A Comprehensive Guide to PLS-SEM Reflective Measurement Model: A Hands-On Approach to Adapting the Hospitality Resilience Scale

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Abstract

The proposed research seeks to offer detailed guidelines for creating a reflective measurement model with PLS-SEM and to tailor the resilience scale for the hospitality industry through the application of the PLS- SEM measurement model. The scale was adapted from the parent scale designed by Kumari and Sangwan (2014), which was shown to have outstanding psychometric properties in the context of the Indian Pharmaceutical Industry. A survey was conducted to collect the data from the 100 employees of luxury hotels working in Uttarakhand Garhwal Zone, India. The scale achieved satisfactory reliability and validity to utilize in the hospitality industry. The composite reliability of each factor was greater than .80, yielding .88,.85,and.88 for autonomy, problem solving-skills and social-competence. The instrument attained a satisfactory level of convergent and discriminant validity. The present study will be helpful for the researchers, academicians, administrators and other stakeholders involved in the hospitality industry to assess the level of resilience of the employees. Understanding the neural roots of resilience can help the hospitality industry improve employee efficiency and wellbeing. To enhance employees' resilience training, resources and support networks can be provided to help them manage stress and control emotions.

Keywords: Hospitality employee's resilience instrument (HERI); Autonomy; Problem-solving skills Social-competence; PLS-SEM

Introduction

The expression "resilience" is derived from Latin, which means "bouncing back, jumping back up, or springing back", which means overcoming adversity through rebounding. Employees in the hotel industry deal with both good and bad customers, psychological distress, and workplace bullying (Ariza-Montesetal.,2017; Anasorietal.,2020). To resolve this challenge, conscientious hotel managers sometimes take proactive steps, such as creating a supportive environment and making some adjustments in the working environment (Ariza-Montes et al., 2017). For instance employees use emotional labor and emotional intelligence techniques to please guests and meet their demands. Using these techniques, however, is difficult because it has its own set of consequences, such as stress, emotional burnout, emotional exhaustion, emotional termination, emotional dissonance, job dissatisfaction, and depersonalization. Resilience in hospitality employees is vital because it helps them deal with daily challenges such as hectic schedules, guest complaints, demanding customers, owner pressure etc. To increase the resilience of hospitality employees, practices such as mindfulness(Anasori et al., 2020), spirituality, and religiosity have been suggested (Chavers, 2013). It is imperative to measure hoteliers' resilience because it helps top-level management to plan training and mindfulness exercises for their employees. The proposed investigation aimed to develop a hospitality employee's resilience instrument (HERI) by adapting its parent scale developed by Sangwan (2014) on resilience for the pharmaceutical industry and checked the psychometric properties of the adapted instrument through the PLS-SEM reflective measurement model.

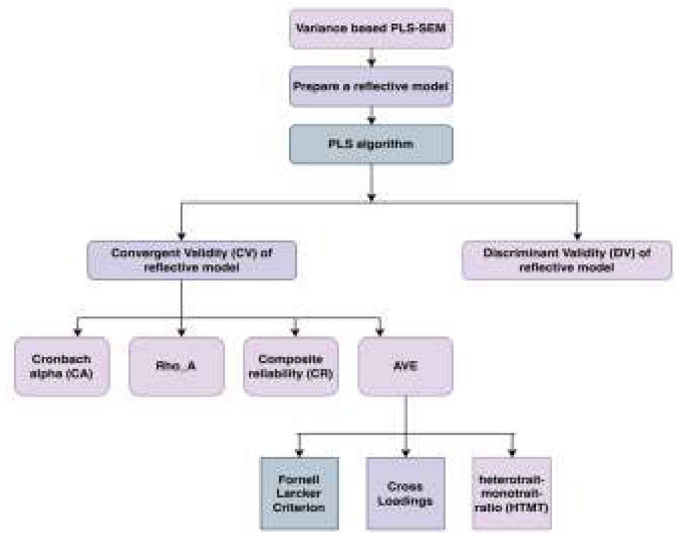
Guidelines to utilize PLS-SEM for developing reflective measurement model

PLS-SEM

The PLS-SEM technique was first put forth by Wold (1975)to address modelling challenges in social science research (Sosik et al., 2009).According toHair et al. (2019b), the PLS-SEM method incorporates thekey procedure shown in Figure-1 for the reflective measurement model.

Two widely used methods for estimating the SEM model's relationships are CB-SEM and PLS-SEM (Hair et al., 2011; Hair et al., 2019a). Until 2010, CB-SEM was the only widely used method by researchers, statisticians, and practitioners for examining the interrelationship between observed and latent (hidden) variables. However, in the past few years, the use of PLS-SEM has risen steeply (Hair et al., 2017). PLS-SEM gained recognition because it allows investigators to evaluate complicated models with several dimensions, indicators variables, and structural paths without striking distributional assumptions known as normality assumptions (Hair et al., 2019b). PLS-SEM estimations include principal component relationship models and are useful in theory development through exploratory research, such as analyzing financial ratios. This approach is effective even when dealing with small populations and limited sample sizes (Rigdon, 2016; Hair et al., 2017), although PLS-SEM can also handle large datasets. It is particularly valuable when the research relies on secondary data (Purwanto and Sudargini, 2021).

Figure 1: Phases of reflective measurement model



According toHair et al. (2019b), for researchers with a small sample size, PLS-SEM is a solution with a model consisting of many dimensions and items (Fornell and Bookstein, 1982;Hair et al., 2017; Petter, 2018;Purwanto and Sudargini, 2021).Comparing the sample size of CB-SEM with PLS-SEM shows that the amount of data required in CB-SEM is much larger than PLS-SEM (Hair et al., 2021).In some cases, CB-SEM recommends a sample size of 100–200. On the other hand, the recommended sample size for running PLS-SEM is a minimum of 30–50 samples (Purwanto and Sudargini, 2021). However, a small sample or complex empirical analysis is not a "silver bullet" to avoid CB-SEM and choosing PLS-SEM (Marcoulides and Saunders, 2006; Sosik et al., 2009). Avoiding the complex analysis is one of the bullish and ill-treated reasons for more and more use of PLS-SEM by many researchers to obtain model solutions with the complex, complicated and smaller data set(Marcoulides and Saunders, 2006;Goodhue et al., 2012).However, it is imperative to understand that using a small sample does not mean that PLS-SEM has some magic to produce effective results in a small sample (Peter, 2018; Hair et al., 2021)However, the reason for this is related to factors such as the population characteristics, which determine when a small sample size is permissible. For instance, the size of the population is influenced by the organization's size and type. Smaller organizations will inherently have smaller sample sizes compared to larger organizations with a greater number of employees (Rigdon, 2016).

Convergent validity

Convergent validity (CV) estimates the level to which two constructs in the measurement model are correlated. The high correlation demonstrates that scale computes well what it is intended to compute(Hair et al., 2010). The coefficient of correlation value for establishing convergent validity (CV) ranges between -1.0 and +1.0 (Hair et al., 2019b). A reflective model's convergent validity (CV) can be determined by its internal consistency reliability, which includes Cronbach's alpha (CA), composite reliability (CR), Rho_A, and the average variance extracted (AVE).

The threshold values for Cronbach's alpha (CA) and CR are nearly equivalent, that is⩾ .70 is considered acceptable (Taber, 2018). One study also reported that CA is acceptable to .70 or .60 (Van Griethuijsen et al., 2015).However, if we go back, Hair et al. (1998) also suggested that the cut-offCAvalue, in any case possibly considered for any scale, could be equivalent to .55 (Samuels, 2015).A value ⩾ .80 is considered good, and a value ⩾ .90 is extremely satisfactory or excellent (Taber, 2018). One of the most significant findings of Taber (2018) was that multiple scientific journals suggested various qualitative descriptions for CA values , which indicates that scientific publications accept alpha values based on educated guesses rather than having a firm understanding. However, an analysis of prior studies reveals that the CA value that was more widely accepted and reported in numerous scientific investigations was ⩾.70 .

An acceptable degree of Rho_A values is another technique for determining convergent validity (CV). The method for estimating the strength of association between two variables is based on Rho_A values. It is recommended that the Rho_A threshold value should be ⩾ .70 . Average variance extracted (AVE) is another method for establishing convergent validity (CV). TheAVEminimum acceptable value should always be at least .50 or higher signifies that constructs explain 50 per-cent or more of the indicators variance that makes up the construct and reveals a good amount of convergent validity (CV) (Hair et al., 2022). Moreover, to calculate theAVE, the sum of the squares of the loadings is divided by its error term0(Purwanto and Sudargini, 2021).

Discriminant Validity

Discriminant validity (DV) checks that each construct in the measurement model is distinct from the other (Hair et al., 2010). Examining the relationship between latent variables is necessary to find the discriminant validity (DV). The two popular methods to analyse the discriminant validity (DV) include: a covariance-based structural equation modelling (CB-SEM), and a variance-based structural equation modelling (VB-SEM also known as PLS-SEM).

Further, Hair proposed two approaches to evaluate discriminant validity (DV) using PLS-SEM: The first one is the Fornell-Larcker criterion, and the second one is the inspection of Cross-loading. However, Henseler et al. (2015) simulation study confirmed that these two approaches needed to be more reliably capable of assessing the lack of discriminant validity (DV) in everyday research conditions. As a result, researchers proposed a new approach based on a Multitrait-multimethod matrix to calculate the discriminant validity (DV), also called the HTMTof Correlations (Henseler et al., 2015). Henseler and his colleagues promoted the HTMT as a modern technique for measuring discriminant validity (DV). According to Henseler et al. (2015), if the HTMT value is large, there is a problem in establishing discriminant validity (DV) (Purwanto and Sudargini, 2021).Henseler et al. (2015) suggested the threshold value of the HTMT = .90) for structural models comprising conceptually similar dimensions that are similar because a threshold value close to .10 indicates a lack of discriminant validity (DV) (Hair et al., 2021). If the value of HTMT comes > .90 threshold value, in that case, no discriminant validity (DV) is established. However, a solution to this problem was proposed by Hair et al. (2019a) if the dimensions are conceptually different, a lower threshold value of HTMT is acceptable, which is .85 for establishing discriminant validity (DV) (Henseler et al., 2015;Purwanto and Sudargini, 2021).

Research methods

Sample size of the study

The data from 100 employees were gathered through a paper-based questionnaire from the premium hotel employees in Uttarakhand's Garhwal Zone, India. The sampling method used was convenience sampling. According to Etikan et al. (2016), in some cases, it is acceptable to use convenience samplings, such as where the researcher is conducting a study and collecting data that is easily accessible on a geographical, spatial, and administrative basis. For the present study, the targeted population encompassed the employees of four and five-star hotels. Participants who needed help to complete the questionnaire, such as busser boys, housekeeping staff, valet parking, security guards, and others, were assisted by researchers. For such employees, researchers ticked the responses after knowing the employees' preferences.

Sampling adequacy

According to the sample size recommendations made by several eminent experts (refer Table-1), a sample of 100 employees was used for the current investigation (MacCallum et al., 1999; Yurdugül, 2008).

Table 1: Recommended sample size

Authors	Suggested sample size	Parentheses
Yurdugül (2008)	*N=between 30 and 50*	*However, any item loading less than <.40 will be removed from the instrument, and principal component analysis (PCA) will be rerun (Samuels, 2015)*
Guadagnoli and Velicer (1988) ; Yurdugül (2008)	*N=between 50 and 100*	*However, any item loading less than <.40 will be removed from the instrument, and principal component analysis (PCA) will be rerun (Samuels, 2015)*
Gorsuch (1983)	*N=100*	*Supported by Kline, (1979)*
Guilford (1954)	*N=200*	*Generally accepted*
Cattell (1978)	*N=250*	*Generally accepted*
Kline (2015); Nunnally and Bernstein (1994)	*N=minimum 300*	*Segall (1994) asserts that the sample size of 300 is insignificant (Yurdugül, 2008)*
Charter (1999)	*N=400*	*The alpha coefficient may be unstable with small sample number (Charter, 2003)*
Yurdugül (2008)	*N=200; 300; 500*	*The recommended minimum sample size for coefficient alpha (Yurdugül, 2008)*
Note: No reliability analysis will be done if the sample size is less than (*N<30)*(Samuels, 2015).		

Demographics

Table 2: Respondents demographics

Demographic Variables	**Survey (N=100)**	
	Count	Percentage (%) Distribution
Gender		
Male	68	68%
Female	32	32%
Age		
18-25	29	29%
26-40	38	38%
40 and above	33	33%
Work Experience		
Less than 1 year	12	12%
1 year	9	9%
1 to 3 years	14	14%
3 to 5 years	33	33%
5 to 10 years	14	14%
More than 10 years	18	18%

As detailed in Table-2, the sample consists of 100 participants, with 68 percent identifying as men and 32 percent as women. This sample size is sufficient for performing exploratory factor analysis (EFA) (Gorsuch, 1983;Kline, 1979; Guadagnoli and Velicer, 1988;Yurdugül, 2008). The distribution of employees by age groups is as follows: 29 employees were aged 18 to 25, 38 were between 26 and 40, and 33 were 40 or older. Experience levels are distributed as follows: employees with less than a year of experience average 12 percent, those with one year of experience average 9 percent, those with one to three years average 14 percent, those with three to five years average 33 percent, those with five to ten years average 14 percent, and those with ten or more years average 18 percent. Each individual was assigned to a unique role, with samples drawn from front desk staff, kitchen staff, middle-level positions, management trainees, and lower-level service staff.

Research instrument

The five-dimension questionnaire developed by Sangwan (2014) was adapted and tested for psychometric properties. In light of the current situation, in which hotel employees only have a little time to devote to surveys, the scale was designed with 12 items to assess their resilience, following all essential steps in measurement development. Such as checking the reliability and validity of the scale adapted (Ewalds-Kvist, 2016;Ahmad, 2021). The suitability of the items was reviewed by three experts, including two professors and a general manager from a premium hotel. Additionally, seven respondents from the service sector were interviewed to identify any inappropriate or irrelevant questions. Based on expert feedback, the scale was refined to nine items across three dimensions (refer Table 3) relevant to the hospitality industry. Further analysis and responses were gathered using a five-point Likert scale with scores ranging from 1 to 5, with 1 demonstrating strongly disagree and 5 showing strongly agree. The PLS-SEM version 3 was used to check the reliability and validity of nine items in the resilience scale.

Table 3: Scale items

Dimensions	Scale items
Autonomy	I perceive the changing situation as an opportunity to learn from it.
	I follow a planned routine, but easily welcome any change.
	I keep myself motivated under any circumstances.
Social-Competence	I am open to discuss problems with others.
	I am able to take help from others in the matters that I cannot solve.
	I understand that the same people sometimes behave differently due to some differences in their state of mind or situations.
Problem-Solving Skills	I try to identify actions that can solve problems.
	I focus on my daily life activities to remain stress free.
	I can view the situation critically, and I am able to reach a decision favourable to my objectives.

Data Analysis

Result of the hospitality employee's resilience instrument (HERI) with detailed guidelines to use PLS-SEM reflective measurement model

Step1 - Convert data file to CSV:

The first step before running PLS-SEM analysis is to convert the data files (Excel or SPSS) to CSV (Comma-delimited version), also known as a comma-separated value file. The collected data wasexamined to ensure that there were no missing values or outliers. If there is a missing value in the data, researchers must first fix it using Prof. Hair's methods. Missing data causes a problem when testing SEM models with CB-SEM or PLS-SEM. The methods for resolving missing data include either reducing the sample size of the data to its original quantity or the imputation of missing data (Hair et al., 2018).

Step2 - The construct reliability of the hospitality employee's resilience instrument (HERI):

A reflective measurement model is used to evaluate the reliability and validity of the items or factors. In this study, the reliability of the scale was assessed using Cronbach's alpha (CA), Rho_A, composite reliability (CR), and average variance extracted (AVE) for each construct. The instrument comprised three dimensions—Autonomy, Social-Competence, and Problem-Solving Skills—each with three items: AUT1, AUT2, AUT3, SC4, SC5, SC6, PSS7, PSS8, and PSS9.

Table-4 displays the internal reliability of the Hospitality Employee Resilience Instrument (HERI), which is based on the constructs autonomy (AUT), social competence (SC), and problem-solving skills (PSS). The CR for all factors exceeded the threshold of .70, with AUT at .88, SC at .85, and PSS at .88 (Diamantopoulos and Winklhofer, 2001;Drolet and Morrison, 2001). Consequently, the research findings indicate that the instrument demonstrates a high level of internal consistency and reliability.

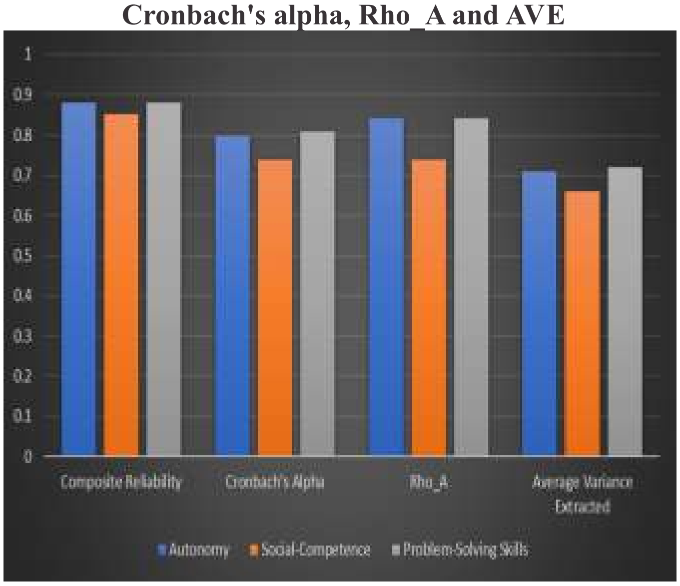
Table 4: Internal consistency

	Matrix Composite Reliability	Rho_A	Cronbach's Alpha	Average Variance Extracted
AUT	.88	.84	.80	.71
SC	.85	.74	.74	.66
PSS	.88	.84	.81	.72

Another method for measuring internal consistency reliability besides CRis Cronbach's alpha (CA). However, the values produced byCAare always less than those produced byCR (). Researchers can determine the individual reliability of each dimension usingCA, which measures the degree of effectiveness of a single item in a sub-scale and correlates it with the aggregate of other items that possess a specified value of .70 (). Each CA value is greater than the threshold limit of .70, which was .80; .74; .81 for autonomy; social-competence; problem-solving skills. The values ranged from .70 to .90, which are deemed "satisfactory to good." The output in Table-4 showed that all values fell within this acceptable range.

The findings indicate that all three dimensions—autonomy, social-competence, and problem-solving skills—showed satisfactory CA and CR values. Additionally, Rho_A is utilized to evaluate CR, with a recommended Rho_Avalue > .70. The Rho_A values for all constructs exceeded .70, meeting this criterion. Figure-2 illustrates the internal consistency, Rho_A, construct validity based on AVE output, as well as convergent and discriminant validity of the Hospitality Employee Resilience Instrument (HERI), all of which were satisfactory and fall within the expected range.

Figure 2: Composite reliability, Cronbach's alpha, Rho_A and AVE



Step3 - The convergent validity (CV) of the hospitality employee's resilience instrument (HERI):

To validate the instrument, it is essential that the constructs and items accurately measure what they are intended to measure. The average variance extracted (AVE) is used to calculate an instrument's convergent validity (CV). AVE is an abbreviated form of convergent validity (CV). To compute the AVE, square the loadings of each indicator on a construct and compute the mean values (Hair et al., 2019a). If the AVE>.50, there is no convergent validity (CV) problem, and the construct explains 50 per-cent of the variance in its items (Hair et al., 2018).In this study, the AVE values for all three dimensions were > .50, suggesting no problem with convergent validity (CV). Table-4 displays the AVE values for autonomy [.71 > .50], social competence [.66 > .50], and problem-solving skills [.72 > .50], confirming that the instrument effectively evaluated these constructs with high convergent validity (CV).

Discriminant validity (DV) of hospitality employee's resilience instrument (HERI)

Discriminant validity (DV) is another approach for assessing an instrument's validity. It empirically measures how distinct the constructs are from one another within the structural model (Hair et al., 2018). To measure discriminant validity (DV), three methods can be used: the Fornell-Larcker criterion, cross-loadings, and the heterotrait-monotrait ratio (HTMT). Table-5 represents the results of the Fornell-Larcker criterion for evaluating the reflective model of the constructs. For autonomy (AUT), the square root of the AVE is .84, which was higher than the values for social competence (SC) at .66 and problem-solving skills (PSS) at .41. Similarly, the square root of the AVE for social competence (SC) was .81.

Table 5: Fornell-Larcker criterion of the resilience instrument

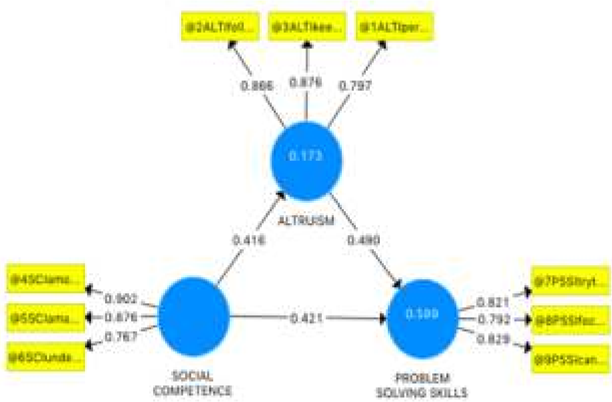
	Autonomy	Social-Competence	Problem-Solving Skills
AUT	.84		
SC	.66	.81	
PSS	.41	.62	.85

The Fornell-Larcker criterion and cross-loadings presented in Table-5 and Table-6 indicate that the discriminant validity (DV) of the constructs was effectively established. Table-5 shows that the square root of the AVE for each construct was higher than its correlations with other dimensions, and each item exhibited higher loading on its corresponding dimension. Table-6 displays the cross-loadings for the constructs of the resilience instrument—autonomy (AUT), social competence (SC), and problem-solving skills (PSS)—confirming that each construct's items loaded appropriately on their intended dimensions.

Table 6: Cross loadings of resilience instrument (HERI)

Items	Autonomy	Social Competence	Problem-Solving Skills
ALT-2	.86	.53	.32
ALT-3	.87	.66	.44
SC-4	.37	.59	.90
SC-5	.45	.54	.87
SC-6	.85	.42	.76
PSS-7	.63	.82	.47
PSS-8	.47	.79	.56
PSS-9	.50	.82	.48
ALT-1	.79	.54	.24

Figure 3: The reflective measurement model representation of outer loadings and R2



Then we calculated the HTMT, an additional method for assessing discriminant validity (DV). The recommended threshold for HTMT is below .90(Hair et al., 2018; Henseler et al., 2015) In this study, HTMT values were satisfactory as all values in Table-7 were < .90 threshold. Consequently, the measurement model shown in Figure-3 indicates that the Hospitality Employee Resilience Instrument (HERI) is a well-developed tool for evaluating employee resilience.

Table 7: Heterotrait-monotrait ratio (HTMT)

	Autonomy	Social-Competence	Problem-Solving Skills
AUT			
SC	.83		
PSS	.47	.79	

Conclusion

The proposed study sought to adapt a resilience scale for hospitality employees by employing a detailed guide to modify the scale using the PLS-SEM reflective measurement model. The scale was adapted from its original version designed for assessing resilience in the pharmaceutical industry. Researchers also sought to create a more concise and precise version of the scale to address issues associated with lengthy instruments, such as respondents' lack of interest in participating in longer surveys, careless responses and loss of interest (Tourangeau, 2018).

Resilience plays a crucial role in a person's ability to manage stress, maintain job satisfaction, and deliver high-quality service, particularly for hospitality workers who often encounter difficult and high-pressure situations. Resilient individuals are better equipped to cope with setbacks, recover from failures, and maintain a positive outlook when facing challenges. This trait is essential across all individuals, industries, and fields. In the hospitality industry, where employees deal with demanding guests and the pressures of premium hotels, their inner resilience—rooted in their mental fortitude and emotional regulation—is key to effectively managing their roles (Traymbak et al., 2022; Amir and Standen, 2019).

Limitations and suggestions

The data collection procedure was crucial. Transparency continues to be a barrier in India, with organizations refusing to share information with outsiders or via any means. Because of their brand names, premium hotels are more resistant to conducting surveys. As a result, the sample gathered was limited in size.

As the database grows, the study will be expanded, and the instrument will become a more reliable tool for measuring the resilience of hospitality employees. The current 9-item revised hospitality employee's resilience instrument (HERI), was tested and validated on hospitality employees, but future research should use it to test its psychometric properties on other areas of services.

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