, and AVE = 0.61). These results confirm that the two factors extracted for characterising workplace innovation included individual creativity and team innovation.

KEYWORDS

workplace innovation, exploratory factor analysis, confirmatory factor analysis.

Introduction

Today's global competition and public pressure have prompted the public sector to focus on innovation as a means of improving productivity and performance. In Australia, due to public management reform in the 1990s, the literature on innovation in the public sector has rapidly expanded [1, 2]. Additionally, the Australian Public Service (APS) has undergone significant administrative reforms since the introduction of the National Competition Policy in 1993 [3] with public sector organisations adopting a more commercial orientation, and becoming more focused on efficiency, effectiveness and accountability [4]. In 2009, the Advisory Group on the Reform of Australian Government Administration was formed with the mission of seeking innovative means of improving the performance of Australian federal de-

partments, leading to an upbeat report 'Ahead of the Game' [5, 6]. To promote innovation, the Australian National Audit Office (ANAO) published a 'better practice' guide which provided a framework to understand the innovation process in the public sector [7]. It gives practical insights on how to search for, assess, implement, and evaluate innovative ideas to improve the quality of services delivered to citizens. In 2010, the Australian Public Service Commission (APSC) published the report 'Empowering Change: Fostering Innovation in the Australian Public Service' which considered how to encourage and strengthen a culture of innovation in the APS [8]. These initiatives suggest that innovation has become an important focus for the APS.

Workplace innovation is viewed as a contextual psychological construct which identifies and measures the behavioural aspects of innovation prac-

tices by individuals in their workplace [9]. In this study, the dimensionality of workplace innovation was analysed using an exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). EFA was employed to analyse the inter-relationship between variables and to explore the factor structure of their measure, then the fit of the model was tested by CFA.

EFA can be used to identify appropriate variables and analyse the relationships among large numbers of variables in the most general form by explaining them in terms of their common underlying dimensions [10]. The results from the EFA in this study provided a number of factors to retain in the workplace innovation construct and a clear estimation of the factor structures for the measures of this construct. To strengthen the outcomes of EFA, CFA was sequentially conducted to confirm the validity of the measurement scale by supporting the recognised factor structures discovered from the EFA process. CFA is a theory-driven technique used to test the hypotheses for a factor structure, which determines the validity of theoretical structures through testing the causal links among variables [11, 12]. By conducting CFA, researchers can assess the structure of factors, identify the dimensions of a construct, and determine whether particular patterns of loadings match the data [10].

The paper begins with a literature review of workplace innovation, then explains the methodology employed, followed by the research results. The paper then discusses the findings and ends with key conclusions from the study.

Workplace innovation

Workplace innovation is created when an individual or a team of individuals focus on improving organisational management and technology [13]. This definition highlights the interactive characteristics of workplace innovation. Pot [14] defines workplace innovation as the implementation of interventions which advance organisational systems, human resource management and supportive technologies. When workplace innovation is aligned with an organisation's strategic objectives, it enables the development and improvement of products, processes and services leading simultaneously to an increase in organisational performance. In order to be successful, workplace innovation depends on creating innovative and self-sustaining processes of learning, reflection, and change. This demands a commitment to; learning from a variety of sources, and enabling staff to develop and use their competencies and creative

abilities to the fullest extent, including empowering job design, self-organised teamwork, engagement in innovation processes, and employee participation in strategic management [13].

Many researchers have emphasised the role of an organisation in the success of workplace innovation [15, 16]. More specifically, most scholars have asserted the role of organisational culture in the successful management of innovation in the public sector [17, 18]. In particular, many studies have defined the culture for innovation from a cultural perspective as supporting creativity, openness and receptiveness to new ideas, risk taking and promoting an entrepreneurial mindset [19, 20]. According to Kim and Yoon [17], culture for innovation is a primary element for creativity and innovation in government organisations.

It has been widely accepted that leadership play a key role in determining innovation and creativity in organisations. Leaders build the process, structures, and climate for an organisation to become innovative and to motivate team expectations toward innovations [21]. Leaders also not only act as behavioural role models for innovative ideas, but can also act as critical champions to boost innovative behaviours and adapting attitudes that are conducive to innovative initiatives [22]. As such, culture and leadership are significant in creating a workplace innovation.

Innovation is generally related to creativity. Creativity is defined as the process of an individual or small group of individuals working together to form novel, useful and appropriate ideas in order to solve problems and increase effectiveness [15, 23] and can be construed as the idea generation element of innovation [24]. Amabile [15] proposes a model in which creativity is a function of three elements: task motivation (a sense of being excited by the work itself and attracted by the challenge of problems); domain-relevant knowledge (knowledge and talents relevant to the task at hand), and creative-relevant skills (a cognitive style favourable to bringing new perspectives to problems). Scott and Bruce [25] comprehended creativity as a notion related to generating novel ideas, and innovation as a notion that includes not only generating but also adopting and implementing novel ideas. Thus, creativity is regarded as the first phase of the innovation process, rather than a separate entity.

Developing the creativity and innovation of both individuals and teams needs strong championship of supervisors and senior leaders [26]. This may come in the form of empowering employees to take action for change and to have a propensity for risk-taking [27], providing incentives for innovation [28], supply-

ing enough budgets to generate innovations [2], using pilot projects to test initiatives [29], and providing freedom for employees and protecting them from bureaucratic hindrances [5].

Individual creativity

Many of the world's most successful organisations implement new business models based on applying individual creativity to promote organisational innovation [30]. Individual creativity at work involves the development of practical and new solutions to workplace challenges, providing a tangible and useful outcome for an organisation [15]. It is a social interaction embedded in the work environment in which the communication and interaction between coworkers can significantly improve individual creativity [23, 31]. When employees perceive a work environment that fails to stimulate individual creativity, a void may occur between the level of individual creative ability and the actual amount of individual creativity practised within the organisation. However, bureaucratic practices in public sectors often prevent leaders' efforts to promote individual creativity [32]. Thus, to encourage individual creativity, leaders should try to understand subordinates' motivations.

Team innovation

Team innovation is an important determinant in the capability of organisations to respond to rapidly changing and challenging working environments. Organisations are increasingly dependent on teams, which are the basic building blocks of modern organisations, to innovate through the effective cross-fertilization of ideas [33, 34]. Team innovation refers to the introduction or application within a team of ideas, processes, products, or procedures that are novel to the team and are designed to be useful [35]. It is the team's ability to develop novel ideas (i.e. creativity) and the ability to put these ideas into practice such that they yield benefits to organisations (i.e. implementation). Implementation processes include selling ideas to other members and making ideas available in the organisation [36]. Team innovation thus can be operationalised as the merger of the quality and quantity of ideas that are generated and implemented. Teamwork is a vital factor of team innovation. Innovative teams frequently have clearly defined objectives and goals, effective leaders, good balance of team roles, effective conflict resolution, and efficient connections with external organisations [37].

Methodology

Opportunities for replicating large data sets in public management studies are starting to emerge. Governments in industrialised countries are now surveying their employees to consider their views and attitudes about the workplace, management, and human resources. For example, the Australian Public Service Commission (APSC) conducts a State of the Service Employee Census to measure employees' perceptions of whether, and to what extent, conditions characterising successful organisations are present in their departments.

This study uses data from the 2014 APS employee census, conducted by the APSC. This survey instrument was administered to gather data from civil servants in Commonwealth departments using an online survey. Although utilising secondary data limits the available sample to a pre-determined selection of respondents, the large sample size of this national survey yielded a sufficient sample for this study. Secondary data sets have been previously used by researchers interested in investigating innovation in the APS [38, 39].

This study draws on the perspectives of engineers as key informants. Therefore, the target population is the engineering profession which is classified in the APSC Job Family Model as the Engineering and Technical Family. 3,570 APS survey respondents reported their type of work as Engineering and Technical profession. Responses with missing values across all of the variables were excluded leaving a total of 3,125 observations available for this study.

The sample population represented a gender mix of 14% female and 86% male the predominantly aged was between 45 and 59 (49%) and 73% had a total length of service of more than 5 years; 68% worked in an operational role (APS 1-6) and were well educated, with 78% holding tertiary qualifications (Bachelor or higher); 86% worked in operational agencies and 91% worked in large agencies (>1,000 employees). The distribution of the demographic profile of participants approximated the distribution of the population from which they were drawn.

The differences in personal attitudes according to different demographic groups (e.g. age, gender, education level) were tested using the mean difference and the effect size of the difference. From the results, there was neither a large mean difference nor a large effect size. This means no significant differences existed in personal attitudes according to the different demographic groups.

The 7 survey items were selected and grouped according to workplace innovation theory. The sur-

vey items were measured on a 5 point Likert scale (Strongly Disagree = 1 and Strongly Agree = 5). To clean the data and decrease systematic errors, missing values, outliers, and the distribution of all measured variables were examined. The missing responses were imputed by the Expectation Maximisation approach prior to factor analysis.

The validity of this workplace innovation scale was evaluated using factor analysis, which was conducted using two sequential approaches: (1) Exploratory Factor Analysis (EFA) and (2) Confirmatory Factor Analysis (CFA). EFA was conducted to condense the large number of items into a smaller, more controllable set of dimensions [10]. In this study, EFA was applied to the construct to determine the adequate number of latent factor structures and to disclose the number of factors underlying, conceptually and statistically, the set of items in each model construct. The results were then affirmed using CFA to provide a foundation for subsequent model assessment and refinement. The CFA results were used to demonstrate whether the model had acceptable levels of fit, convergent validity, discriminant validity and unidimensionality.

Results

Descriptive analysis

Descriptive analysis was employed to gain a feel for the data. These results are presented in Table 1 based on the values of mean and standard deviation. Mean value is the central tendency measurement, used to describe the average opinion of the respondents and to obtain an overall picture of the respondents' perceptions regarding each variable. This section evaluates and interprets the mean values of all 7 variables.

Employees' personal attitudes towards innovation seemed to be quite positive with all mean values within this scale higher than medium level, ranging from 3.12 to 3.89. Most employees reported feeling their individual creativity was supported. They felt comfortable to voice opinions differing from their col-

leagues, as indicated by the highest mean value in this construct (variable W4; 3.89). The majority of employees also felt they received support for innovation, including autonomy (variable W1; 3.73) and opportunity to experiment (variable W2; 3.59). However, employees were less likely to agree that they had the opportunity to be innovative in terms of time (variable W3; 3.12). Employees were also asked to provide their views on aspects of innovation in their work group. Most employees reported the work group analysed their work for process improvement (variable W5; 3.69) and improved service delivery (variable W7; 3.76). Employees were likely to believe it was their personal responsibility to improve the quality of their work (variable W6; 3.82).

The normality of the data was calculated using statistics of skewness and kurtosis and comparing them with the 'rule of thumb values' of ± 2.58 [10]. Skewness measures symmetry which affects tests of means, while kurtosis measures how the peakedness of a distribution impacts tests of variances and covariances. The skewness values were inside the threshold as they ranged from -1.18 to -0.31 , indicating similar participant responses for these questions. The kurtosis values also fell within the recommended range with result of -0.67 to $+1.77$, which again fell within the recommendation range (see Table 1). This is in accordance with the assumption that in samples of 200 or more, the effect of skewness and kurtosis disappears [40].

Exploratory factor analysis

In order to assess the factorability of the data and ensure sampling adequacy, Bartlett's test of sphericity and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy were applied. The KMO value of the variables was 0.847, which indicated sampling adequacy such that the values in the matrix was sufficiently distributed to conduct factor analysis [41]. The value obtained by Bartlett's test of sphericity, $\chi^2(21)$ was 9,258.44, which was highly significant at $p < 0.001$ level, indicating that the data were approximately multivariate normal [41, 42].

Table 1
Covariance structure analysis: descriptive statistics.

Variable	Mean	SD	Skewness	Kurtosis
W1: I am able to explore new ideas.	3.73	0.88	-0.93	1.07
W2: I would be supported if I tried a new idea.	3.59	0.98	-0.70	0.20
W3: I have the time to explore new ideas.	3.12	1.08	-0.31	-0.67
W4: I feel comfortable to voice a different opinion.	3.89	0.88	-1.18	1.77
W5: My work group looks for ways of doing a better job.	3.69	0.82	-0.68	0.61
W6: Improving the quality of our work is our responsibility.	3.82	0.70	-0.70	1.39
W7: My work group improves the service we provide.	3.76	0.84	-0.87	1.08

A principal component analysis (PCA) with varimax rotation was initially conducted to examine the validity of the construct. PCA was chosen as a data extraction method because its primary objective was to summarise and reduce data as well as define the factors needed to represent the structure of a variable [10]. PCA takes the data set and extracts the maximum variance from each component. Varimax rotation, which can load variables to factors clearly, was conducted to maximise the variance of factor loadings and minimise the number of variables that had high loadings on each other [40, 42]. A total of seven variables were selected to operationally define the workplace innovation (WIT) construct. The presence of two components with eigenvalues greater than 1 was indicated by the initial principal component analysis.

A geometrical approach can be utilised by the EFA where factors in a coordinate system can be visualized by variables plotted on the axes of a graph [43]. When variable coordinates are close together on each axis, this represents a strong relationship between that variable and the particular factor. As shown in Fig. 1, the variables were plotted as functions of each factor. The variable coordinates on the factor axis act as a reference frame for the factor loadings. High factor loadings for four variables (W1, W2, W3, and W4) show strong relationships with factor 1 (Individual Creativity: horizontal axis) but these variables has a low correlation with factor 2 (Team Innovation: vertical axis). In comparison, three variables have strong relationships with team innovation but low correlation with individual creativity.

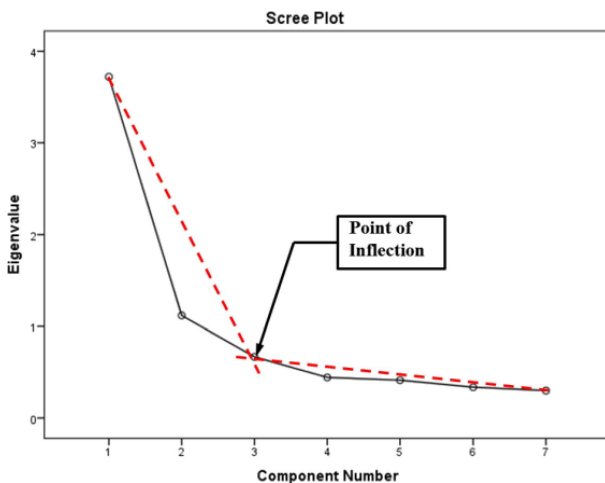


Fig. 1. A geometrical representation of factor analysis.

The Catell's scree test uses a graphical plot of the eigenvalue of the factor in the order of the extracts where an abrupt change of slope in the graph shows the maximum number of factors to be extracted and

the number of factors which need to be retained [42]. A horizontal and a vertical line starting at each end of the curve were inserted to determine whether an abrupt change of slope had occurred. The result was that after the second component, an abrupt change of slope was present for the scree plot (see Fig. 2).

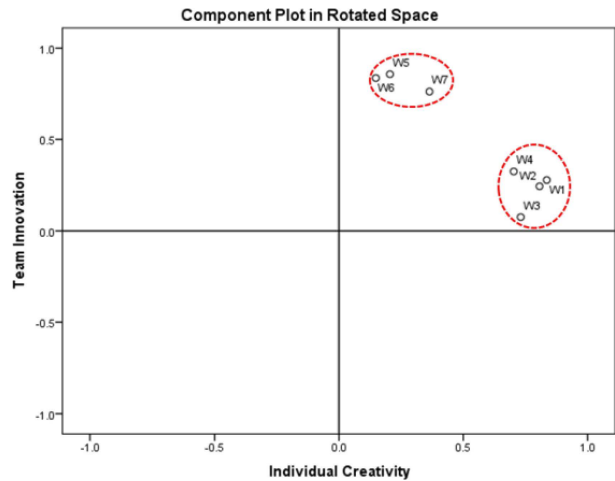


Fig. 2. Scree plot for workplace innovation.

Prior to extracting factors, communality estimates must be generated. Communality is the proportion of observed variance accounted for by the common factors. These values represent the total amount of variance for an item explained by the extracted factors. The communality is denoted by h^2 and is the summation of the squared factor loadings of a variable across factor [40]. The aim of factor analysis is to explain variance through common factors. This means, usually if a variable has low communalities (less than 0.20) where 80% is unique variance, it is excluded from the analysis [44]. To obtain the communalities, the following formula is used [45]:

$$h_j^2 = a_{j1}^2 + a_{j2}^2 \dots \dots + a_{jm}^2, \quad (1)$$

where a equals the loadings for j variables.

Using the factor loadings in Table 2, the communality of variable W1 was calculated using the aforementioned formula:

$$h_{W1}^2 = 0.836^2 + 0.279^2 = 0.776. \quad (2)$$

The factor loadings and the contribution of each variable to the factors is shown in Table 2. As illustrated, W1 has the highest contribution to Factor 1. Based on the indicated communality and the knowledge of the two factors 77.6% of variable W1 can be predicted. High variable communality indicates the set of factors can explain much of the variance of a variable [12]. From the result, there was no communality less than 0.20 [44]. Thus, all 7 variables were retained for further analysis.

Table 2
Rotated factor loadings of the WIT construct.

Variable: description	Rotated component		Communalities
	1	2	
W1: I am able to explore new ideas.	0.836	0.279	0.776
W2: I would be supported if I tried a new idea.	0.807	0.245	0.711
W3: I have the time to explore new ideas.	0.731	0.076	0.540
W4: I feel comfortable to voice a different opinion.	0.703	0.326	0.600
W5: My work group looks for ways of doing a better job.	0.205	0.857	0.776
W6: improving the quality of our work is our responsibility.	0.148	0.836	0.721
W7: my work group improves the service we provide.	0.364	0.762	0.713

Based on the eigenvalue and the Catell’s scree test criterion, two factors were extracted from the WIT construct. This two-factor solution explained 69.1 percent of the total variance. As presented in Table 2, the factor loadings of all seven variables were well above the 0.50 cut-off loading. All seven variables making up each of these two factors were significant without cross loadings. For component 1, the variables with high loadings were mainly concerned with individual creativity (WIT1). For component 2, the variables with high loadings centred on team innovation (WIT2).

The level of overdetermination indicates the degree to which each factor is clearly shown to have a sufficient number of variables and the extent to which each factor is adequately defined by a set of indicators [46]. Highly overdetermined factors occur when high factor loadings exist for at least three to four variables. These factors have moderate to high communalities (i.e., between 0.40 and 0.70 or higher), and demonstrate good simple structure [47]. Both factors had three or more items per factor, with factor loadings ranging from 0.703 to 0.857 and communalities ranging from 0.540 to 0.776, suggesting relatively strong data.

Confirmatory factor analysis

The EFA results presented in the previous section provided valuable insights into the dimensionality of the latent variables and confirmed the reliability of the measurement scales underpinning the model constructs. However, while the EFA provided preliminary results for the factor structure of each construct, the analysis was insufficient to conclusively establish the appropriate dimensionality of the measures. Therefore, confirmatory factor analysis (CFA) was performed to assess the overall goodness-of-fit of all the constructs to determine the validity of the measures [16, 48]. The CFA was conducted to assess construct validity and unidimensionality, which were critical elements in the measurement theory [10, 11]. Construct validity is concerned with whether there

is sufficient accuracy in reflection of theoretical concepts and if the items in a scale meaningfully measure the construct. The unidimensionality refers to the existence of a single construct underlying a set of observed variables, thus unidimensionality is established when an empirical item is significantly associated with the empirical representation of a single construct [10, 11]. A unidimensionality test was performed to examine the measurement errors and eliminate weak factor loadings as well as to check the adequacy of the model through a re-specified model and measure reliability.

To develop the CFA, the researcher should have reasonable prior knowledge of the factors and other theoretical findings to clarify the interrelationship among the measured variables. In this study, workplace innovation was not only theoretically established, but also had been empirically tested in previous studies. Therefore, the CFA was supplementarily conducted for scale refinement and validation purposes and the factor structure illustrated a set of relationships to represent how the measured items represented latent factors. The process examined the factor structures for each construct to check how well they fitted the data and analysed the models’ indices for construct validity and unidimensionality.

To determine how well the specified factor model represented the data, goodness-of-fit indices were examined. There are several indices to assess model-fit and they are categorised into two groups, namely absolute fit indices and incremental fit indices. Absolute fit indices are a direct measure of the degree to which the specified model reproduces the observed data, which can determine how well the theory fits the sample [10, 49]. The most fundamental absolute fit index is a Chi-square (χ^2) statistic used to measure the discrepancy between a hypothesised model and data [50]. However, the chi-squared test has been found to be sensitive and bias to sample size, thus this value will tend to rise as the sample size increases [12]. Root mean squared error of approximation (RMSEA) is also widely reported to estimate the

lack of fit to the saturated model. The root mean square residual (RMR) is the square root of the mean of the squared residuals which is an average of the residuals between the observed and estimated measures. Goodness-of-fit index (GFI) indicates the proportion of the variance in the sample variance-covariance matrix. Adjusted goodness-of-fit index (AGFI) can be used to compensate the GFI index in which the value of the index is adjusted for the number of parameters [49].

Incremental fit indices are concerned with the degree to which the model of interest is superior to the alternative baseline models by computing based on a comparison between the baseline model and expected model [49]. Incremental-fit index (IFI), normed fit index (NFI), comparative fit index (CFI), and Tucker Lewis index (TLI) are the most commonly indices reported in this category. The IFI indicates the issues of parsimony and sample size. The NFI compares the improvement of the overall fit of the researcher’s model to a null model, while the CFI is a modified version of the NFI taking the sample size into account. The TLI indicates a correlation for model complexity [48].

Model fit is assessed through an inferential Chi-square (χ^2) and several descriptive goodness-of-fit indices. Since the Chi-square (χ^2) is known to be inflated in samples with $N > 200$ [51], the Chi-square (χ^2) and degree of freedom (df) are reported as descriptive information rather than a strong inferential test of whether a model can be accepted or rejected. According to Hair et al. [10], at least one incremental index (CFI or TLI) and one absolute index (RMSEA or SRMR) must be reported. However, the availability of many different fit indices presents problems of selection to researchers because there is a lack of consensus regarding which absolute and incremental goodness-of-fit indices are optimal for gauging model-fit and should be reported [12, 50]. Therefore, multiple alternative fit indices were employed to measure the degree of model-fit [49]. For the model to be considered as having an acceptable fit, all eight indices were measured against the criteria as shown in Table 3.

In addition to producing goodness-of-fit indices, the modification indices (MI) and standardised residuals are useful statistical calculations for detecting model misspecification [11, 48]. The decrease in Chi-square if the two error term variables are allowed to correlate is shown by modification indices. The standardised differences between individual observed covariance and the estimated covariance are indicated as standardised residuals. Variables associated with modification indices which are greater than the threshold level of 5.0 justify further investigation for potential re-specification [11, 48], whilst standardised residuals between -2.58 and 2.58 are considered acceptable. Standardised residual values between -2.58 and -4 and between 2.58 and 4 may be problematic and deserve some attention but may not require any modifications to the model [10].

The model re-specification is conducted to improve the fit of the model [52]. Two methods can be used to re-specify the model: deleting non-significant variables from the model or adding paths to the model based on empirical data. Re-specification is guided by the analysis of the modification indices and examination of the standardised residuals. However, these outputs should only be used as a guideline, and should not dictate model re-specification, thus empirical rationalisation and theoretical considerations must also be considered to support model re-specification guided by these indices [53].

To accurately calculate the model parameters and fit indices, the maximum likelihood (ML) was used to achieve model fit. The ML is based on establishing parameter estimates, which maximise the likelihood that the observed covariance of the data reflects the population under investigation. Maximum likelihood of all parameters is also simultaneously estimated to minimise the discrepancies between the covariances of observed data and the proposed model [12]. The distribution of the data in this study was considered normal, and thus its use as maximum-likelihood data for CFA analysis was expected to produce reliable results [12, 48]. The ML can also be used for data with minor deviations from normality and is still fairly robust under the condi-

Table 3
Summary for goodness-of-fit indices.

Category	Indicator	Purpose	Acceptance level
Absolute fit indices	GFI	Evaluate the proportion of variance	> 0.90
	AGFI		
	RMSEA	Estimates how well the model fits	< 0.08
	RMR		< 0.05
Incremental fit indices	IFI	Determine the degree to which the model of interest is superior to the alternative baseline models	> 0.90
	NFI		
	CFI		
	TLI		

tion of moderate non normality [10]. The ML requires a sample size of at least 100 to achieve reliable findings [10], while the general rule considers a sample size of 100 to 200 as a ‘good sample size’ [49]. Therefore, a sample size of 3,125 seemed to fit very well with these recommendations.

Construct validity is assessed using statistical and practical procedures to determine whether the scores from an instrument are significant and can be used to understand a sample from a population [54]. Assessing construct validity using the CFA evaluates the extent to which a measure is related to other measures based on theoretical concepts and involves an assessment of convergent validity and discriminant validity. Convergent validity refers to the extent to which the measured variables of a specific factor have a high proportion of variance in common and assess the same factor, while discriminant validity refers to the degree to which a factor is truly distinct from other factors [10]. The measurement of convergent validity is determined through the magnitude of the standardised factor loadings and their significance level. The high value of factor loadings with the corresponding significant *t*-values indicates that an observed variable is able to measure a latent construct [55]. Hair et al. [10] recommend that a benchmark value of substantial magnitude of factor loading should be greater than 0.50. In situation where the factor loading is found to be larger than 1, it is referred to as a Heywood case. A model with this estimate is unacceptable because the factor explains more than 100% of the variation in this measure [48]. Moreover, a variable should also have an R^2 value (or squared multiple correlation, SMC) greater than 0.50 in order to demonstrate an adequate reliability [55].

The reliability of the model was evaluated through Cronbach’s alpha (α), followed by an assessment of the factors’ composite reliability (CR) and average variance extracted (AVE). Cronbach’s alpha determines how consistent the responses are across items within the scale. A Cronbach’s alpha value greater than 0.70 indicates that the scale is reliable [56]. Composite reliability measures the internal reliability of all the variables in their measurement of a construct. An average variance extracted determines the amount of variance in the measured indicators captured by the latent construct. Bagozzi and Yi [57] suggested 0.60 and 0.50 as the minimum value of composite reliability and average variance extracted, respectively. CR and AVE values were calculated using the following equations [10]:

$$CR = \frac{(\sum \lambda)^2}{(\sum \lambda)^2 + \sum e}, \quad (3)$$

$$AVE = \frac{\sum \lambda^2}{\sum \lambda^2 + \sum e}, \quad (4)$$

where λ is standardised factor loading and e is the standardised error.

Discriminant validity provides evidence that a construct is distinct from other constructs and captures the phenomena and concepts that other constructs do not [12]. Initial evidence of discriminant validity is provided by an inspection of the correlation coefficient between each pair of constructs. If two constructs have a significantly high correlation coefficient (i.e. greater than 0.850), then it might reflect the same concept and should be incorporated as a single construct [40]. Unidimensionality can be established when the variables load only a single construct. In order to be considered unidimensional, all model fit indices must meet the acceptable level [58].

The CFA was tested using Analysis of Moment Structures software package (AMOS). The measurement of the CFA for the WIT construct conformed to a rigorous threshold level of goodness-of-fit. The factor loading, *t*-value and significance level of each variable yielded a measure for the convergent validity; the value of R^2 provided a measure with which to assess the reliability of the variables; and the value of the correlation between the factors indicated the discriminant validity. The results of the CFA conducted on AMOS have been presented in Fig. 3.

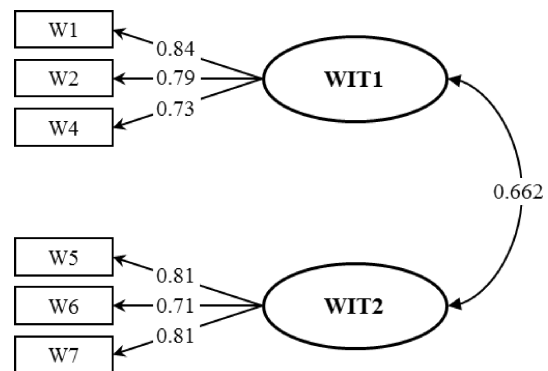


Fig. 3. CFA model of WIT construct.

Initially, the goodness-of-fit indices identified a poor degree of fit with the data. Each possible parameter which is not currently free to be estimated is examined for its modification indice to indicate the expected drop in overall Chi-Square value if a parameter is to be freed in the model [59]. The variable W3 was associated with relatively high modification indices, indicating this variable as a source of the misspecification. Therefore, variable W3 was removed in the model respecification process. The results of the CFA conducted on the WIT construct have been presented in Table 4.

Table 4
Summary of CFA results.

Workplace innovation	Loadings	t-values	R ²
<i>Individual Creativity (WIT1)</i>			
W1	0.84	f.p.	0.71
W2	0.79	44.41	0.63
W4	0.73	41.29	0.53
<i>Team Innovation (WIT2)</i>			
W5	0.81	f.p.	0.65
W6	0.71	37.98	0.50
W7	0.81	42.12	0.65

In examining patterns for large standardised residuals after respecification, two pairs of standardised residuals exceeded the absolute value of 2.58. As presented in Table 5, the standardised residual value was -3.13 for items W2 and W5 and 4.89 for item W4 and W7. However, as the standardised residual values were determine from a substantive point of view, there was no need for modification. Moreover, from a theoretical point of view, each variable of the two pairs appeared to measure different concepts (i.e. no possible definitional overlap).

Table 5
Standardised residual covariance matrix.

Item	W1	W2	W4	W5	W6	W7
W1	0.00					
W2	0.43	0.00				
W4	-0.43	-0.23	0.00			
W5	-1.64	-3.13	-0.63	0.00		
W6	-1.77	-1.86	0.40	1.97	0.00	
W7	2.00	1.90	4.89	-0.34	-1.39	0.00

The respecified model yielded an acceptable level of fit: $\chi^2 = 165.35$, $df = 8$, GFI = 0.98, AGFI = 0.95, RMSEA = 0.08, RMR = 0.02, IFI = 0.98, NFI = 0.98, CFI = 0.98, and TLI = 0.96. All variables had loadings greater than 0.50 and all t-values were highly significant ($p < 0.001$), confirming convergent validity. There was no problem of a Heywood case because all the factor loadings were estimated to be smaller than 1. The R² values of all the variables were greater than 0.50, which was indicative of the reliability of the variables. The correlation coefficient between the two factors was 0.662, thus indicating discriminant validity. Based on the acceptable level of the fit indices, this two-factor model was considered to have upheld unidimensionality.

Table 6 summarises the reliability of each factor. Both factors have a Cronbach alpha greater than 0.70, which shows measurement scales consisting of a set of homogeneous items to measure the meaning of the factor. Composite reliability for each factor

in the CFA model was above 0.60, demonstrating that these factors had adequate internal consistency and were sufficient in their representation of the construct. Both factors also had AVE values greater than 0.50, indicating that more variance was captured by the variables within each factor and shared more variance in the factor than with the other factor. This also means that the construct relative to the amount of variance was due to measurement error. The final value of Cronbach's alpha of workplace innovation construct was 0.849, thus confirming the reliability of this construct.

Table 6
Reliability tests of WIT construct.

Factor	α	CR	AVE
Individual Creativity (WIT1)	0.83	0.86	0.62
Team Innovation (WIT2)	0.82	0.88	0.61

Conclusions

Workplace innovation is crucial for many of today's organisations. In order to formalise the concept of workplace innovation, reliable and valuable measurement is needed. This can help organisations generate valuable creative ideas and implement high quality innovative practices. The aim of the research is to enhance current understandings of workplace innovation and to improve the way it is measured. Workplace innovation is proposed in this study to consist of two related dimensions, namely, individual creativity and team innovation. This study investigated the construct validity of workplace innovation through both exploratory factor analysis (EFA) and confirmatory factor analysis (CFA).

EFA was performed using principal component analysis (PCA) with varimax rotation to assess the dimensionality of the workplace innovation construct. To interpret the meaning of each factor, the salient variables were identified and used as the indicators for the explanation. The salient variables identified for each extracted factor were higher than 0.5, indicating a substantial degree of contribution of each variable to its extracted factor. Thus, 7 variables with factor loadings ranging from 0.703 to 0.857 were retained. The study results support that the accuracy of the factor solutions of the EFA model is dependent on the magnitudes of communalities and factor loadings as well as the level of overdetermination. This finding confirms the results from other studies which have highlighted the importance of high factor loadings, high communalities, and a reasonable level of overdetermination in obtaining quality factor solutions [47, 60].

To assess the reliability and validity of the workplace innovation construct, CFA was conducted using the maximum likelihood estimation method. To improve the model fit, the structure of the construct was slightly refined by eliminating variable W3, which had relatively high modification indices. After the model re-specification process, the CFA model fit very well with the collected data and the relationships between the observed variables and latent variables were significant.

The validity and reliability of the construct were confirmed in the EFA and in the CFA. The results from both methods were consistent and identified two dimensions of workplace innovation including individual creativity (WIT1) and team innovation (WIT2). Workplace innovation requires the generating force of both individual creativity and team innovation to create and implement new processes, products, services, and methods of delivery in the public sector [61]. Therefore, these measures are deemed appropriate proxies that can be used to measure workplace innovation among engineers in the APS.

To improve workplace innovation, it is necessary to measure and consider individual creativity and team innovation. Objective measures such as patent counts, technical reports, or dollar value of return on investment of innovative products can usually only be assessed for specific tasks of scientists and R&D workers [62]. However, objective measures could not be used to measure engineering tasks which are more structured, routine, and technical service oriented. Most engineers' jobs do not commence in a vacuum, but instead require incremental performance improvements or modifications to existing products, processes, or systems. Therefore, research should be undertaken in the engineering work context. Accordingly, it is anticipated that workplace innovation measurements would be useful for senior managers to effectively assess, and improve, individual creativity and team innovation within their organisation. Senior managers could utilise workplace innovation ratings to design interventions which would increase creative and innovative resources, resulting in engineers experiencing opportunities to exercise their creativity and implement innovative ideas, thereby enhancing workplace innovation. This study can be implemented with TRIZ approach which is set of novel methods, techniques and tools for inventive design [63]. Both approaches could collectively develop engineers to be more innovative during their practice of engineering design, new product development and process improvement.

The study has provided important findings, however there is also a potential limitation. Individual

level variables were collected using self-reports, based on the preliminary nature of this study. This means respondents may not have presented true representations for sensitive items, and as such were not included. Nevertheless, the validity of self-reports is also justified because they can be used to measure objective and subjective data [64]. In addition, the large sample permitted the findings to be generalised to a larger population [65]. Furthermore, self-reported bias does not appear to be a serious problem for the study findings due to evidence of construct validity between the variables.

Future research could also examine the relationships between organisational factors and workplace innovation using the developed measurements. Suggestions for future empirical research include investigating workplace innovation practices, types of leadership, organisational culture, and career satisfaction factors to increase understanding of the relationships between them. Such investigations could help provide a framework to aid Commonwealth departments in encouraging creativity and innovation among their engineers.

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