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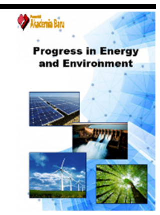

Testing Measurement Invariance for Green Cleaning Services Implementation across Malaysian Cleaning Industry Stakeholders' Group

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ABSTRACT

Measurement invariance is one of the most important aspects of model development process without which the interpretations of research findings on population sub-groups may be vague and invalid. This study tested the measurement invariance of critical success factors for green cleaning implementation and performance model across different stakeholders in Malaysian Cleaning Industry. The study is essential to check if the proposed model and its underlying constructs have appropriate structural orientation regarding critical success factors for green cleaning performance and meaning across comparable varied groups. A quantitative, non-experimental, cross-sectional survey design was adopted for the study and data were collected from 500 participants who were chosen from three categories of respondents namely contractors, consultants and clients organisations using a combination of non-probability and stratified random sampling techniques. The data was analysed with the aid of the Statistical Package for Social Sciences and Analysis of Moment Structures Software (versions 22.0.0). The results show that all the three measurement invariance models tested have achieved acceptable goodness-of-fit indices. The study outcome also indicates that the critical success factors for green cleaning services implementation model are invariant across the three different stakeholders in the Malaysian cleaning industry. The findings suggest practical implications for cleaning service providers', facilities managers and clients on the need to invest in the critical success factors mainly human, physical, financial and social resources and to productively align such for effective green cleaning services implementation to achieve competitive organisational performance.

Keywords:
Green cleaning, critical success factors, performance and measurement invariance

1. Introduction

Conventional cleaning services has been blamed as one of the significant contributors to poor indoor air quality, environmental contamination and decay of the eco-system [1-3]. Thus, green

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cleaning technology was introduced to mitigate the troubles related to conventional practices. Many issues and difficulties are experienced in the green cleaning services implementation regardless of its remarkable potential and advantages. The motivation behind this study is to test measurement invariance for green services implementation for competitive Organisation performance. The investigation is necessary to give fundamental answers for the effective execution of green cleaning services for Malaysian green cleaning stakeholders.

A thorough Green cleaning (GC) program involves a full strategy to cleaning and accentuations on effective cleaning to produce healthier buildings and diminishes outdoor environmental impacts. As indicated by Ashkin [4] and BETCO [5], green cleaning is characterised as "cleaning to protect health while at the same time diminishing the hurtful impacts on the environment." Two fundamental ideas are demonstrated in this definition. First, it distinguishes the need to concentrate on the health of the occupiers and the janitorial staff of the buildings. Also, it perceives the huge ecological impacts connected with the conventional cleaning business. The author, notwithstanding, noticed that green cleaning is not simply the substitution of traditional chemical-based cleaning products with "certified" green options. However, it is a good step to begin. Green cleaning is an innovation that re-examines how to create a healthy high-performing building that lessens adverse effects on the environment.

Diverse factors impact the achievement of a successful green cleaning programme. Though product selection is essential, in any case, its effect will be negligible with inappropriate cleaning methodology that leaves offices grimy and put in danger the wellbeing of occupiers, visitors and environment. In this manner, green cleaning grasps a far-reaching programme including chemicals, equipment, processes, paper, mops, liners, matting and all that are utilised in productive cleaning program. According to Zainol *et al*. [6], its goal is to diminish the use of chemicals, energy and water. Hence, green cleaning objective stress decreasing human-health and environmental risks while sustaining or even upgrading the effectiveness of cleaning programs [7]. Despite the potential advantages of green cleaning (GC), it is faced with implementation difficulties. These problems include a low level of awareness, training and education; lack of green cleaning requirements; ineffective communication; and the limited supply of green products and material [8, 9]. These factors contribute to the failure of green cleaning project implementation. For a program to be effective as indicated by Ogunlana [10], it is vital first to ascertain the failure factors. These factors have been categorised by Atamamen *et al*., [9] under five different types of resources namely physical, human, financial, social and organisation. Careful examination of past studies revealed lack or inadequate research on the correlation between these barriers and success factors on green cleaning implementation and performance.

It is the opinion of this study that investigations into testing measurement invariance for green cleaning services implementation across Malaysian Cleaning Industry stakeholders' group will generate a working environment and wide acceptance of green cleaning practices to all stakeholders for a sustainable, high-performance green cleaning programme. Group invariance analysis is an SEM framework for testing any number or types of contrasts between comparative models evaluated for different groups of respondents [11]. Hence, the key objectives of this study comprise, first to define various measurement invariance tests and secondly to test GC CSFs measurement among cleaning contractors, consultants and clients demonstrating them with Amos. This will help to check whether there are any significant differences between individual group models by comparing the same model across different samples of respondents in the measurement model. In the following sections, literature about green cleaning and measurement invariance is reviewed. Then research methods including data collection and analysis are explained. Finally, conclusions are drawn for GC CSFs measurement scales, and implications are discussed.

2. Green Cleaning Services Implementation and Its Importance

Conventional Green cleaning technology was introduced as a response to the call of how cleaning industry could work towards sustainable development. This sustainability initiative is becoming progressively in demand owing to the rising anxieties about the environmental, health and climate change effects of conventional cleaning practices (their strong water use, waste generation, energy consumption, and greenhouse gas emissions and the resulting health hazards).

2.1 Importance of Green Cleaning Services Implementation

The crucial advantage of green cleaning with its accentuation on cleaning for health and the environment leads into several measurable gains for building owners, managers, janitorial staff and building occupiers. Unlike conventional cleaning that is associated with risky Volatile Organic Chemicals (VOCs), airborne dust and other indoor pollutants presenting diverse health threats among building occupants and employees resulting to increased absenteeism and lower productivity on the job [12]. Green cleaning however enhances indoor air quality [13] results in decreased absenteeism and higher productivity on the job [14, 15]. This innovative cleaning system also boosted employee recruitment and retention thereby improving morale among existing workers, decreases turnover and eases recruitment of new staffs [5, 16, 17]. Green cleaning practice has the potential for higher rental income in light of the fact that the advantages of indoor air quality can propel inhabitants to spend more for a given work area. It complies with new governmental regulations as governments and stakeholders increasing their regulation of VOCs and other hazardous chemicals [18].

Furthermore, there are minor complaints about green buildings where green cleaning is appropriately implemented particularly now that public awareness has instigated building inhabitants to become progressively intolerant of ineffective and unsustainable cleaning. It also improved public image as a result of increased public awareness of issues surrounding green environments. The practice results in more extended lasting buildings, longer life of a facility's carpets, floors, furnishings, computers, HVAC systems and other components. It facilitate source reduction especially the use of concentrated chemicals through a chemical management system instead of ready to use products. This will make an impact on the materials dumped into landfills every year. Additionally, the utilisation reused materials, paper and plastic, reduce waste generation.

2.2 History of Measurement Invariance

As pointed out by Putnick *et al.,* [19], measurement invariance assesses the psychometrics of a construct across groups or measurement occasions and shows that a construct has a similar meaning to those groups or across repeated measurements. Measurement invariance takes various forms and is indispensable to psychological and formative research as it is an essential requirement for comparing group means. Therefore, the test is a crucial tool if the investigator has the intention to conduct group comparisons between two or more groups [20-23]. Measurement model as depicted by Dimitrov [24] is the degree to which the parameters of a model are invariant. According to Liu [22] that the primary concern with measurement invariance is the level of which a particular construct or a measure of a construct retain it means across the group or over time.

A construct that lacks invariance is typically alluded to as "non-invariance". The confirmation of measurement invariance occurs when the relationships among observed variables and factors are equivalent across groups. This suggests that a given measure operates in a similar way across groups. A partial measurement invariance according to Cotter *et al.,* [25], is said to occur if the relationships are alike across groups for some (yet not all) items in a measure. Measurement invariance is an essential requirement for making comparisons across different groups. Without proof of measurement invariance, cross-group comparisons can prompt wrong deductions. Measurement invariance is a requirement for making comparisons across different groups. Without proof of measurement invariance, cross-group comparisons can lead to incorrect inferences.

The importance of testing measurement invariance entered the domains of literature over 50 year's back [26, 27]. Undeniably, measurement invariance is fast becoming a trend in psychological and developmental research. As noted by Little, Rensvold *et al.*,[28], Steenkamp *et al.*, [29] and Vandenberg [30, 31], methodologists are progressively focused attention to the importance of measurement invariance, particularly within a structural equation modelling framework around the turn of the 21st century. Vandenberg [31] summarised the measurement invariance literature, defined the stepladder approach to its testing, and offered scholars with step-by-step guides to carrying out invariance tests. As indicated by Vandenberg *et al.,* [32], there is adoption enthusiasm concerning measurement invariance and this passion continued to crest in the succeeding decade. However, these fervours have not been complemented by adequate advice, clarification, best practices, or understanding [19].

2.3 Rationale for Measurement Invariance

Tests of measurement invariance are necessary because there are conditions that debilitate the quality of the measurement tools, but are not covered by established methodologies such as the computation of reliability coefficients [31]. Measurement invariance tests make certain that measurement models executed under different conditions would lead to the similar representations of the equivalent construct. The proof of measurement invariance as specified by Vandenberg *et al.*, [32] is a rational criterion to the evaluation of underlying hypotheses concerning group differences irrespective of whether the comparison is as simple as a between-group mean difference test or as complex as testing whether a theoretical model is invariant across groups. If measurement invariance cannot be defined, the theoretical inferences of models for between-group comparison will misperceive with measurement non-equivalence and cannot be construed explicitly. Therefore, the violation of the assumption of measurement invariance as noted by Vandenberg *et al*. [32] is as adverse to basic elucidations of hypothetical models as the inability to demonstrate construct reliability and validity.

Fulfilling the criteria of reliability and construct validity for each group is not adequate for between-group comparisons. The measurement structure for each group must also be invariant or at least partial invariant so that results of between-group comparison could be justified. Some scholars propose that measurement invariance should be added to the conventional benchmarks of reliability and validity [33]. This mirrors the essentialness of setting up measurement invariance of measurement scales under various conditions. Currently, measurement invariance is viewed as a crucial issue in psychological testing [34] that has social and also statistical significances [35, 36]

2.4 Analytic Approaches for testing Measurement Invariance

While specific tests of differences can be executed for unique research questions, a general framework has evolved for comparing the measurement models and then the structural models across the groups. Invariance tests are of two types namely tests of measurement and structural invariance. Measurement invariance relates to tests of relationships between indicators and their latent variables while structural invariance deals only with aspects of the latent constructs (e.g.

structural coefficients). This distinction is similar to the one made by Anderson *et al*. [37] that measurement invariance models measure the invariances between the construct and its measurement items, e.g., factor loadings, item intercepts and error variances while the structural invariance models evaluate the similarity of the structural path coefficients between the latent variables. However, the study is limited to measurement model.

In spite of the fact that there are unique techniques for testing different parts of measurement invariance, a standout amongst the most widely recognised strategies to examine measurement invariance is multi-group confirmatory factor analysis (MCFA) [38] Confirmatory factor analysis (CFA) explores whether the hypothesised measurement model fits the data well, multi-group confirmatory factor analysis on the other hand could be utilised to compare the measurement model across groups accurately. The progressive analytic approach in multi-group CFA includes three stages, consistent with the three invariance conditions of configural, metric, and scalar invariance [38, 32]. This article is centred on three critical invariance conditions, comprising of configural invariance, metric invariance, and scalar invariance. Configural invariance relates to a qualitatively invariant measurement pattern of latent constructs across groups. Metric invariance refers to a quantitatively invariant measurement model of latent constructs across groups. Scale invariance relates to invariant mean levels of latent constructs across groups.

2.4.1 Configural invariance

As described by Milfont *et al.,* [39] is the first stage of measurement invariance. The test is utilised to affirm that same basic factor structure exists in all of the groups indicating that respondents from various groups conceptualise the constructs in the same way. Configural invariance as defined by Abrams *et al.,* [32,40] connote the same pattern of fixed and free factor loadings (and other parameters) across groups, however no identicalness requirements. According to Widaman *et al*., Vandenberg *et al.* and Byrne *et al*., [32,41,42], this level requires that similar item must be related to the same factor in each group; though, the factor loadings may vary across groups. Configural invariance is tested by running individual CFAs in each group. Researchers confirm that each group CFA model has the same number of constructs and items associated with each construct. It must also be shown that each model meets the appropriate levels of model fit and construct validity [11]. When configural invariance is sustained, it suggests that the same latent construct, nevertheless, it does not infer that the association of latent constructs with manifest observations are the same across groups.

Where there is an establishment of configural invariance, the data gathered from each group breaks down into the similar number of factors, with the same items associated with each factor [43]. However, when perceptions are inattentive such that respondents' opinions of the construct depend on their cultural context, configural non-invariance manifest itself [44]. The model of configural invariance helps as a significant benchmark model to which we can compare more constricting models. Hence, the subsequent step is to inspect the more constrained metric invariance. The same measurement model could be examined separately for each group by using CFA to establish configural invariance The models fit could be assessed utilising the standard criteria suggested by Hu *et al*., [45] such as robust chi-square, Comparative Fit Index (CFI), Tucker-Lewis Index (TLI) > .90.The Root Mean Square Error of Approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR) to be < .08. The decision is when the same measurement model fits the data well across groups, configure invariance is therefore supported.

2.4.2 Metric invariance

This is also called weak Factorial Invariance which gives empirical comparison of factor loadings between MCFA models and includes the identicalness of factor loadings [11]. As stated by Abrams *et al.* [40] it tests whether the magnitude of the factor loadings is the same across groups. Metric invariance establishes the sameness of the relationships between latent constructs and their indicators. Constraints are set so that factor loadings are equivalent across the groups. This model tests if diverse groups respond to the items similarly; that is, if the strengths of the relations between particular scale items and their principal construct are the equal across the groups [39]. While the loadings are equivalent for every indicator across groups, each measured variable has its own unique loading estimate. As indicated by Bollen and Joreskog and Sorbom [46, 47], factor loadings signify the power of the linear relationship between each factor and its accompanying items.

When metric invariance is sustained, it shows that the same latent construct could be represented by the same manifest observations equivalently across groups. When metric invariance is not sustained, inconsequential to compare the means of latent constructs since they demonstrate psychologically different constructs. The baseline model allows the factor loadings to be unreservedly evaluated across multi- groups. The invariance model constrains the factor loadings to be equal across multiple groups. Differences between the two nested models are observed with the $\Delta CFI < 0.10$ [48, 49]. This general guideline of $\Delta CFI < 0.10$ applies to all models in invariance tests of. Although, the most usually utilised test to check model fit globally is the χ^2 test but is reliant on the sample size, discards realistic models if sample is large and it fails to reject poor models if sample is somewhat small [48, 49]. A non-significant result of the chi-square difference test would show that the invariance model is a good depiction of the data since it fits the data equally relative to the baseline model but has better parsimony [50]. Conversely, a significant result of the chi-square different test would specify that the baseline model is a better representation of the data, signifying that the psychological meanings of the latent constructs vary across groups. Simulation studies comparing multiple goodness-of-fit indices (e.g., chi-square, AIC, RMSEA, and CFI) have suggested ΔCFI as it is independent of model complexity and sample size and a ΔCFI less than .01 indicates invariance [48, 49]

Therefore, ΔCFI is adopted in this study to test measurement invariance. It is important that to note that full metric invariance where all latent constructs have the same psychological meanings across groups, could be uncommon in practical settings. For this situation, partial metric invariance, where several of the latent constructs exhibit the same psychological meanings across groups, could warrant further examination of scalar invariance on those latent constructs. The final step of invariance examination is to examine scalar invariance by comparing the means of the latent constructs. Basically this step could be conducted by utilising the similar nested-model comparison strategy as presented in the previous step. In this case, the baseline model would permit the means to be freely estimated across multiple groups. The invariance model would constrain the means to be equivalent across multiple groups. However, different statistical programs could have different default specifications with respect to the mean structures.

2.4.3 Scalar invariance

Scalar invariance which is otherwise known as Strong Factorial invariance is tested by requiring factor loadings and intercepts to be invariant across groups. This level of invariance is attained when the scores from different groups show the same factor loading as well as the same intercept [41]. This level of invariance is required for comparing latent mean differences across group [41]. When scalar invariance is upheld, it would suggest that disparate groups could show an equal mean level of the similar latent construct [32]. The third stage tests for the equality of the intercepts of the measured variables (i.e. means) on the constructs [11]. Scalar or intercept invariance is required to compare latent means [39]. Establishing scalar invariance indicates that the observed scores are related to the latent scores on the latent construct, i.e. individuals who have the same score on the latent variable would obtain the same score on the observed variable regardless of their group. This model is tested by constraining the intercepts of items to be the same across the group.

3. Research Methodology

3.1 Rationale for Measurement Invariance

A questionnaire survey was undertaken, and 301 valid questionnaires were collected from three groups of respondents namely cleaning contractors, consultants and clients located in Malaysia. The results of the pilot study indicated that the data satisfied normality, validity and reliability tests. All questionnaire items were measured on a scale ranging from 1 (strongly disagree) to 7 (strongly agree). The sample was randomly drawn from a list of cleaning contractors, facilities managers and clients. Five hundred questionnaires were distributed to the three respondents' group. The response rate was up to 61 percent. Therefore, the sample was representative.

3.2 Data Analysis

The collected survey data were input into SPSS and analysed with Amos 22.0. Table I shows the descriptive statistics for the CSFs for GC services implementation. The reliabilities of both sub-scales are beyond the cut-off value of 0.7 [51, 52, and 53]. The hypothetical measurement model GC CSF is shown in Figure 1.

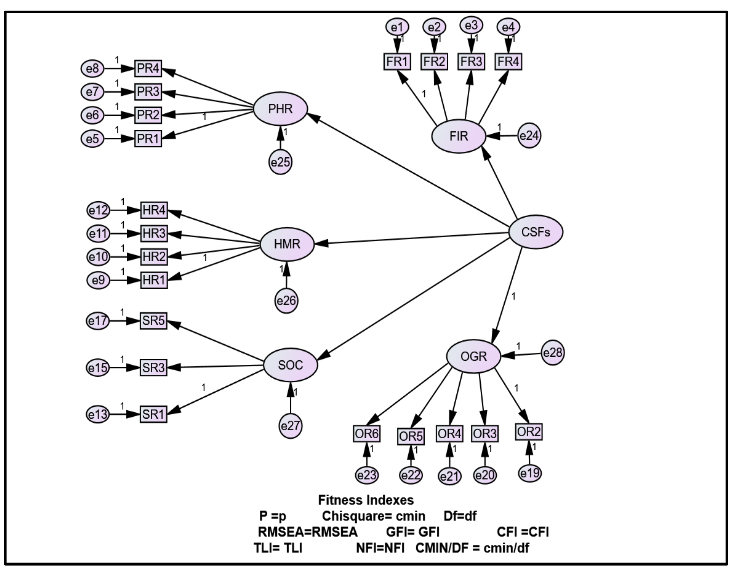

Fig. 1. The hypothetical measurement model GC CSF

3.3 Multi -Group Analysis

Before conducting multi-group analysis, the proposed model is evaluated with the full data set mutually. In this study, the focus of multi-group analysis is amongst the three respondents group namely: Contractors, Consultants and Clients. The subsequent step is to test the model with separate groups. The proposed model is tested with each group of data, and the fit is evaluated. Then, the multi-group analysis is executed using Amos, the configural invariance is tested, and the result is shown in Table 1. Configural Model with no equality constraints across the groups is tested, which is the baseline model or pattern model for the following comparisons. Model 1, the equality constraints are set on factor loadings and Model 2, the measurement intercepts are equal across groups.

Table 1
Summary of Goodness-of-Fit Statistics for Tests of Measurement Multi-Group Invariance

Model	RMSEA	SRMR	TLI	CFI	ΔCFI	Invariance Among Respondents Groups
Configural Model	0.031	0.053	0.967	0.972		Supported
Model 1	0.031	0.053	0.967	0.969	0.003	Supported
Model 2	0.031	0.059	0.968	0.970	0.002	Supported

Model-data fit measurement invariance can be assessed using various criteria. Overall model fits evaluation is executed using standardised root mean square residual (SRMR), the root mean square error of approximation (RMSEA), the robust comparative fit index (CFI) and Tucker-Lewis index (TLI). The acceptable level of fit for CFI/TLI is a value > 0.90 and a value of ≤ 0.05 for RMSEA [54]. A cut-off value of 0.08 for SRMR is considered acceptable [54]. A cut-off-value of 0.08 for SRMR is considered acceptable [55-57].

Two invariance tests were carried out, and each Measurement model was compared with the configural Measurement model. More precisely, a ΔCFI > .01 suggests a significant decline in fit [48]. The configural invariance model was established as acceptable levels of fit for CFI, TLI, IFI, and RMSEA were attained. The fit indices are: $\chi 2$ =766.144; $p<.000$; CFI=0.972; TLI=0.969; IFI=0.972; RMSEA=0.031) [57]. The fit indices from this multi-group configural model are used as baselines to compare successive invariance models (e.g. Δ CFI). Detail results about these models 1 and 2 (metric and scaler) are indicated in the following sub-sections.

4. Results and Discussions

After the establishment of configural invariance (pattern invariance), which is the baseline model, the metric invariance was evaluated. Attaining metric invariance of factor loadings indicates that the construct has the same meaning to respondents across different groups. While the configural invariance tests whether or not the same items measure the construct across multiple groups, metric invariance tests whether the magnitude of the factor loadings is the same across groups. Thus, metric invariance is achieved when the factor loading (ג) of each item is necessarily equal across groups. Similar factor loading pattern would mean one unit of change in one group is equal to one unit of change in the other group [58]. This configural invariance model was compared to the full metrics invariance model constraining the factor loadings to be equal across groups. As indicated in the Table 2, calculation of these results entails taking their differences from the CFI values as reported for the configural model. According to Cheung *et al*. and Meade *et al*. [48, 49], a ΔCFI less than .01 shows invariance. Based on this rule of thumb, the fully metric invariant model was not worse than that of the configural invariance model as the ΔCFI is 0.003.Thus, it was concluded that metric invariance was established; indicating the strength of each item-factor relationship was approximately alike across groups.

Following the establishment of metric invariance, scalar invariance was assessed. For continuous data, scalar invariance is satisfied if the intercepts of each item are necessarily equal across groups. The intercept signifies the predicted value of the observed variable when the latent trait value equals zero. That is, scalar invariance is established if individuals with the same GC CSF latent construct obtain the same value of the observed variable, regardless of their group membership. Simply put, the contractors, clients and consultants use the response scale in the same way (i.e., choose the same response option [30]. To test scalar invariance, the intercepts of each item were constrained to be equal across the two groups. The determination of scalar invariance permits for the differentiating of factor means because scalar invariance assumes scores from multi- groups have not only the same unit of measurement (metric invariance) but also the same origin (equal intercepts) [58]. The fit of this model was compared to the fully metric invariant model. The ΔCFI fell within the accepted amount (0.002), indicating support for scalar invariance across the three groups. The results show that all the three measurement invariance models tested have achieved acceptable goodness-of-fit indices.

The study outcome indicates that the critical success factors for green cleaning services implementation and performance model are invariant across the three different stakeholders in the Malaysian cleaning industry. The findings suggest practical implications for cleaning service providers', facilities managers and clients on the need to invest in the critical success factors mainly human, physical, financial and social resources and to productively align such for effective green cleaning services implementation to achieve competitive organisational performance

5. Conclusion

It is crucial to validate the measurement invariance before any scientific inference is made. This is essential for valid research findings, especially where the different population is involved. As more and more researchers are working on that direction which is reflected by the increasing number of collaborative research across countries, measurement invariance will play a more significant role in a well-designed study. However, such validating evidence is often not presented in the green cleaning project management field. Lack of measurement invariance equivocates conclusions and casts doubt on the theory of interest [59]. If the cross-group differences are indeed identified, they deserve more attention and should be considered as further research objects instead of being viewed as impediments to research [48]

In this study, various methods to test measurement invariance are demonstrated. The measurement invariance is tested within the framework of MCFA. Sequential tests are conducted to validate the measurement invariance of GC CSFs among different stakeholders in cleaning industry to increase researchers' awareness about measurement invariance issue in the green cleaning project management field. From the data analysis results, full measurement invariance of CSF for GC implementation is supported. Furthermore, it is recommended that the measurement invariance tests should be conducted within Asian countries and if possible with a different continent. Together with the reliability and validity test, measurement invariance test will play a significant and active role in verifying new measurement scales. Goodness-of-fit indexes for testing measurement invariance deserve more empirical studies in future.

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