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Modeling and assessing forged concepts in tourism and hospitality using confirmatory composite analysis☆

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ABSTRACT

Confirmatory composite analysis (CCA) was recently proposed as a viable approach to modeling and assessing forged concepts, i.e., theoretical concepts that emerge from their components within their environment. This study introduces CCA to the field of tourism and hospitality research and shows how CCA can be conducted using estimators known from structural equation modeling (SEM) with latent variables as implemented in common SEM software. It shows how emergent variables can be employed to model forged concepts and how CCA can be used for assessing them. In doing so, we explain the four major CCA steps comprising (1) model specification, (2) model identification, (3) model estimation, and (4) model assessment. To illustrate and guide scholars in applying CCA, we provide an empirical example from the field of tourism and hospitality research.

1. Introduction

A crucial task in the social sciences, that include tourism and hospitality as a research field, is to study theoretical concepts such as attitudes and personality traits, which are regarded as ontological entities that exist in nature (Bagozzi & Phillips, 1982), i.e., so-called behavioral concepts (Yu et al., 2021). To operationalize such concepts, researchers regularly develop scales (Kock et al., 2018). Following DeVellis (2017, pp. 30), we use a scale "to measure phenomena that we believe to exist because of our theoretical understanding of the world but that we cannot assess directly". The dominant tool used to statistically evaluate scales is structural equation modeling (SEM) with latent variables, and in particular, confirmatory factor analysis (CFA, Jöreskog, 1969; Netemeyer et al., 2003).

Besides behavioral concepts, researchers study forged concepts (Henseler & Schuberth, 2021; Yu et al., 2021) – also known as aggregate constructs (Edwards, 2001), artifacts (Henseler, 2017; Müller et al., 2018), composite attributes (Mikulić, 2018), formed concepts (Hubona et al., 2021), or strong concepts (Höök & Löwgren, 2012). In contrast to behavioral concepts, forged concepts do not exist in nature per se; rather, they emerge from their components within the particular forged concept's environment. For that reason, such a concept is typically modeled as an emergent variable, i.e., a composite of components, embedded in the composite model. The composite model is especially suitable to operationalize forged concepts as it resembles a forged concept's characteristics, i.e., a set of components that forms a new whole (Henseler & Schuberth, 2021). Examples of theoretical concepts in tourism research that have been modeled as composites are tourist engagement (Rasoolimanesh et al., 2019) and trust in service robots (Park, 2020). To statistically evaluate composite models, i.e., to assess whether a set of components forming a forged concept act as a new whole, confirmatory composite analysis (CCA) was introduced (Schuberth et al., 2018).

CCA is similar to CFA; however, instead of assuming a reflective measurement model in which a latent variable represents the theoretical concept, a composite model is assumed in which the theoretical concept is modeled as an emergent variable. Originally, CCA was limited to approaches that emerged outside the realm of SEM, such as the iterative partial least squares (PLS) algorithm (Henseler &

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Schuberth, 2020; Schuberth, Zaza et al. , in press; Wold, 1975) and MAXVAR which is an approach to generalized canonical correlation analysis (Kettenring, 1971; Schuberth et al., 2018). This was due to the fact that for a long time it was not clear how emergent variables can be specified in SEM, particularly if they are correlated with other variables of the model as happens in the CCA context (see e.g., Aguirre-Urreta & Marakas, 2014a, 2014b; Rigdon et al., 2014). To overcome this problem, the recently proposed Henseler–Ogasawara (H–O) specification can be used (Henseler, 2021; Schuberth, 2022), since it allows flexibility in modeling emergent variables.

In our article, we present CCA as applicable to tourism and hospitality research. While CFA and SEM are the tools of the trade that empirically validate reflective and formative scales of behavioral concepts, respectively, CCA is the appropriate tool for assessing the components that form a forged concept. This study demonstrates how CCA can be conducted using commonly applied SEM software for model estimation, thereby making all the advantages of SEM accessible to researchers applying CCA. In doing so, we present the CCA steps and demonstrate its application using an empirical example from tourism and hospitality research.

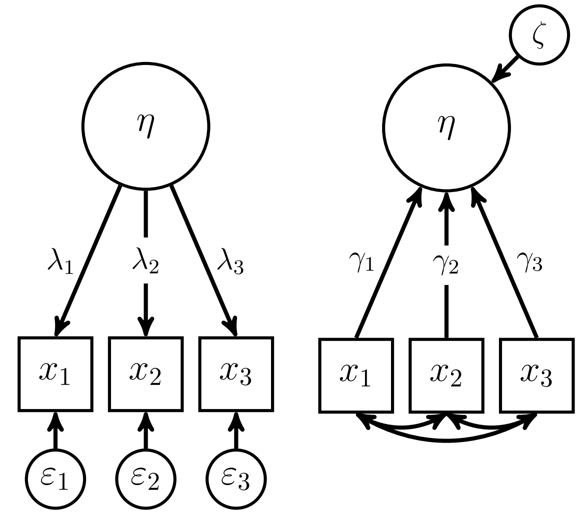
The remainder of this article is organized as follows: Section 2 highlights that tourism research deals with at least two types of theoretical concepts, namely, behavioral and forged concepts. Additionally, it emphasizes that measurement models, regardless of whether they are reflective or causal-formative, are not suitable to operationalize forged concepts. Consequently, CFA should not be used to assess forged concepts. Instead, the composite model should be used for operationalizing forged concepts, and CCA is the appropriate means for empirically assessing it. In Section 3, we give a concise overview of CCA and the steps involved, which are model specification, identification, estimation, and assessment. In particular, we show how a composite model as studied in CCA can be specified using the H–O specification. Section 4 demonstrates how CCA can be conducted in the open-source R package lavaan using an empirical example from tourism and hospitality research. Finally, in Section 5 we close the paper with a discussion.

2. Theoretical concepts of tourism research and their operationalization

Tourism research studies “the system involving the discretionary travel and temporary stay of persons away from their usual place of residence for one or more nights, excepting tours made for the primary purpose of earning remuneration from points en route”. (Leiper, 1979, pp. 403) Against this background, tourism research deals with a circulatory system based on common resources where input (resource use) and output (productivity) are closely related to tourists (Northcote & Macbeth, 2006). Consequently, tourism research can be regarded as a multidisciplinary field that incorporates theories and concepts from various affiliated disciplines.

To a large extent, tourism research can be assigned to behavioral science which draws on theories of sociology, anthropology, and psychology (Leiper, 1979). Illustratively, we refer to tourism research fields that rely on theories of affective science (e.g., Gao & Kerstetter, 2018), cultural anthropology (Ellis et al., 2018; Richards, 2018), visual anthropology (Sofield & Marafa, 2019), and cognitive psychology (Skavronskaya et al., 2017). Although the boundaries between these disparate fields are often blurred, they can all be assigned to the behavioral sciences. Tourism research, therefore, deals with various theoretical concepts from the behavioral sciences. These theoretical concepts, which we identify here as behavioral concepts, are often regarded as ontological entities that exist in nature and thus can be measured (Borsboom, 2008; Borsboom et al., 2003). Consequently, studying behavioral concepts largely occurs in the scientific realism paradigm (Cadogan & Lee, 2022; Rigdon, 2012).

Classically, the reflective measurement model comprising a latent variable is used to operationalize such concepts (Bagozzi & Phillips,



(a) Reflective measurement model (b) Causal-formative measurement model

Fig. 1. The two dominant measurement models.

1982; Bollen & Bauldry, 2011). This model, as displayed in Fig. 1(a), is grounded in the classical test theory (Novick, 1966) which dates back to Edgeworth (1888). It assumes that the theoretical concept is the common cause underlying a set of measures (Reichenbach, 1956), i.e., a scale, and therefore is responsible for the measures’ covariance structure. Specifically, the reflective measurement model assumes that a set of measures (x), also often referred to as effect indicators (Bollen & Bauldry, 2011), are measurement error-prone manifestations of a latent variable η representing the theoretical concept. The variance in an indicator that cannot be explained by the latent variable is captured by a random measurement error ϵ.

CFA is a commonly used statistical method for empirically validating reflective measurement models, i.e., for empirically validating a reflective scale (DeVellis, 2017; Jöreskog et al., 1979; Lee & Kyle, 2012). The tourism literature provides various examples of using CFA to empirically validate reflective scales. For instance, Ghosh and Mandal (2018) used CFA to empirically validate their proposed scale for measuring the seven dimensions of medical tourism experience. Similarly, Wu et al. (2022) applied CFA to empirically validate their proposed scale for measuring the five dimensions of community citizenship behavior in rural tourism destinations.

Besides the reflective measurement model, the causal-formative measurement model has been introduced and discussed in various fields such as marketing (Diamantopoulos & Winklhofer, 2001), information systems research (Petter et al., 2007), consumer research (Jarvis et al., 2003), and tourism research (Murphy et al., 2009). The latter model arose from the idea that not all observed variables measuring a theoretical concept have to be measurement error-prone manifestations of it, but can be causal antecedents, so-called causal indicators (Blalock, 1964; Bollen & Bauldry, 2011; Bollen & Lennox, 1991; Jöreskog & Goldberger, 1975). Consequently, the theoretical concept is not assumed to be a given set of measures’ underlying common cause, and therefore the causal-formative measurement model does not impose any constraints on the correlations between its causal indicators. As in the reflective measurement model, the theoretical concept is represented by a latent variable η in the causal-formative measurement model as displayed in Fig. 1(b). However, the role of the observed variables x differs in the two measurement models. While in the reflective measurement model the observed variables are consequences of the latent variable, in the causal-formative measurement model the observed variables are antecedents, i.e., they affect the latent variable. Since the observed variables do not cause the complete variation in the latent variable, a disturbance term ζ captures the remaining variance. The preferred statistical method to empirically validate formative scales is SEM with latent variables (Diamantopoulos, 2011). Examples of causal-formative measurement models in tourism research are given in the studies of Narangajavana et al. (2017) and Lin and Kuo (2016), who used SEM with latent variables to assess their causal-formative scales used in measuring the intensity of social media use and tourist experience, respectively. Žabkar et al. (2010) provide another example by employing a causal-formative scale to measure overall perceived destination quality.

The choice between a reflective and causal-formative scale is not always straightforward. It should be driven mainly by the nature of the indicators at hand (Jarvis et al., 2003; Mikulić & Ryan, 2018). If indicators present effects of the theoretical concept, the reflective measurement model should be employed, while if the indicators are regarded as causal antecedents of the concepts, the causal-formative measurement should be used (Bollen & Lennox, 1991). For more details, see also Bollen and Diamantopoulos (2017). This means that a behavioral concept can be measured in (at least) two ways, namely in a reflective or a formative way (Mikulić & Ryan, 2018). Notably, applying the wrong measurement model in choosing between the reflective or causal-formative model, can lead to biased and inconsistent estimates, and thus to questionable conclusions (Bollen & Lennox, 1991; Murphy et al., 2009).

Besides behavioral concepts, tourism research also deals with forged concepts. In contrast to behavioral concepts which are assumed to exist, forged concepts are assumed to be constructed or defined by their components. Consequently, they are not naturally occurring phenomena, but emerge from associated elements within their environment (Yu et al., 2021). Thus, they are context-specific. For instance, with the rise of e-tourism, customer generated content (CGC) and user generated content (UGC) found on various social media platforms give references that become important concepts in analyzing tourists' preferences, behavioral intentions, or potential lifestyles (Dedeoğlu et al., 2020). Attributes-based online information of different dimensions (e.g., ratings and reviews, sharing trip experiences, tourism recommendations) can design a specific CGC and UGC (Guo et al., 2017; Narangajavana Kaosiri et al., 2019). Similarly, tourist engagement is indispensable in tourism marketing research and can be regarded as a forged concept. From different perspectives, scholars continuously investigate the elements of tourists' engagement to study its impact on tourism management, e.g., on how brand strategy is considered (So et al., 2014; Taheri et al., 2014). Additionally, technological experience based on smart devices can be regarded as a forged concept. The tourism destination's technological resources can substantially affect tourists' experiences, therefore, how technologies impact tourists' behavior has gained increasing attention in tourism research (Liberato et al., 2018; Yoo et al., 2017). Further, perceived destination quality can be regarded as a forged concept which is "the aggregate of all its indicators, such as transport, destination brand, attractions, hospitality, entertainment, etc." (Cong, 2016, p. 52) Another example is tourist destination image which can be considered a concept that is "formed by three distinctly different but hierarchically interrelated components: cognitive, affective and conative" (Gartner, 1994, p. 193).

To operationalize forged concepts, measurement models – regardless of whether they are reflective or causal-formative – are hardly suitable. First, both measurement models rely on measurement theory, which assumes that the theoretical concept exists in nature. Therefore, the theoretical concept "always precedes the indicators whether they are causal-formative or reflective (effect) indicators" (Bollen & Diamantopoulos, 2017, p. 587). Second, both measurement models assume a causal relationship between the observed variables and the concept. This contradicts the understanding of a forged concept as one which is formed or defined by its components. Consequently, measurement models ignore important aspects of forged concepts, neglecting the facts

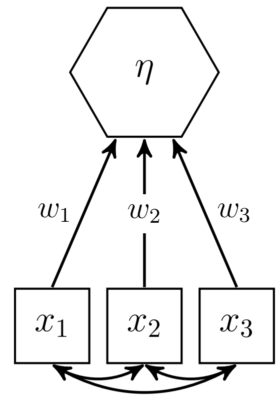


Fig. 2. Composite model.

(i) that they are human-made and do not otherwise exist in nature, and (ii) that they show a definitional relationship to their components, rather than a causal one. Therefore, neither CFA nor SEM with latent variables are recommended to model and assess forged concepts.

To model forged concepts, the composite model was proposed (e.g., Cole et al., 1993; Edwards, 2001; Henseler, 2015, 2017; Schuberth et al., 2018). As Fig. 2 shows, in the composite model the theoretical concept is represented by a composite η, i.e., by a linear combination of observed variables x. This contrasts with the reflective and causal-formative measurement in which the theoretical concept is represented as a latent variable. As Bollen and Lennox (1991, p. 310) emphasized, "the linear composite is not equivalent to the latent variable". Moreover, the composite model assumes that the concept is fully made up of its elements, and therefore no disturbance term is modeled on the construct level. This fittingly replicates the idea of a forged concept and its emergence, i.e., the idea that something new can be created out of a set of components (O'Connor & Wong, 2012). Consequently, omitting a component from the composite model alters the construct's meaning, which is, in contrast to a widely held misbelief, not the case in the causal-formative measurement model (Aguirre-Urreta et al., 2016). Further, the composite model assumes either that the components are free from random measurement errors, or that random measurement errors are negligible. Where this is not the case, researchers can model the components as single-indicator latent variables and fix the random measurement error variances to take the components' reliability into account. Also, the composite in the composite model is not only a linear combination of variables; it also conveys all the information between its components and the other variables in the model (Dijkstra, 2013, 2017), i.e., it acts as a new whole. To highlight this fact, this type of composite is also referred to as an emergent variable (Benitez et al., 2020; Henseler, 2021; Schuberth, Zaza et al. , in press; Yu et al., 2021).

The dominant statistical approach in assessing composite models and thus empirically validating whether a set of components acts as a new whole, is CCA. In contrast to CFA, CCA does not assess measurement theory, but synthesis theory. Similar to measurement theory as the auxiliary theory for behavioral concepts, synthesis theory has been proposed as an auxiliary theory for forged concepts (Henseler & Schuberth, 2021). It is based on the axiom of unity which states that a set of components forming an emergent variable is independent of all other variables in the model, given the emergent variable. Hence, to assess emergent variables, CCA examines the proportionality constraints between the components and other models' variables which the composite model imposes. In the following section, we present the CCA steps, including the H–O specification of emergent variables, which allows the use of common SEM software for model estimation (Schuberth, 2022).

3. Confirmatory composite analysis

The outline of CCA was first sketched by Jörg Henseler and Theo K. Dijkstra (Henseler et al., 2014), and subsequently fully elaborated by Schuberth et al. (2018). Although similar to CFA, it differs in that CFA is at the heart of measuring theoretical concepts (Nunnally & Bernstein, 1994), i.e., CFA is used to assess and empirically validate reflective measurement models and measurement theory, while CCA is used to empirically validate composite models and synthesis theory (Henseler & Schuberth, 2021; Schuberth et al., 2018). Notably, CCA should not be confused with the assessment steps known in partial least squares structural equation modeling, which were recently also named 'confirmatory composite analysis' (Hair et al., 2020). For a critical discussion of CCA and the PLS-SEM assessment steps, we refer to Schuberth (2021).

CCA has been introduced in various fields, such as business research (Henseler & Schuberth, 2021), managerial science (Schuberth et al., 2020), information systems research (Hubona et al., 2021), and behavioral development (Schamberger et al., 2022). Although a few studies have applied CCA in the context of tourism research (e.g., Rasoolimanesh et al., 2019; Sanchez-Franco et al., 2019), its application was limited to approaches that emerged outside the realm of SEM, such as the iterative PLS algorithm (Wold, 1975) or MAXVAR, which is one of Kettenring's (1971) approaches to generalized canonical correlation analysis. However, a recently introduced specification, i.e., the H–O specification, allows for modeling emergent variables with the same flexibility as researchers are accustomed to in modeling with latent variables in SEM (Henseler, 2021; Schuberth, 2022). Consequently, CCA can now be conducted using common commercial SEM software such as Mplus (Muthén & Muthén, 1998–2017), Amos (Arbuckle, 2020), or the open-source R package lavaan (Rosseel, 2012), including their implemented estimators. In the following exposition, we elaborate the CCA steps and show how the H–O specification can be applied in the CCA context.

3.1. Model specification

CCA is a confirmatory approach that is grounded in explanatory statistical modeling. Therefore, a statistical model is specified to obtain an understanding of the studied population (Lehmann, 1990). In particular, this means that a researcher's theory needs to be translated into a statistical model, which provides a simplistic description of the population being investigated (Bollen, 1989). Consequently, a researcher's theory provides the basis for the model specification in CCA. The building blocks of the theories studied in the CCA context are forged concepts. As discussed above, to model forged concepts, the composite model provides a hand in glove fit.

To specify a composite model as studied in CCA, a researcher has to decide on the components that make up the forged concept. These are then used as variables to build an emergent variable. Note that although here we focus mainly on observed variables as components of the emergent variables, this is by no means mandatory, and latent variables can serve as components as well, for example to model aggregate constructs (Edwards, 2001) or composite attributes (Mikulić, 2018). Moreover, the researcher has to model the forged concept's environment and thus specify the relationships between the emergent variable and the model's other variables. Hereby, other variables can be observed, latent, or emergent variables. Since CCA's main goal is to assess the synthesis theory, i.e., to determine whether a set of variables act as a new whole (Henseler & Schuberth, 2021), the emergent variable is not embedded in a structural model, but related to the other model's variables via covariances.

Inspired by principal component analysis, in the H–O specification not only one composite, but as many composites as components are extracted from a set of components, i.e., one emergent variable (η) and multiple excrescent variables (ν). While the emergent variable represents the concept of interest, the excrescent variables have no surplus meaning. Further, the relationships between the components and the emergent and excrescent variables are expressed by composite loadings instead of by weights, which allows for flexibly modeling emergent variables. For an elaboration of the H–O specification, we refer to Schuberth (2022).

Fig. 3 depicts an exemplary model studied in CCA using the H–O specification of emergent variables. This model consists of three observed components x_1 to x_3 which together form the emergent variable η, illustrated here by a hexagon, and representing the forged concept of interest. In addition, two excrescent variables ν_1 and ν_2 are formed from the three components. Since the excrescent variables are also composites, they are displayed as smaller hexagons. The relationships between the components and the emergent and excrescent variables are expressed by composite loadings λ. Additionally, the model consists of two observed variables y_1 and y_2 that are part of the forged concept's environment and are allowed to covary with the emergent variable. The covariances between the emergent variable and the two observed variables y_1 and y_2 are denoted by σ. We note that there are no random measurement errors associated with the emergent variable's components.

3.2. Model identification

To allow for a meaningful interpretation of the parameter estimates, we need to ensure that the model is identified, i.e., that there is only one set of parameters that satisfies the specified model's constraints. Otherwise, if there are several sets of parameters that are equally consistent with the model constraints, the model would not be identified. In this situation, the preference for one set of parameters is arbitrary and therefore the obtained parameter estimates and their interpretation are not trustworthy (Bekker et al., 1994). Following here, we provide concise guidelines to ensure that the parameters of the H–O specification are identified. Note that we limit our focus to identifying the parameters associated with emergent and excrescent variables; if the model also contains latent variables, the identification rules for latent variables need to be taken into account as well (e.g., Bollen, 1989).

To ensure identification of the model parameters in the H–O specification, the scales of the emergent and the excrescent variables need to be fixed. Hence, we recommend fixing one loading per emergent and excrescent variable to one. Note that no component is allowed to serve multiple times as scaling variable. Considering our example model in Fig. 3, x_3 serves as scaling variable for the emergent variable η, and x_2 and x_1 serve as scaling variables for the excrescent variables ν_1 and ν_2, respectively. Additionally, further composite loadings of the excrescent variables need to be constrained to zero to avoid an over-parameterization of the model. Therefore, additional composite loadings of the excrescent variables can be fixed in a cascading fashion. In our illustrative model, we fix the composite loading of x_3 on ν_2 to zero. Moreover, the excrescent variables are uncorrelated with the emergent variable (including potential other variables in the model). Finally, the emergent variable cannot be isolated, i.e., it must correlate with at least one other variable not forming the emergent variable. For a more technical description of the identification constraints, we refer the reader to Schuberth (2022).

3.3. Composite model estimation

The model can be estimated once it has been specified and its identification is ensured. In general, estimates for a composite model's parameters can be obtained in various ways. Originally, approaches that emerged outside the realm of SEM were proposed, such as the iterative PLS algorithm (Henseler & Schuberth, 2020; Wold, 1975) or MAXVAR (Kettenring, 1971; Schuberth et al., 2018). However, these approaches show various drawbacks in comparison to classical SEM

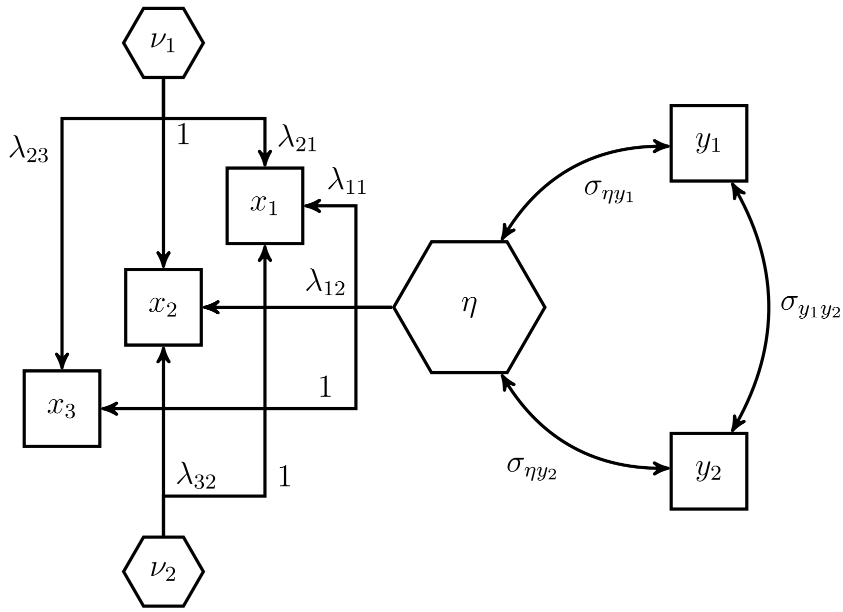


Fig. 3. Example specification of a CCA model.

estimators. For example, statistical inference is based on bootstrap. Recent research has shown that the Bollen–Stine bootstrap (Bollen & Stine, 1992), which has been proposed to assess the exact fit of a CCA model (Schuberth et al., 2018), is outperformed by mean and variance corrected versions of the chi square test in case of larger models (Ferraz et al., 2022). Moreover, these approaches are limited in terms of model specification, e.g., it is not possible to constrain parameters in PLS.

Researchers who rely on the H–O specification can overcome these issues because commonly used SEM estimators can be used for model estimation. Such estimators include weighted least squares (Browne, 1984) and maximum likelihood (ML Jöreskog, 1970), as well as its versions that are robust against a violation of the normality assumption (e.g., Satorra & Bentler, 1994). Consequently, researchers applying CCA can gain all the benefits that they are accustomed to having with SEM, such as dealing with missing values (e.g., Allison, 2003; Muthén et al., 1987) and constraining parameters.

A supposed disadvantage of the H–O specification is that no weight estimates are obtained by default since the model is specified in terms of composite loadings. However, as Schuberth (2022) has shown, the weight estimates used to form the emergent and excrescent variables can be obtained as the elements of the inverse of the composite loading matrix. Since most SEM software allows for specifying new parameters, this feature can be exploited to obtain the (standardized) weight estimates. See also Section 4.

3.4. Composite model assessment

Once a researcher has estimated the model, the next step is to assess and interpret the model. In CCA, model assessment includes assessing the overall model fit and assessing the emergent variable (Henseler & Schuberth, 2020; Schuberth et al., 2018). In general, the overall model fit is assessed to ascertain that the data at hand conforms to the (constraints of the) specified model. In the CCA context, overall model fit assessment helps to evaluate whether an emergent variable fully conveys the information between its components and other variables in the model, i.e., we examine whether the axiom of unity of the synthesis theory holds (Henseler & Schuberth, 2021). Put differently, we assess whether the components of an emergent variable act as a whole instead of a mere loose collection of parts. Additionally, we assess the emergent variable to examine whether the obtained parameter estimates are in line with a researcher's theory.

As in SEM and CFA, overall model fit assessment is a crucial step in CCA, and it can be done in various non-exclusive ways. The advantage of using the H–O specification is that researchers are not limited by approaches that emerged outside the realm of SEM to assess the overall fit of their models, e.g., by PLS (Schuberth, Rademaker et al., 2022). In fact, researchers can draw on all developments in SEM that have been proposed for assessing the overall model fit, such as tests for exact fit, fit indices (Schermelleh-Engel et al., 2003), equivalence tests (Yuan et al., 2015) and bootstrap selection (Grønneberg & Foldnes, 2018). Besides assessing the overall model fit, researcher should assess the emergent variable, i.e., the estimated weights, composite loadings, correlations between the emergent variable and other variables in the model, and their significances to investigate whether they align with her theory and expectations.

4. Empirical example

To demonstrate the application of CCA, we consider Lyu et al.'s (2021) study, which originally examined the effects of restaurant-suppliers' co-creation on behavioral intention, perceived food value, perceived service value, and overall image. While the authors operationalized behavioral intention, perceived food and service value, and overall image through reflective measurement models, they suggest that the composite model be employed to operationalize restaurant suppliers' co-creation. Specifically, they assume that the following four components compose restaurant suppliers' co-creation: (i) frequency of visiting food ingredient suppliers (x_1), (ii) frequency of joint effort with food ingredient suppliers (x_2), (iii) frequency of auditing/evaluating the food ingredient suppliers (x_3), and (iv) frequency of ingredients presentation (x_4). To examine whether these four components emerge into a new variable, we apply CCA. Since we are not interested in the effect of co-creation on its consequences, we allow all constructs, i.e., latent and emergent variables, to be correlated as shown in Fig. 4. Further, for the sake of this demonstration, we replace the latent variables by their sum scores. Otherwise, the reflective measurement and composite models would be assessed jointly. In this case one could speak of a confirmatory composite and factor analysis (CCFA) because a mixture of emergent and latent variables is examined (Hubona et al., 2021). To take the reliability of the used sum scores into account, we follow Nunnally and Bernstein (1994, Equation 7-6) and fix the variances of the random measurement errors to (1-reliability) times

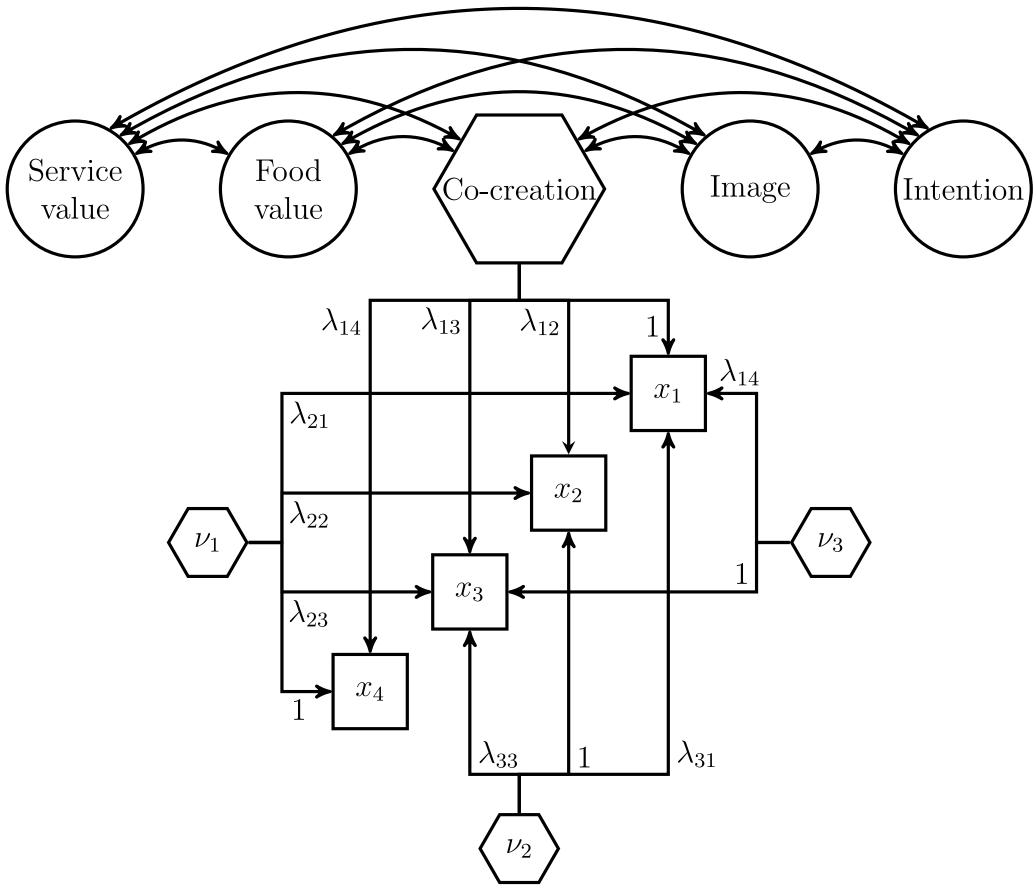


Fig. 4. Model comprising co-creation.

the variance of the respective sum scores. As reliabilities, we use the Jöreskog ρ_C reliability estimates as reported in Table 3 of Lyu et al. (2021).

In contrast to the original study, we apply the H–O specification as illustrated in Fig. 4. In doing so, we model co-creation as an emergent variable embedded in a composite model. Since the emergent variable is composed of four components, three excrescent variables must be additionally specified, i.e. ν_1 to ν_3, as explained in the previous section. To ensure model identification, we fix the composite loading of x_1 on the emergent variable to one, i.e., x_1 serves as scaling variable for the emergent variable. Similarly, x_4, x_2, and x_3 serve as variables that fix the scale of the excrescent variables ν_1, ν_2, and ν_3, respectively. Further, we fix the composite loadings of x_4 on ν_2, x_2 on ν_3, and x_4 on ν_3 to zero. Finally, all covariances between the excrescent variables and other variables in the model are fixed to zero.

We conducted the complete data analysis in the statistical programming environment R (R Core Team, 2021). In doing so, we used the original dataset of Lyu et al. (2021). The data was collected via a survey, and comprises 365 observations. For more details about the data collection, we refer to the original study of Lyu et al. (2021). In contrast to the original study which used PLS for model estimation, we used the ML estimator with robust standard errors and a Satorra–Bentler scaled test statistic (MLM Satorra & Bentler, 1994) as implemented in the R package lavaan (Version 0.6–11.1682 Rosseel, 2012). Additionally, to obtain the weight estimates, we have exploited the feature of lavaan that allows to specify new parameters. Specifically, the weight estimates to form the emergent variable are calculated as the elements in the first row of the inverted composite loading matrix. For that purpose, researchers can draw on software that supports symbolic calculations, such as Wolfram's Mathematica (Wolfram Research, 2021). The composite loading matrix for our empirical example is displayed in Eq. (1).

$$\begin{array}{c c} & \begin{array}{cccc} \eta & \nu_1 & \nu_2 & \nu_3 \end{array} \\ \begin{array}{c} x_1 \\ x_2 \\ x_3 \\ x_4 \end{array} & \begin{pmatrix} 1 & \lambda_{21} & \lambda_{31} & \lambda_{14} \\ \lambda_{12} & \lambda_{22} & 1 & 0 \\ \lambda_{13} & \lambda_{23} & \lambda_{33} & 1 \\ \lambda_{14} & 1 & 0 & 0 \end{pmatrix} \end{array} \tag{1}$$

Subsequently, the standardized weights to form the emergent variable can be obtained as the unstandardized weight estimates times the ratio of two standard deviations, i.e., the standard deviation of the corresponding component and the standard deviation of the emergent variable. The complete model specification is provided in the online supplementary material.

The estimation with lavaan converged normally. Considering the overall model fit, the robust chi-square test indicates no model misfit (χ^2 = 19.798, df = 9, p > 0.01). Similarly, the various fit indices indicate that the model fits the data reasonably well (Schermelleh-Engel et al., 2003): robust comparative fit index (CFI) = 0.987, robust Tucker–Lewis Index (TLI) = 0.960, robust root mean square error of approximation (RMSEA) = 0.064 (with 90% confidence interval of [0.024;0.102]), and robust standardized root mean square residual (SRMR) = 0.028. Consequently, we find no empirical evidence against the synthesis theory, i.e., the four components emerge into a new variable, namely co-creation.

Table 1 reports the standardized composite loading ($\hat{\lambda}^{\text{std}}$) and weight estimates ($\hat{w}^{\text{std}}$), including their 95% percentile bootstrap confidence intervals based on 1964 bootstrap runs (36 of the 2000 bootstrap estimations did not converge). Considering the standardized weight estimates, the four components contribute positively to forming the emergent variable co-creation. However, as the 95% percentile bootstrap confidence intervals covering zero highlight, two of the four

Table 1
Standardized parameter estimates including their 95% percentile bootstrap confidence intervals.

Component	$\hat{\lambda}^{\text{std}}$	95% CI	$\hat{w}^{\text{std}}$	95% CI
x_1	0.776	[0.614;0.888]	0.304	[0.049;0.576]
x_2	0.631	[0.393;0.793]	0.078	[−0.254;0.374]
x_3	0.926	[0.787;0.976]	0.633	[0.312;0.872]
x_4	0.651	[0.395;0.815]	0.198	[−0.112;0.475]

components show a non-significant weight, i.e., the weights of x_2 and x_4. Therefore, we additionally investigated the standardized composite loadings. As Table 1 shows, all composite loadings are significantly different from zero. Following Benitez et al. (2020), we decided not to remove the two components as this might alter the meaning of the emergent variable and thus violate its content validity. Further, the correlations between co-creation and service value, food value, image, and intention range from 0.282 to 0.520 and are significant, showing a relationship of co-creation with its environment. Consequently, the CCA results do not provide evidence against the theory that co-creation emerges from its four proposed components.

5. Discussion

Our study raises awareness that (at least) two types of theoretical concept are studied in the fields of tourism and hospitality research, namely behavioral concepts and forged concepts. The definition of a theoretical concept determines whether a given concept is regarded as a behavioral one, i.e., as a theoretical concept that exists in nature and therefore can in principle be measured, or as a forged concept, i.e., as a theoretical concept that is defined by or composed of its components. Consequently, different definitions of a concept can lead to a theoretical concept being understood as behavioral or as forged. Once a concept is clearly defined, the type of concept determines its operationalization. For behavioral concepts, measurement models like the reflective and causal-formative measurement model can be used to operationalize them. However, measurement models, regardless of whether they are reflective or causal-formative, are hardly suitable to operationalize forged concepts, as these models ignore the key characteristics of forged concepts, namely that forged concepts do not exist in nature per se and show a definitional rather than a causal relationship with their components. For forged concepts, the composite model is the preferred modeling approach.

Previous literature, including publications in tourism and hospitality research, refers to ‘formative constructs’ (e.g., Cong, 2016; Murphy et al., 2009) whose description resembles our description of a forged concept. Unfortunately, the term ‘formative construct’ is not consistently defined in the literature and thus can have several meanings (Bollen & Diamantopoulos, 2017). On the one hand, a formative construct can refer to a latent variable that is affected by a set of observed variables, so-called causal indicators, and by a disturbance term (MacCallum & Browne, 1993), where the disturbance term captures all remaining causes on the latent variable that are not represented by the indicators (Diamantopoulos, 2011). This understanding of a formative construct is equivalent to our description of a latent variable embedded in a causal-formative measurement model. Note that in the causal-formative measurement model the construct is not defined by a set of variables, because it always precedes its measures (Bollen & Diamantopoulos, 2017). This is also highlighted by more recent research on the causal-formative measurement model which emphasizes that “the meaning of the latent variable is not determined by its relationships to the causal indicators but rather through its role as a common factor to other latent variables and their indicators” (Aguirre-Urreta et al., 2016, p. 95). Consequently, and in contrast to a wide-spread misbelief (e.g., Jarvis et al., 2003; MacKenzie et al., 2005; Petter et al., 2007), dropping a causal indicator does not alter the construct’s meaning. On the other hand, a formative construct can refer to constructs that are fully composed or formed by a set of variables. Or, to cite Petter et al. (2007, Abstract), “[f]ormative constructs occur when the items describe and define the construct rather than vice versa”. This understanding of a formative construct equals our description of a forged concept which the composite model captures well. In line with Bollen and Diamantopoulos (2017, p. 587) “we see composite–formative indicators as neither measures nor causes (antecedents) of the composite variable that they create” but as components, i.e., constituting elements. Against this background, statements such as “only a formative mode is applicable if indicators form or cause the image of a destination” (Mikulić & Ryan, 2018, p. 466) are problematic, since there is a difference between forming and causing. Therefore, we advise future research to be clear about the definition of their theoretical concepts and to choose a model for operationalizing concepts, which matches the concept’s characteristics. Otherwise, researchers will most likely face biased and inconsistent estimates and draw questionable conclusions from their models (Bollen & Lennox, 1991; Murphy et al., 2009; Sarstedt et al., 2016; Schuberth, 2021).

To empirically assess the components of forged concepts, we present CCA. It is similar to CFA; however, instead of empirically validating reflective scales of latent variables, CCA is used to empirically validate that components assumed to compose an emergent variable actually do form a new whole within the forged concept’s environment. In doing so, we rely on the recently introduced H–O specification, which allows researchers to employ common SEM software for estimating composite models and thus to draw on all the developments in SEM when a CCA is conducted. To demonstrate the application of CCA with its four key steps, i.e., model specification, model identification, model estimation, and model assessment, we considered an empirical study of Lyu et al. (2021) about restaurant suppliers’ co-creation. Specifically, we used CCA to investigate whether the four components Lyu et al. (2021) proposed to form restaurant suppliers’ co-creation, indeed act as a new whole. Our results provided no empirical evidence against the components forming a new whole, i.e., against restaurant suppliers’ co-creation. Note, we emphasize that a lack of statistical disconfirmation does not automatically imply a confirmation. Besides, as with all empirical studies, replication would be a crucial step in gaining more confidence in postulated theories.

In our study, we limit the focus to observed variables as components forming an emergent variable. However, this is by no means mandatory and the tourism literature provides various examples where modeling theoretical concepts as emergent variables composed of latent variables is required, e.g., to model composite attributes (Mikulić, 2018). Other more concrete examples are perceived food souvenir quality and tourist engagement which specific studies have proposed to be composed of nine and five dimensions, respectively, each measured by a set of reflective indicators (Ho et al., 2020; Rasoolimanesh et al., 2019). Although CCA relying on the H–O specification can also be used to assess such emergent variables, we encourage future research to propose guidelines.

CRediT authorship contribution statement

Yuqing Liu: Writing – original draft. **Florian Schuberth:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Yide Liu:** Data curation, Resources. **Jörg Henseler:** Writing – review & editing, Supervision, Conceptualization.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jbusres.2022.07.040.

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