Guest editorial

Partial least squares – structural equation modeling in hospitality and tourism

David Hand's 2008 presidential address to the Royal Statistical Society:

"[. . .] statistics is not merely a question of working within a well-defined world of axioms and operations but is fundamentally about relating such a system to the real world" (Hand, 2009, p. 301, cited in Rigdon 2014, p. 163).

1. Introduction

Partial least squares – structural equation modeling (PLS-SEM) has been largely used across a variety of academic disciplines such as international business (Richter *et al.*, 2016), marketing (Hair *et al.*, 2012b), human resource management, (Ringle *et al.*, 2018), accounting management (Nitzl, 2016), strategic management (Hair *et al.*, 2012a), tourism (do Valle and Assaker, 2016) and hospitality (Ali *et al.*, 2018). However, there are some confusing issues, in particular across preference of using PLS-SEM as a composite-based approach compared to covariance-based SEM (CB-SEM) as a common-factor based approach, as well as the application and assessment of different types of measurement models such as reflective, formative and composite. This editorial tries to clarify these issues.

2. Composite-based and factor-based approaches of structural equation modeling

Partial least squares is a composite-based form of SEM contrary to CB-SEM that is known as the factor-based SEM approach (Rigdon *et al.*, 2017). Both PLS-SEM and CB-SEM are applied when unobserved variables are involved in the model, but they use different algorithms and have different objectives (Richter *et al.*, 2016). PLS-SEM focuses on maximization of explained variance of endogenous constructs (Rigdon *et al.*, 2017) and is more a prediction-oriented approach (Cepeda *et al.*, 2016; Shmueli, 2016); however, CB-SEM represents a construct as a common factor and focuses on minimizing the discrepancy between the model-implied covariance matrix and the empirical covariance matrix (Rigdon *et al.*, 2017).

CB-SEM assumes both, common and unique variances, in each indicator where common variance is identical for all indicators of each construct, but unique variance is different, representing the associated error for each indicator (Rigdon, 1998; Sarstedt *et al.*, 2016). CB-SEM calculates the covariance between the indicators based on these common variance and aims to minimize the discrepancy between the covariance from data and model using maximum likelihood (ML) estimation approach, or some robust alternatives such as Bollen's two stage least squares and then estimate the parameters in the model such as loadings, weights and path coefficients. Therefore, CB-SEM is called a common factor or factor based approach (Rigdon, 2016; Sarstedt *et al.*, 2016).

However, instead of dividing the variance of indicators to common and unique variances, PLS-SEM approach calculates the score of construct by combining all variances of observed indicators and then estimates the path coefficients to maximize the explained variance of endogenous construct using ordinary least squares (OLS) method (Rigdon, 2012, 2016). Therefore, in PLS-SEM, the construct is linear composition of observed indicators, and it is called composite-based approach (Sarstedt *et al.*, 2016).

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Consequently, CB-SEM and PLS-SEM apply different statistical approaches to estimate the parameters (Rigdon, 2016). As mentioned earlier, the CB-SEM is called common factor based approach, and it only focuses on the covariance between the indicators of each construct, and the score of constructs are not considered or needed in the estimation of parameters (Rigdon *et al.*, 2017). The score of constructs (score for each respondents) can be an infinite set of values to create common variance, which is called factor indeterminacy in CB-SEM (Rigdon, 2012, 2016). However, composite-based approaches derive determinate scores for the constructs by linear combination of observed indicators (Rigdon, 2012). Hence, the score of construct in both common factor and composite based approaches (e.g. CB-SEM and PLS-SEM) are proxies of true factors and are arbitrary entities. And by using different methods to estimate model's parameters, each one has some advantages as well as disadvantages (Rigdon *et al.*, 2017). For instance, the issue of factor indeterminacy limits the usage and application of the factor-based approaches in prediction-oriented studies (Rigdon, 2012). The application of PLS-SEM is particularly increasing, due to the proven limitations of CB-SEM in instances where the objective of research is prediction or theory development, the proposed relationships are not sufficiently explored, the model includes different types of constructs such as formative, composite and reflective measurement models (Hair *et al.*, 2017a; Rigdon, 2016; Sarstedt *et al.*, 2017). Some recent studies suggested to avoid using PLS-SEM, due to estimating biased results (Rönkkö and Evermann, 2013) including overestimatation of the outer model parameters such as outer loadings and weights, and underestimatation of path coefficients. However, some recent studies (Sarstedt *et al.*, 2016, 2017) confirmed that the over and under estimation of results is not because of using PLS-SEM itself, and rather is due to characteristics and nature of data (Rigdon, 2016). When the data are generated based on a common-factor model (i.e. the covariance between the indicators are used to generate data), the nature of data would be common-factor based, and this data may over estimate or under estimate the model parameters using PLS-SEM. However, if the data is generated from a composite model and based on the linear combination of indicators, the PLS-SEM produces unbaised results (Hair *et al.*, 2017b; Sarstedt *et al.*, 2016). In addition, CB-SEM produces much greater bias, when the model parameters are estimated for composite based data (Sarstedt *et al.*, 2016). Thus, when we are not certain about the nature of data (e.g common-factor or composite based), using PLS-SEM is preferred, because using CB-SEM for composite based data produces greater bias than PLS-SEM for common-factor based data (Sarstedt *et al.*, 2016). Developing the criteria to identify the nature of data and distinguish common-factor and composite based nature of data certainly is a significant area for future studies in SEM context.

3. Reflective, formative and composite constructs

As per the measurement theory, there can be three types of measurement models/constructs including reflective, causal-formative and composite (Henseler, 2017; Sarstedt *et al.*, 2016). As composite constructs are also a special type of formative constructs (Sarstedt *et al.*, 2016), therefore, formative constructs can be categorized into causal-formative and composite-formative constructs (Bollen and Bauldry, 2011; Henseler, 2017; Sarstedt *et al.*, 2016). The type of construct is specified based on the nature of the construct and the observed items used to measure it (Henseler, 2017; Sarstedt *et al.*, 2016). Reflective constructs are measured by the indicators, which reflect the meaning and concept of same attribute, are highly correlated and interchangeable and each individual item can be taken out without changing the meaning of construct (Hair *et al.*, 2017a; Jarvis *et al.*, 2003; Sarstedt *et al.*, 2016). In reflective constructs, the measurement error is taken into consideration on indicator level, the direction of relationship is from construct to indicator. Each indicator includes a common variance from the construct and an error term, which is supposed to be uncorrelated with the other indicators and the errors in the model (Henseler *et al.*, 2017). Equation (1) shows the relationship between observed indicator x_i (i = 1, [. . .], I) and construct X of reflective construct, which λ_i indicates outer loading, and ε_i error term associated with observed indicator:

$$x_i = \lambda_i \times X + \varepsilon_i \tag{1}$$

However, for causal-formative constructs (which will be mentioned as formative constructs hereafter), the indicators refer to a specific concept and represent a conceptual unity (Bollen and Bauldry, 2011). Contrary to a reflective construct, the indicators form the construct and the indicators are not necessarily correlated. In addition, changes in the indicators will change the conceptual meaning of the construct, so removal/deletion of indicators of formative constructs is suggested to be avoided (Hair *et al.*, 2017a). The measurement error in formative constructs is taken into consideration on the construct level, and represents the missing indicators, which can cause to form the construct, but are not included in the model by the researcher (Diamantopoulos, 2006). In other words, when formative indicators are used to conceptualize a specific concept, all possible indicators (causes) to represent the meaning of concept should be included. However, including all indicators is not possible practically because of the limited knowledge, and the measurement error in formative constructs represent this missing part (Sarstedt *et al.*, 2016). Equation (2) shows the relationship between observed indicators x_i (i = 1, [. . .], I), and construct X of formative construct, which w_i indicates outer weight, and δ error term associated with construct:

$$X = \sum_{i=1}^{l} x_i \times w_i + \delta \tag{2}$$

The third type of constructs is called composite constructs that resemble the formative constructs in terms of associations between constructs and the items. However, it must be noted that composite constructs do not have error terms (Bollen and Bauldry, 2011; Sarstedt *et al.*, 2016). It implies that there are no missing indicators and all the indicators under observation explain the absolute conceptualization of the construct (Henseler, 2017). In practice, this can happen because the relationships between indicators and composite construct are not portraying cause and effect, rather the indicators represent the ingredients/composition of the construct (Henseler, 2017). Hence, composite constructs are artifacts and error free constructs, as shown in equation (3). Composite constructs do not necessarily represent a conceptual unity, and only can be a combination of some indicators to design or represent a new entity in the model (Bollen and Bauldry, 2011; Henseler *et al.*, 2016), and that this entity can be changed from one study to another (Sarstedt *et al.*, 2016). For instance, socio-economic characteristics of respondent in one study can be defined by age, income, and education level, but in another study more indicators can be involved. Therefore, socio-economic characteristics is a composite construct with a different conceptualization in different studies (Henseler *et al.*, 2016; Sarstedt *et al.*, 2016). However, in some circumstances, a the indicators of a composite construct can also represent a conceptual unity, in particular, when a higher order construct with a few number of dimensions have to be established. For instance, the concepts of residents' perceptions toward tourism development consists of economic, social, cultural and environmental perceptions, and these dimensions make up the perception construct (Rasoolimanesh *et al.*, 2018). In this case, these dimensions can perfectly represent and establish the construct without any missing parts, and in the same time altogether represents a specific concept (Sarstedt *et al.*, 2016):

$$X = \sum_{i=1}^{l} x_i \times w_i \tag{3}$$

The review of the literature in hospitality and tourism research (Ali *et al.*, 2018; do Valle and Assaker, 2016) reports the application of various types of indicators such as formative and reflective. However, very few studies investigated the assessment of composite construct. It is to be noted that many concepts in the literature such as service quality, place branding and destination image etc., can be considered as composite constructs. Moreover, review studies in hospitality and tourism research also reveal lack of application of appropriate criteria to assess formative constructs (Ali *et al.*, 2018; do Valle and Assaker, 2016).

4. Model assessment in PLS-SEM

To assess a model using composite-based SEM approach such as PLS, two steps should be followed including assessment of the measurement model and the structural model. As mentioned earlier, there are three different measurement models and each of these warrants a different assessment criteria. Since PLS has been established as a prediction-oriented approach, some recent developments should also be considered (Ali *et al.*, 2018; Rigdon, 2012; Sarstedt *et al.*, 2014). The following sections discuss some of the latest standards to be reported towards model assessment in PLS.

4.1 Reflective measurement model

To assess reflective constructs, indicators' reliability, internal consistency or construct reliability, and validity including convergent and discriminant validity should be established. The outer loadings should be higher than 0.708 to establish indicator reliability, although loading higher than 0.5 is acceptable, if measurement model pass the threshold of internal consistency and convergent validity criteria (Hair *et al.*, 2017a). The value of Cronbach's alpha, composite reliability (CR), and ρ_A should be higher than 0.7 to establish internal consistency (Ali *et al.*, 2018). Moreover, to establish convergent validity, the average variance extracted (AVE) should be greater than 0.5, and to establish discriminant validity more conservative heterotrait-monotrait (HTMT) (Henseler *et al.*, 2015), in addition to the Fornell–Larcker approach, should be applied (Ali *et al.*, 2018). To apply HTMT method to assess discriminant validity, recent studies suggest to use the HTMT-based inference test to compare HTMT value with 1, but for well-established constructs, we can compare HTMT with threshold of 0.85 and 0.9 (Franke and Sarstedt, 2018; Hair *et al.*, 2017b).

4.2 Formative measurement model

As discussed earlier, the measurement error for formative measurement model is taken into account on the construct level and represents the missing indicators which are not included in the model (Sarstedt *et al.*, 2016). To conceptualize a formative construct, all possible indicators (causes) should be included, however, it has practical limitations (Sarstedt *et al.*, 2016). Therefore, performing redundancy analysis to assess the explained variance of formative construct by current indicators is a requirement to assess measurement model (Jun-Hwa *et al.*, 2018). To perform redundancy analysis, the effect of formative construct on same construct measured by one or more reflective indicators should be assessed. The path coefficient between formative and reflective construct should be at-least 0.707, indicating 50 per cent explained variance by involved indicators in formative construct (Jun-Hwa *et al.*, 2018). Assessment of multi-collinearity between indicators of formative construct is a significant issue, and should also be checked (Ali *et al.*, 2018). The multi-collinearity or variance inflation factor (VIF) of indicators should be lower than the threshold of 5 (Hair *et al.*, 2017a). Moreover, an indicator's contribution to the construct by assessment of significance of outer weight using 95 per cent bias-corrected and accelerated (BCa) bootstrap confidence intervals is another measure to report as part of the formative construct assessment (Aguirre-Urreta and Rönkkö, 2018; Streukens and Leroi-Werelds, 2016). Full collinearity assessment was recently recommended to assess discriminant validity of measurement model, when the model includes formative constructs (Rasoolimanesh, *et al.*, 2017). This is important for researchers to consider and come up with measures to assess discriminant validity of formative constructs because uncertainty about discriminant validity can result in confusion if "certain results confirming hypothesized structural paths are real or whether they are a result of statistical discrepancies" (Farrell, 2010, p. 324).

4.3 Composite measurement model

To assess composite constructs, recent literature proposed three criteria: nomological validity, reliability and weights (Henseler, 2017; Van Riel *et al.*, 2017). To establish nomological validity, confirmatory composite analysis should be conducted which means that the overall model fit indices should not be worse with composite construct than without it (Henseler *et al.*, 2017). The test of overall model fit using bootstrapping to assess the differences between the model-implied and the empirical correlation matrix can be applied using the geodesic discrepancy (d_G), unweighted least squares discrepancy (d_ULS) and standardized root mean square residual (SRMR) (Henseler *et al.*, 2016). The values for SRMR, d_G and d_ULS should be lower than the upper level value of the 95 per cent confidence interval ($CI_{0.95}$) (Henseler *et al.*, 2016). In addition to nomological validity, the reliability of composite construct can be calculated based on Mosier (1943) equation and ideally should be 1 because composite constructs are error free (Henseler, 2017). Finally, the significance, size and sign of weight of indicators of composite construct should be evaluated. However, to assess significance and sign of weights, the multi-collinearity among indicators (Diamantopoulos and Winklhofer, 2001) should be checked because high multi-collinearity may influence the signs or confidence intervals (Henseler, 2017; Van Reil *et al.*, 2017).

4.4 Structural model evaluation

To assess the structural model using PLS-SEM, the size, sign and significance of path coefficient should be checked and reported (Ali *et al.*, 2018; Hair *et al.*, 2017a). PLS-SEM does not assume normal data distribution, so the significance testing needs to apply resampling methods such as bootstrapping, jackknifing or stable methods (Kock, 2018). To test the significance level of path coefficients, the *t*-values and bias-corrected and accelerated (BCa) bootstrap confidence intervals are suggested in recent research (Ali *et al.*, 2018). Using bootstrapping resampling method, the recent literature recommends 10,000 resampling (Streukens and Leroi-Werelds, 2016). Another common criteria to assess structural model are coefficient of determination R^2, the f^2 effect size and the Stone–Geisser index (Q^2) (Ali *et al.*, 2018; Hair *et al.*, 2017a). However, the recent literature discussed the limitations of these model's in-sample prediction criteria to assess model's predictive performance (Shmueli *et al.*, 2016), and recommended the out-of-sample predictive performance (Shmueli *et al.*, 2016). Shmueli *et al.* (2016) developed the PLSpredict procedure to assess the out-of-sample predictive performance of PLS path models. Nevertheless, we expect PLSpredict to become a standard procedure in PLS-SEM-based model assessment, however, to date, research has not yet developed clear guidelines for using PLSpredict, which hinders its application in tourism, hospitality management, and other fields of business research.

5. The papers of the special issue

The guest editors for this special issue are pleased to present a comprehensive picture of the different options from which researchers can choose when deciding to adopt PLS as a predictive tool in hospitality and tourism research. PLS' orientation toward prediction is by no means a novelty, but by presenting a complete set of papers that discusses the topic and its application, this special issue takes a new approach. The readers find papers ranging from conceptual and theoretical analyses to recent applications of PLS in the hospitality and tourism industry. In the following, the guest editors provide a brief overview of the papers in this special issue. These contributions provide researchers with very rich and practical information on how to analyse models with PLS.

5.1 PLS path modeling – a confirmatory approach to study tourism technology and tourist behavior

The paper by Tobias Müller, Florian Schuberth and Jörg Henseler is the one to discuss the practical application of composite and common factor models in the context of technology in travel and hospitality research. In their paper, they apply PLS in its current form, i.e. as a full-fledged approach for confirmatory purposes using an empirical example. This paper also guides scholars in assessment of PLS results including tests for overall model fit.

5.2 The agony of choice for medical tourists: a patient satisfaction index model

Jana Rosenbusch, Ida Rosnita Ismail and Christian M. Ringle propose a novel patient satisfaction index (PSI) model. The PSI is also an important benchmark instrument for medical tourism. They test their index model by applying PLS and report the evaluation criteria for composites. They also apply and report the Importance Performance Map Analysis (IPMA).

5.3 Development and validation of a formative scale of technological advancement in hotels from the guest perspective

The third paper in this special issue is done by Maria-Eugenia Ruiz-Molina, David Servera-Francés, Francisco Arteaga-Moreno and Irene Gil-Saura. In this paper, they develop and validate a formative scale for the measurement of the degree of technological advancement in hotels through a MIMIC model estimated by applying PLS.

5.4 Methods for modeling reflective-formative second order constructs in PLS: an application to online travel shopping

Paulo O. Duarte and Suzanne F. Amaro in their paper discuss the estimation of PLS models with second-order formative constructs. This paper also provides a comparison of different approaches typically used to estimate a formative second-order construct and present useful guidelines for researchers to decide which methods needs to be used for assessment of formative second-order constructs.

5.5 Globalization of workforce: PLS approach to higher-order value construct in a study abroad context

The paper by Manuel Rivera, Kevin Murphy and Jalayer Khalilzadeh is an application of PLS path modeling. This paper indicates that PLS can be used to assess the theory of consumption value for study abroad experiential learning. This study sheds light on hospitality students' perceived value, satisfaction and internationalization intentions when they complete a study abroad internship program. This study is operationalized by simultaneously considering formative and reflective models.

5.6 Model specification issues in PLS-SEM: illustrating linear and non-linear models in hospitality services context

This paper by Keyoor Purani and Deepak Kumar illustrates the significance of choosing appropriate algorithms for testing the nature of relationships by comparing findings using two different PLS-SEM software packages. By comparing results of SmartPLS 3.2 and WarpPLS 5.0 software and theoretical understanding from environmental psychology literature, it illustrates that the results and their interpretations may not be in line with theory, if model specifications are not correctly implemented and are not addressed through usage of software with a relevant algorithm to test them. The study highlights the implications for model specification issues such as type of variables and nature of relationships that tourism and hospitality researchers often face and also how use of appropriate algorithms can overcome limitations of model testing for complex models and provide empirical rigor to support theory.

5.7 The interrelationships between self-determined motivations, memorable experiences and overall satisfaction: a case of older Australian educational tourists

Lintje Sie, Kelly Virginia Phelan and Shane Pegg in this paper apply PLS-SEM to assess the relationships between older travellers' self-determined motivations, memorable travel experiences and overall satisfaction with the educational holidays. This study also examines the mediating effects of memorable travel experiences on the relationships between motivations and overall satisfaction.

5.8 The influence of quality on satisfaction and customer loyalty with an importance-performance map analysis: exploring the mediating role of trust

Rocío Carranza, Estrella Díaz and David Martín-Consuegra in this paper apply PLS-SEM to verify the existence of loyalty among fast-food customers and its dependence on fast-food service quality, comprised of service quality, food quality and store atmosphere. They also discuss the concept of composite and common factor models and report mediation analysis as well as IPMA.

5.9 How do destination Facebook pages work? An extended TPB model of fans' visit intention

The paper by Xi Leung and Lan Jiang is an application of PLS path modeling to propose and test an extended theory of planned behavior model to explain how following destination Facebook pages impacts travelers' visit intentions. The study uses PLS-SEM in predicting behavioral intention through a reflective-formative higher-order model and reports mediation analysis and IPMA.

5.10 Predicting world heritage site visitation intentions of North American park visitors

Elizabeth A. Halpenny, Shintaro Kono and Farhad Moghimehfar in their paper investigate factors that predict intensions to visit world heritage sites (WHS) by taking the theory of planned behavior (TPB) as the theoretical base. PLS-SEM is used to:

- identify three reflective models (attitude toward visiting WHS, perceived behavioral control and intension to visit WHS in the future);
- three formative models (attitude toward WH designation, social influence (subjective norms) to visit WHS and WH tourism brand equity); and
- a structural model.

5.11 An explanatory and predictive PLS-SEM approach to the relationship between organizational culture, organizational performance and customer loyalty: the case of health clubs

In this paper, Jerónimo García-Fernández, Silvia Martelo-Landroguez Luisa Vélez-Colon and Gabriel Cepeda-Carrión analyze the impact and predictive capacity of organizational culture on both customer loyalty and organizational performance in health clubs using data from managers and customers of health clubs in Spain. A composite concept is adopted to analyze the relationships between different constructs and their indicators by applying predictive PLS-SEM.

5.12 Profitability in the hotel sector: a PLS approach

This paper by Rubén Lado-Sestayo and Milagros Vivel-Búa analyses the determinants of hotel profitability through the application of PLS path modeling deepens the study of their heterogeneity through clustering techniques. Specifically, this study uses PLS path modeling to estimate an eclectic model that incorporates the dimensions identified as determinants of hotel profitability. Subsequently, hotels are classified using clustering techniques to study which combination of hotel characteristics, location, competitive environment and tourist destination achieve higher profitability.

5.13 Deploying partial least squares to investigate the influence of managerial assumptions on corporate social responsibility in the hotel industry

The paper by Osmana Al-Kwifi, Allam Abu Farha and Zafar Ahmed is an application of PLS path modeling to investigate the interplay between managerial assumptions and institutional corporate social responsibility and to determine how such fit affects performance.

Even though the discussion on PLS method is increasing, its application in hospitality and tourism research is under-whelming (Ali *et al.*, 2018). Consequently, guest editors for this special issue selected high-quality papers for publication where some of them advance and explain the recent advances of PLS-SEM and others report application of the method. The *JHTT* special issue provides a forum for topical issues that demonstrate PLS path modeling's usefulness in hospitality and tourism applications. A description of the method, its empirical applications and potential methodological advancements that increase its usefulness for research and practice are specifically emphasized. As such, the special issue aims at two audiences: academics involved in the fields of hospitality and tourism and practitioners, such as consultants. Accordingly, theoretical, methodological and empirical manuscripts were considered as long as the topic had strong implications for hospitality and tourism research and practice. The special issue editors believe that this special issue will be

the starting point for a more intensive use of PLS-SEM in the hospitality and tourism discipline and for additional advances that will exploit PLS' capabilities in this area. The guest editors and authors gratefully acknowledge the valuable comments and encouraging support of Cihan Cobanoglu (Editor-in chief of *JHTT*) during the preparation of this special issue. The reviewers also deserve the heartfelt recognition of the special editors for their remarkable contribution to the quality of this special issue. As usual, they were diligent, meticulous, constructive, and extremely competent. The special issues editors specifically express their gratitude to the following reviewers: Azadeh Shafaei (Australian Council for Educational Research), Azizan Marzuki (Universiti Sains Malaysia), Babak Taheri (Heriot-Watt University), Chritian M. Ringle (Hamburg University of Technology), Dan Wang (Hong Kong Polytechnic University), Faizan Ali (University of South Florida - Sarasota-Manatee), Farhad Nikhashemi (Sunway University), Francis Chuah (Universiti Utara Malaysia), Gabriel Cepeda-Carrión (University of Seville), Hengky Latan (Universitas Kristen Petra), Hossein Olya (Oxford Brookes University), Ida Ismail (Universiti Kebangsaan Malaysia), Graduate School of Business Jalayer khalilzadeh, (University of Central Florida), Jörg Henseler (University of Twente), José Abrantes (Polytechnic Institute of Viseu), José L. Roldán (Universidad de Sevilla), Jun (Justin) Li (South China Normal University), Jun-Hwa Cheah (Universiti Teknologi Malaysia), Kisang Ryu (Seojong University), Lanyun Zhang (University of Nottingham - Ningbo China), Marko Sarstedt (Otto von Guericke Universität Magdeburg), Mastura Jaafar (Universiti Sains Malaysia), Mehran Nejati (Edith Cowan University), Mohd Falahat (Universiti Tunku Abdul Rahman), Murad Ali (King Abdulaziz University), Muslim Amin (King Saud University), Naser Valaei (Sunway University), Nastaran Taghizadeh, (Universiti Utara Malaysia), Rob Hallak (University of South Australia), S. Mostafa Rasoolimanesh (Universiti Sains Malaysia), Sajad Rezaei (Universitat Hamburg Fakultat Wirtschaftsund Sozialwissenschaften), Soumya Ray (National Tsing Hua University), Sangwon Park (Hong Kong Polytechnic University), Shaian Kiumarsi (Universiti Sains Malaysia), T. Ramayah (Universiti Sains Malaysia).

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