COMPARATIVE ANALYSIS OF FACTOR-BASED AND COMPOSITE-BASED STRUCTURAL EQUATION MODELS: FACTORS AFFECTING WORD-OF-MOUTH OF TOURISTS IN KHUNG BANG KACHAO*

Vatanyoo Rasmidatta**

Abstract

Structural Equation Models (SEMs) are commonly categorized into two main types: factor-based SEM and composite-based SEM. Each type is suitable for analyzing different forms of hypothetical constructs. Factor-based SEM is well-suited for analyzing factors, while composite-based SEM is tailored for analyzing composites. However, the majority of past research has favored composite-based SEM, particularly Partial Least Squares (PLS), for analyzing factors. Such practices can introduce biases into the analysis.

This article provides an illustrative example from the tourism and hotel management domain by analyzing hypothetical constructs in two scenarios: one where the constructs are treated as factors and another where they are treated as composites. The study includes six constructs: service quality, atmosphere, perceived value, satisfaction, revisit intentions, and word-of-mouth. In the first scenario, the research objective is theory testing, while in the second scenario, the research aims to assess the model’s predictive capabilities when applied to datasets beyond those used for the analysis.

The constructs of service quality, atmosphere, and perceived value are assumed to influence satisfaction, while satisfaction and service quality are hypothesized to impact revisit intentions. Perceived value, satisfaction, and revisit intentions are further assumed to trigger word-of-mouth.

Keywords: Structural Equation Models (SEMs), Factor-Based SEM, Composite-Based SEM, Partial Least Squares (PLS), Hypothetical Constructs, Theory Testing, Predictive Modeling, Tourism, Hotel Management.

INTRODUCTION

Structural Equation Modeling (SEM) has gained widespread acceptance in the field of tourism marketing (Leruksa et al., 2023). One possible reason for the popularity of this analytical method may be its ability to simultaneously test the influence of hypothetical constructs. These hypothetical constructs can take two forms: factors and composites (or components). Factors are often employed to represent psychological constructs that require multiple indicators to measure conceptual unity, such as satisfaction or perceived service quality, whereas composites are typically human-created constructs, such as the marketing mix or an index.

In the realm of tourism marketing, factor-based hypothetical constructs are predominantly utilized (Wattanacharoensil et al.,...
2024). This observation is evident in globally recognized journals, such as the Journal of Travel & Tourism Marketing (JTTM), where the majority of research articles treat hypothetical constructs as factors. A similar trend is observed in Thai journals, where factors are widely adopted as representative of hypothetical constructs. Limited research explicitly distinguishes between the types of hypothetical constructs—factors and composites (Fakfare et al., 2023). Furthermore, specifically regarding SEM, the utilization of Partial Least Squares SEM (PLS-SEM) has become more prevalent than in the past (Manosuthi et al., 2020a; Meeprom et al., 2023). PLS-SEM is categorized as a composite-based SEM, making it suitable for estimating parameters of composite-based models. However, researchers often employ PLS-SEM to analyze factors. In such cases, although simulations suggest that bias resulting from mismatching is not substantial (Sarstedt et al., 2016), we advocate for the use of SEM that aligns with the nature of the hypothetical constructs to avoid potential issues.

The primary objective of this article is to apply composite-based SEM to test factor and composite models, mitigating any bias arising from a mismatch. Given the widespread use of factors in ABAC journal and Journal of Travel and Tourism Marketing (JTTM: the leading tourism marketing journal), coupled with the increasing popularity of composite-based SEM, we posit that providing guidelines for applying composite-based SEM to analyze factors and account for bias from SEM-type and hypothetical construct-type mismatching would be beneficial. This article employs hotel data from Khung Bang Kachao, analyzing both factor-based and composite-based models using composite-based SEM.

BRIEF REVIEWS OF HYPOTHETICAL CONSTRUCTS IN THE JTTM AND THE ABAC JOURNAL

From a multivariate statistical perspective, multiple indicators can be employed collectively as proxies for variables of interest. For instance, consider a scenario where four indicators, namely “price satisfaction,” “service satisfaction,” “atmosphere satisfaction,” and “convenience satisfaction,” are utilized as proxies for a construct known as the “satisfaction index”. In this context, the satisfaction index is considered a hypothetical construct or latent variable. The classification of hypothetical constructs into two categories—factors and composites (or components)—is a contemporary trend.

The categorization of constructs can be simplified by assessing whether the variables in question are behavioral constructs or human-made constructs (Henseler, 2017). When dealing with behavioral constructs, factors are commonly used as statistical proxies, reflecting the entirety of the construct through multiple indicators. In contrast, for human-made constructs or artifacts, composites are often employed as statistical proxies, representing the construct as a sum of its constituent indicators. Regrettably, previous research in the field of tourism marketing has generally omitted explicit classification of constructs as factors or composites. This presents a challenge as the statistical analysis of different construct types requires distinct SEM (Structural Equation Modeling) assumptions. For researchers using off-the-shelf software such as AMOS, LISREL, or MPLUS for analysis, these programs assume that all constructs in the research model are factors, categorizing this approach as factor-based SEM. Thus, when constructs are factors, factor-based SEM analysis is appropriate. Conversely, when using SmartPLS, although the software now has the capability to analyze factors, it defaults to assuming constructs are composites when using PLS as the estimator, making it fit with composite models.

Notably, composite-based SEM techniques have evolved, with techniques such as PLScc using ADANCO and GSCAm using GSCA Pro, allowing researchers to analyze factors (Manosuthi et al., 2021b). Despite the fact that current research indicates that using PLS for estimating factors, results in limited bias from mismatching, we advocate that
Comparative Analysis of Factor-Based and Composite-Based Structural Equation Models: Factors Affecting Word-Of-Mouth of Tourists in Khung Bang Kachao

Researchers should consider employing PLS-c or GSCAm, both of which allow for a more comprehensive comparison with factor-based SEM. The use of composite-based SEM (e.g., PLS) for analyzing factors, even in the presence of bias as mentioned earlier, is still prevalent among social science researchers, both in globally renowned journals such as the Journal of Travel & Tourism Marketing (JTTM) (Table 1) and within the ABAC Journal (Table 2). If looked at as a percentage, within JTTM, there are 2 articles that employ mixed factor-composite models analyzed with IGSCA-SEM, accounting for 2.5% of SEM-oriented articles published since 2020.

In the context of the ABAC Journal, approximately 6% of articles utilize mixed factor-composite models analyzed with IGSCA-SEM. However, regarding bias resulting from mismatched analysis in the ABAC Journal, the value stands at approximately 23% since 2020.

Table 1 Classification of Constructs in the Journal of Travel and Tourism Marketing

<table>
<thead>
<tr>
<th>Hypothetical Construct</th>
<th>Factor-based SEM</th>
<th>Composite-based SEM</th>
<th>Attenuated Composite-based SEM (e.g., PLS-c, GSCAm, or IGSCA)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Factor-based SEM</td>
<td>(Adam et al., 2020; Al-Ansi et al., 2021; Badu-Baiden et al., 2022; Chen et al., 2020; Chen et al., 2021; Chi &amp; Han, 2021; Chi et al., 2022; Choe et al., 2021; Choi et al., 2020; Chua et al., 2023; DekaHili &amp; HalleM, 2020; Duman et al., 2020; Fakfare et al., 2020; Guan et al., 2021; Han, Koo, et al., 2020; Han, Lee, et al., 2020; Huang et al., 2021; Hung &amp; Wang, 2021; Hwang, Choe, et al., 2021; Hwang, Kim, et al., 2021; Hwang et al., 2022; Ji &amp; Yang, 2022; Joo &amp; Woosnam, 2022; Joo et al., 2023; Kautish et al., 2021; S. H. Kim et al., 2020; Le et al., 2021; Leung &amp; Ma, 2020; Li et al., 2021; Lin et al., 2022; Liu et al., 2022; Lo, 2020; Lu et al., 2020; Lv et al., 2022; Manosuthi et al., 2020b; Mehran et al., 2020; Moon et al., 2021; Ok et al., 2020; Paker &amp; Gök, 2021; Peng et al., 2020; Quan et al., 2023; Radic et al., 2022; Rather, 2020; Ruan et al., 2022; Russell et al., 2022; Sharma et al., 2022; Shen et al., 2020; Shin &amp; Jeong, 2022; Shin &amp; Kang, 2021; Singh et al., 2023; Stangl et al., 2023; Su et al., 2020; Suess et al., 2020; Taylor, 2020; Tsaur &amp; Tsai, 2023; Tsaur et al., 2022; Woosnam et al., 2021; Xie &amp; Luo, 2021; Xu, Wang, et al., 2023; XU &amp; Gursoy, 2020; Yen et al., 2021; Yin et al., 2023; Yu et al., 2022; J. Yu et al., 2021; Y. Yu et al., 2021)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Composite-based SEM</td>
<td>(Chiu et al., 2023; Han et al., 2021; Hao &amp; Chon, 2021; M. J. Kim et al., 2020; Lee et al., 2023; Lee &amp; Lee, 2021; Lin &amp; Ryu, 2023; Mwesiumo et al., 2021; Pikkemaat et al., 2020; Quan et al., 2022; Tsai &amp; Fong, 2021; Wang et al., 2020; Wang et al., 2022; Xu, Pratt, et al., 2023; Zhang et al., 2021)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Attenuated Composite-based SEM (e.g., PLS-c, GSCAm, or IGSCA)</td>
<td>(Wattanachoensil et al., 2023)</td>
<td>(Fakfare et al., 2021; Manosuthi et al., 2021a, 2022b)</td>
<td></td>
</tr>
</tbody>
</table>
### Table 2 Classification of Constructs in the ABAC Journal

<table>
<thead>
<tr>
<th>Hypothetical Construct</th>
<th>Factor</th>
<th>Composite</th>
<th>Mix</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Factor-based SEM</strong></td>
<td>(Amonhaemanon &amp; Isaramalai, 2020; Ativetin, 2021; Auemsuvarn &amp; Ngamcharoenmongkol, 2022; Batada, 2021; Borirakcharoenakit et al., 2022; Cattapan et al., 2023; Chaisuwan, 2021; Chantamas et al., 2020; Chitthanom, 2020; Chokpitakkul et al., 2020; Chuchuen &amp; Chanvarasuth, 2022; Dankaew &amp; Silpcharu, 2020; Dhasan &amp; Kowathanakul, 2021; Ekasari et al., 2023; Hareebin, 2020; Huang &amp; Bunchapattanasakda, 2023; Intayos et al., 2021; Jaengprajak &amp; Chaipoopiratana, 2022; Jitsoonthornchaikul, 2022; Keeratipranon &amp; Theerawanviwat, 2023; Khetjenkarn &amp; Agmapisarn, 2020; Khongsawatkiat &amp; Agmapisarn, 2023; Khoso &amp; Akaraborworn, 2022; Khuntawee &amp; Koowattanatianchai, 2022; Kim &amp; Jindabot, 2021; Kim et al., 2022; Kim et al., 2022; Kitcharoen, 2021; Kitjaroenchai &amp; Chaipoopiratana, 2022; Kumar et al., 2023; Laliwan &amp; Potipiroon, 2022; Maneechaeye &amp; Potipiroon, 2022; Muensriphum et al., 2021; Naglis &amp; Inprom, 2020; Niyawanont &amp; Wanarat, 2021; Noosong et al., 2021; Noypa et al., 2021; Pengman et al., 2022; Phairat &amp; Potipiroon, 2022; Poolsawat, 2021; Prasongthai, 2023; Pumjaroen &amp; Sethapramote, 2023; Rattanaburi, 2023; Sangthong &amp; Soonsan, 2023; Satchapappichit, 2020; Siri &amp; Lorsuwannarat, 2020; Sunghthong et al., 2023; Suwannakul &amp; Khetjenkarn, 2022; Tadawattanawit et al., 2023; Tarurhor, 2021; Tassawa &amp; Khumhome, 2023; Thongyai &amp; Potipiroon, 2022; Tochawai et al., 2023; Ueasangkomsate et al., 2021; Uppathampracha, 2022; Vilaisri et al., 2023; VÖ, 2021; Zhu &amp; Thøgersen, 2023)</td>
<td>(Ahmadi et al., 2023; Batool et al., 2023; Chaipoopiratana &amp; Minakan, 2023; Chinnapong et al., 2021; Fadilah &amp; Ramayah, 2023; Ma &amp; Aung, 2022; Prasongthai, 2022; Purwanto, 2021; Qamar &amp; Qureshi, 2022; Ru-zhe et al., 2023; Seriwatana &amp; Charoensukmongkol, 2020; Sriram et al., 2021; Terason et al., 2022; Thepprasarn &amp; Suntrayuth, 2022; Ubadillah et al., 2022; Wening &amp; Moertono, 2023; Widyaningtyas et al., 2022; Wiwoho et al., 2023; Zhu, 2021)</td>
<td>(Khanngoen et al., 2023)</td>
</tr>
<tr>
<td><strong>Composite-based SEM</strong></td>
<td>(Chumwichan et al., 2023; Leruksa et al., 2023; Napontun et al., 2023; Napontun &amp; Senachai, 2023; Senachai et al., 2023)</td>
<td>(Khanngoen et al., 2023)</td>
<td>(Khanngoen et al., 2023)</td>
</tr>
<tr>
<td><strong>Attenuated Composite-based SEM</strong> (e.g., PLSc, GSCA, GSCAM, or IGSCA)</td>
<td></td>
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</tr>
</tbody>
</table>
Composite-Based SEM for Composites and Factors

Once researchers have classified hypothetical constructs as entirely composite, the choice of employing composite-based Structural Equation Modeling (SEM) for analysis becomes evident. Currently, the most favored estimators are Partial Least Squares (PLS) and Generalized Structured Component Analysis (GSCA), both of which are considered unbiased estimators when estimating composite models. Past research has demonstrated that GSCA outperforms PLS in terms of parameter recovery (Cho & Choi, 2020). Furthermore, as summarized by Manosuthi et al. (2021b), estimating in mode A (reflective) tends to yield higher accuracy than in mode B (formative) (Cho & Choi, 2020).

In terms of analysis, we recommend commencing with Confirmatory Composite Analysis (CCA), an approach developed by Schuberth et al. (2018) that is analogous to Confirmatory Factor Analysis (CFA) (Hubona et al., 2021). Researchers have a variety of estimators from which to choose (e.g., MAXVAR, MINVAR, PLS, GSCA), but it is essential to identify a model that can estimate all parameters adequately. If opting for PLS or GSCA, researchers must specify the saturated relationships of all composites. Model fit in this context is evaluated primarily using the Standardized Root Mean Square Residual (SRMR), assessed through Null Hypothesis Significance Testing. Rejecting the null hypothesis indicates that SRMR is not equal to 0, signifying a lack of model fit. Model fit is a critical consideration as it reflects the level of accuracy with which the model reproduces the relationships within the collected data compared to the model implied by theory. Therefore, achieving model fit implies that empirical data are consistent with the hypothesized relationships among composites.

Nevertheless, there are instances where a model that exhibits an exceptionally good fit, often termed an “overfit” or “perfect fit” model, may not be suitable. This is because such models tend to capture noise and may struggle to generalize well to external data. Consequently, a comprehensive testing approach must encompass both internal and external evaluations. Internal testing can be conducted by examining the significance levels of the Standardized Root Mean Square Residual (SRMR) for composites and the overall structural model. External testing, on the other hand, involves validation against an independent dataset, commonly assessed using Q-squared statistics and the comparison of targeted Root Mean Square Error (RMSE) against RMSE Benchmark values. The fundamental criteria for model evaluation are that Q-squared should be positive, and the targeted RMSE should be smaller than the Benchmarked RMSE for all indicators (Hair et al., 2019). Meeting these criteria indicates that the model possesses predictive power and is generalizable (Hair et al., 2019).

In cases where researchers specify the measurement model as factor-based, we recommend employing factor-based Structural Equation Modeling (SEM). However, for those researchers who opt for composite-based SEM, we advise choosing between PLSc and GSCAm. Both of these estimators have been adjusted to attenuate error terms, akin to the treatment in factor-based SEM (Manosuthi et al., 2022a). It is important to note that when researchers select PLS or GSCA, parameter estimates may introduce bias. Therefore, it is not recommended to use PLS-SEM or GSCA for estimating factors. Model analysis follows a similar procedure as outlined above. Researchers should begin by verifying the measurement model before evaluating structural relationships.

As Hair et al. (2019) put it, internal evaluation begins with Confirmatory Factor Analysis (CFA), considering fit indices such as SRMR, with a common threshold set at 0.8. If SRMR is below 0.8, the model is generally considered to fit well. The assessment of the structural model can be conducted using fit indices such as SRMR or CFI. Generally, to conclude that a model fits well it must meet the specified criteria, namely that the SRMR value is less than 0.8 and a CFI value is greater than 0.9. Meanwhile, regarding out-
of-sample predictive power testing criteria, researchers can compare RMSE values, where the target RMSE should be lower than the benchmark RMSE for all indicators. Additionally, a positive Q-squared value indicates that the model has predictive relevance.

The subsequent sections illustrate these principles using a hypothetical example that simulates a case of hotel tourism in Khung Bang Kachao. In this example, all variables are assumed to be suitable for both factor and composite scenarios to ensure appropriateness.

**Hypothetical Example**

Tourism in Thailand is one of the key industries driving the country’s economy. Its significance to the overall economy was evident in 2019 when the total value of domestic tourism-related products reached 3.01 trillion Thai Baht, accounting for 17.79% of the country’s gross domestic product (GDP). However, it’s essential to note that the tourism sector has been heavily impacted by the COVID-19 pandemic. According to the United Nations World Tourism Organization (UNWTO), in 2020, international tourist arrivals worldwide declined by 74% compared to the previous year, resulting in an 81.16% reduction in foreign tourist revenue for Thailand in 2021 when compared to 2019. There are expectations that the global tourism industry may gradually return to normalcy between early 2026 and mid-2028 (Likitsarun et al., 2023). Tourism is more than just leisure; it serves as a tool for generating income, creating jobs, and improving people’s quality of life. It encourages investments, stimulates economic growth, mitigates urban migration by providing local employment opportunities, and contributes to environmental conservation efforts both within Thailand and globally. Thailand’s tourism economy is expected to see growth primarily from increased revenue within the tourism industry, which relies heavily on international tourism. International tourism contributes nearly twice as much revenue as domestic tourism within Thailand’s tourism industry.

Amidst the changing landscape of the tourism sector, and heavily influenced by the repercussions of the COVID-19 pandemic, the Thai government, through the Ministry of Tourism and Sports, has devised a revised National Tourism Development Plan (2021-2022). This plan aims to revitalize short-term tourism and lay the groundwork for long-term growth, thereby enhancing the resilience of localities and the nation as a whole. The primary focus is to ensure that travelers perceive the unique identities and standout features of various destinations, fostering creativity and innovation within these tourism hubs. As we enter 2022, there is growing optimism that this year will mark a turning point for various businesses and a new beginning for travelers who yearn to explore once more. However, it’s crucial to acknowledge that the hotel and restaurant sector has felt the direct impact of the pandemic more acutely than other industries (Bank of Thailand, 2022). Therefore, it is imperative for hotels and accommodation providers to adapt and fortify themselves against future challenges. One of the foremost strategies for businesses is to attract new customers and entice returning ones swiftly. In highly competitive tourism regions, word-of-mouth marketing, often referred to as “mouth-to-mouth” communication, plays a pivotal role in influencing consumer decisions. It is a form of informal communication that arises from personal experiences with products or services. Whether these experiences are positive or negative, they can motivate and persuade others to take an interest and make decisions regarding those products or services. Word-of-mouth marketing operates in both face-to-face and online settings, enabling the rapid dissemination of opinions about products or services with proven impact. It is essential to prioritize existing customers, as they tend to spend more and cost less to retain than acquiring new ones. This, in turn, simplifies the process of building customer loyalty, increasing sales, and securing a customer base for the future.

Consumer travel behavior has adapted to
the times and to recent events, resulting in a diverse range of traveler preferences. This includes cultural tourism, community-based tourism, agritourism, and eco-tourism, which have gained significant popularity in recent years. Notably, places like Bang Ka Chao in Phra Pradaeng District, Samut Prakan Province, have witnessed a surge in popularity. Samut Prakan is one of the four provinces within the Eastern Gulf of Thailand Tourism Development Zone, comprising Samut Prakan, Samut Songkhram, Samut Sakhon, and Chachoengsao. Bang Ka Chao, often referred to as the “Green Lung,” is a vast green area located near Bangkok, encircled by the Chao Phraya River. It resembles a large island and is renowned among both Thai and international tourists. TIME magazine has even ranked it as the 7th best urban oasis in the world. It is situated in the Phra Pradaeng District of Samut Prakan Province.

Furthermore, the Ministry of Natural Resources and Environment has designated the Bang Ka Chao area, encompassing 11,819 acres and six sub-districts, as an environmentally protected zone in 2019. However, due to the impact of COVID-19 on tourist arrivals, accommodation providers in the Bang Ka Chao area have faced substantial challenges. In such circumstances, the success of word-of-mouth marketing can be instrumental in attracting greater numbers of visitors, including those both new and returning. Word-of-mouth marketing stems from customer satisfaction, which is derived from the quality of service, the ambiance of the accommodation, and the perceived value. Satisfied customers are more likely to spread the word, leading to increased patronage and business success for accommodation providers in the Bang Ka Chao area.

Hypothetical Constructs Used in this Study

Service Quality

Service quality, as posited by Parasuraman et al. (1985), is the ability to meet the needs of service businesses by bridging the gap between customer expectations and their perceptions of the service received. It is widely acknowledged that service quality often precedes customer satisfaction. Service quality encompasses five core dimensions (Lovelock, 1996; Zeithaml et al., 1990):

Tangibility: This dimension relates to the physical evidence of a service, including the visible aspects that convey care, concern, and attentiveness, from the service provider. It makes the service more perceivable to customers.

Reliability: Reliability represents the service provider’s ability to deliver services as promised, instilling feelings of trust and dependability in customers. It ensures that customers feel that they can rely on the service provider.

Responsiveness: Responsiveness entails the readiness and willingness to serve, promptly meeting customers’ needs and desires. It enables easy and convenient access to services.

Assurance: Assurance is the ability of the service provider to demonstrate competence, and knowledge, and to provide efficient responses to customer needs. This instils feelings of confidence in customers, as they are receiving top-quality service.

Empathy: Empathy is the capacity to cater to individual customer needs and preferences, addressing each customer’s unique requirements with care and consideration.

These dimensions collectively define the quality of service and play a pivotal role in customer satisfaction and loyalty.

Atmosphere

Heide et al. (2009) emphasize the significance of atmosphere as a determining factor for customer or guest satisfaction, loyalty, positive word-of-mouth, and ultimately, business success. Atmosphere is the overall feeling that customers experience when they enter a hotel. If customers do not feel impressed and genuinely comfortable, they may lack inspiration and enthusiasm to return for future visits. The atmosphere of a hotel, including natural surroundings, scenic views, spatial design, and room decor, plays a pivotal role in shaping these perceptions.
Perceived Value

Perceived value encompasses all the benefits that customers receive from consuming a product or service. It represents an overall evaluation by customers regarding the benefits of the product concerning what is received and what is given up. What is received may refer to the advantages gained from using the product, while what is given up can signify what customers sacrifice to obtain the product, such as a financial contribution or other terms (Zeithaml, 1988; Dougall et al., 2000). Furthermore, perceived value can be viewed as the ratio or exchange between quality and the concept of value for money (Petrick et al., 2001). In essence, it’s a holistic assessment by customers of whether the expenditure justifies the value received (Sweeney et al., 1996).

Satisfaction

Satisfaction refers to the attitude or evaluation of feelings that customers have when they compare their pre-purchase expectations with actual performance (Oliver, 1980). Customers experience satisfaction when they receive a product or service that exceeds their previously set expectations (Zhao et al., 2019; Zhu et al., 2020). Furthermore, studies have found that customer satisfaction typically stems from three main factors: (1) customer expectations, (2) the quality of products and services from the customer’s perspective, and (3) the perceived value that customers receive (Fornell et al., 1996).

Word-of-Mouth

Word-of-mouth is an informal method of communication that occurs among product users or individuals who have experienced the services provided by service providers. This form of communication is considered highly credible because it is based on real experiences from those who have actually used the product or received the service. Word-of-mouth communication has the power to motivate and influence others’ interest and decision-making when it comes to purchasing products (Solomon, 2011). Word-of-mouth generated from satisfaction with a product or service impacts behavior and the likelihood of returning for repeat purchases (Kotler et al., 2022). Therefore, word-of-mouth aids in establishing business stability, achieving success, increasing sales, and building a customer base for the future (Eisingerich, Auh, & Merlo, 2014; Kim & Hanssens, 2017; Lovett, Peres, & Xu, 2016). The success of word-of-mouth can significantly enhance a business’s market presence and reputation.

Hypothetical Research Framework

As previously mentioned, in this example, we consider two scenarios. In the first scenario, hypothetical constructs and their indicators are conceptualized using a factor model approach. In the second scenario, the indicators are assumed to be combined into indices.

In the first scenario, behavioral constructs are assumed to be factors, including service quality (SQ) with 3 indicators, atmosphere (AT) with 4 indicators, perceived value (PV) with 3 indicators, satisfaction (SAT) with 3 indicators, revisit intention (RI) with 2 indicators, and word-of-mouth (WoM) with 2 indicators. For the second scenario, although these variables may appear to resemble behavioral constructs in psychology, marketing professionals have designed indices to make the desired measurements; these include the service quality index, atmosphere index, perceived value index, satisfaction index, revisit intention index, and word-of-mouth index.

It is essential to emphasize that these assumptions are made for the sake of clarity and ease of comprehension for the readers. Furthermore, it is assumed that the primary objective of the research in the first scenario is to test the data’s consistency with theory. In contrast, the second scenario places a greater emphasis on predictive accuracy and the extension of findings to other samples assumed to belong to the same population.
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Figure 1 Hypothetical Research Framework for a Factor Model (Case 1) and a Composite Model (Case 2)

Table 3 Confirmatory Factor Analysis and Reliability Testing

<table>
<thead>
<tr>
<th>Type</th>
<th>Construct</th>
<th>Indicator</th>
<th>FB-SEM</th>
<th>GSCAm</th>
<th>CI ( \hat{\lambda}_i ) (GSCAm)</th>
<th>AVE</th>
<th>Alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>Factor</td>
<td>AT</td>
<td>AT1</td>
<td>.807</td>
<td>.784</td>
<td>.7303; .8325</td>
<td>0.6418</td>
<td>0.8639</td>
</tr>
<tr>
<td></td>
<td></td>
<td>AT2</td>
<td>.895</td>
<td>0.956</td>
<td>0.9157; 0.9782</td>
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<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>AT3</td>
<td>.855</td>
<td>0.825</td>
<td>0.7805; 0.8713</td>
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<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>AT4</td>
<td>.604</td>
<td>0.596</td>
<td>0.5347; 0.6657</td>
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</tr>
<tr>
<td>Factor</td>
<td>SQ</td>
<td>SQ1</td>
<td>.850</td>
<td>0.830</td>
<td>0.7882; 0.8784</td>
<td>0.7315</td>
<td>0.8873</td>
</tr>
<tr>
<td></td>
<td></td>
<td>SQ2</td>
<td>.888</td>
<td>0.922</td>
<td>0.8771; 0.9663</td>
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</tr>
<tr>
<td></td>
<td></td>
<td>SQ3</td>
<td>.820</td>
<td>0.808</td>
<td>0.7626; 0.8624</td>
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<tr>
<td>Factor</td>
<td>PV</td>
<td>PV1</td>
<td>.758</td>
<td>0.740</td>
<td>0.6610; 0.8120</td>
<td>0.6075</td>
<td>0.8182</td>
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<td></td>
<td></td>
<td>PV2</td>
<td>.801</td>
<td>0.780</td>
<td>0.7066; 0.8526</td>
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<tr>
<td></td>
<td></td>
<td>PV3</td>
<td>.763</td>
<td>0.815</td>
<td>0.7388; 0.9022</td>
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<tr>
<td>Factor</td>
<td>SAT</td>
<td>SAT1</td>
<td>.813</td>
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<td>0.7550; 0.8771</td>
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<tr>
<td></td>
<td></td>
<td>SAT2</td>
<td>.894</td>
<td>0.914</td>
<td>0.8646; 0.9695</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>SAT3</td>
<td>.833</td>
<td>0.817</td>
<td>0.7669; 0.8695</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Factor</td>
<td>RI</td>
<td>RI1</td>
<td>.812</td>
<td>0.881</td>
<td>0.8428; 0.9163</td>
<td>0.7804</td>
<td>0.8730</td>
</tr>
<tr>
<td></td>
<td></td>
<td>RI2</td>
<td>.797</td>
<td>0.885</td>
<td>0.8490; 0.9191</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Factor</td>
<td>WoM</td>
<td>WoM1</td>
<td>.867</td>
<td>0.809</td>
<td>0.7672; 0.8560</td>
<td>0.6553</td>
<td>0.7858</td>
</tr>
<tr>
<td></td>
<td></td>
<td>WoM2</td>
<td>.893</td>
<td>0.810</td>
<td>0.7624; 0.8572</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. CFI (FB-SEM/GSCAm) = 0.9682/.955, SRMR (FB-SEM/GSCAm) = 0.031/.043, FB-SEM = Factor-Based SEM using Maximum Likelihood Estimator, CI = Confidence Interval, AVE = Average Variance Extracted
RESULTS

Case 1: Factor Model (Estimated by Composite-Based SEM)

Confirmatory Factor Analysis
The results of the Confirmatory Factor Analysis (CFA) reveal a strong alignment between the measurement model tested and the empirical data, as evidenced by a Comparative Fit Index (CFI) value of 0.955 and a Standardized Root Mean Square Residual (SRMR) value of 0.043. Furthermore, all factors exhibit Average Variance Extracted (AVE) values exceeding 0.5. Additionally, the Cronbach’s alpha coefficients for all constructs range from above 0.7 to below 0.95. Although two indicators (AT4 and PV1) exhibit factor loadings slightly below the conventional threshold of 0.7, the AVE values surpass the 0.5 threshold, indicating robust convergent validity. Detailed results are presented in Table 3. Moreover, in Table 4, the Heterotrait-Monotrait (HTMT) ratio is consistently below the 0.85 threshold for all pairs, demonstrating discriminant validity among the factors. Notably, it is observed that both Factor-Based Structural Equation Modeling (SEM) employing the Maximum Likelihood (ML) estimator and Composite-Based SEM with error attenuation using the GSCAm estimator yield congruent findings.

Structural Model Analysis
Table 5 provides a comprehensive view of the results obtained from the model fit tests and parameter estimations conducted in both Factor-Based Structural Equation Modeling (SEM) and the use of the GSCAm estimator. Remarkably, these analyses yield highly congruent and closely aligned outcomes. Multicollinearity issues do not exert adverse impacts on result interpretation, as all factors

Table 4 Advanced HTMT Ratio (HTMT2) to Assess Discriminant Validity

<table>
<thead>
<tr>
<th></th>
<th>AT</th>
<th>SQ</th>
<th>PV</th>
<th>SAT</th>
<th>RI</th>
<th>WoM</th>
</tr>
</thead>
<tbody>
<tr>
<td>AT</td>
<td>0.7519450</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SQ</td>
<td>0.5945716</td>
<td>0.6960068</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PV</td>
<td>0.5621417</td>
<td>0.6180700</td>
<td>0.6542587</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SAT</td>
<td>0.4520030</td>
<td>0.5207364</td>
<td>0.4439705</td>
<td>0.5880380</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RI</td>
<td>0.5543442</td>
<td>0.5403928</td>
<td>0.5629520</td>
<td>0.7754526</td>
<td>0.6347586</td>
<td></td>
</tr>
</tbody>
</table>

Table 5 Results of the Structural Model Analysis using GSCAm

<table>
<thead>
<tr>
<th>Relationship</th>
<th>Std. Path</th>
<th>GSCAm</th>
<th>CI_Percentile 95%</th>
<th>VIF</th>
<th>Effect Sizes</th>
<th>Adj R-sq</th>
</tr>
</thead>
<tbody>
<tr>
<td>AT =&gt; SAT</td>
<td>.221</td>
<td>.182</td>
<td>0.0407; 0.3266</td>
<td>2.2104</td>
<td>0.0291</td>
<td>0.4789</td>
</tr>
<tr>
<td>SQ =&gt; SAT</td>
<td>.149</td>
<td>.195</td>
<td>0.0038; 0.3677</td>
<td>2.7538</td>
<td>0.0268</td>
<td></td>
</tr>
<tr>
<td>PV =&gt; SAT</td>
<td>.418</td>
<td>.405</td>
<td>0.2554; 0.5497</td>
<td>1.9504</td>
<td>0.1627</td>
<td></td>
</tr>
<tr>
<td>SQ =&gt; RI</td>
<td>.257</td>
<td>.254</td>
<td>0.1375; 0.3788</td>
<td>1.5835</td>
<td>0.0663</td>
<td>0.3776</td>
</tr>
<tr>
<td>SAT =&gt; RI</td>
<td>.430</td>
<td>.428</td>
<td>0.3084; 0.5327</td>
<td>1.5835</td>
<td>0.1868</td>
<td></td>
</tr>
<tr>
<td>PV =&gt; WoM</td>
<td>.073</td>
<td>.072</td>
<td>-0.0725; 0.2082</td>
<td>1.7361</td>
<td>0.0086</td>
<td>0.6413</td>
</tr>
<tr>
<td>SAT =&gt; WoM</td>
<td>.572</td>
<td>.563</td>
<td>0.4050; 0.7145</td>
<td>2.1145</td>
<td>0.4212</td>
<td></td>
</tr>
<tr>
<td>RI =&gt; WoM</td>
<td>.270</td>
<td>.270</td>
<td>0.1514; 0.3939</td>
<td>1.5316</td>
<td>0.1345</td>
<td></td>
</tr>
</tbody>
</table>

Note. CFI (FB-SEM/GSCAm) = 0.968/.955, SRMR (FB-SEM/GSCAm) = 0.033/.043, FB-SEM = Factor-Based SEM using Maximum Likelihood Estimator, CI = Confidence Interval, VIF = Variance Inflating Factor, Adj-R-sq = Adjusted R-squared
Comparative Analysis of Factor-Based and Composite-Based Structural Equation Models: Factors Affecting Word-Of-Mouth of Tourists in Khung Bang Kachao

exhibit Variance Inflation Factors (VIF) values below 3. Effect size measurements reveal that Perceived Value (PV) contributes most significantly to the variance in Satisfaction (SAT), while SAT demonstrates the highest contribution to the variance in Revisit Intentions (RI) and Word-of-Mouth (WoM).

Generalizability analysis, as presented in Table 6, confirms the model’s substantial predictive power and its aptness for utilization with new data. This assertion is corroborated by the positive values of Q-squared for all indicators and the lower RMSE target relative to the RMSE benchmark for all indicators.

Case 2: Composite Model Estimated by Composite-Based SEM

Confirmatory Composite Analysis

The results of the Confirmatory Composite Analysis (CCA), as presented in Table 7, underscore the compatibility of the measurement model under examination with empirical data, as indicated by an impressively low Standardized Root Mean Square Residual (SRMR) value of 0.0248. Additionally, the Average Variance Extracted (AVE) surpasses the recommended threshold of 0.5 for all factors. Furthermore, the Cronbach alpha values exceed 0.7 and fall below 0.95 for all constructs. It is noteworthy that while no significant component weights are found for one indicator (AT2), the historical context of research and the necessity for content validity of the composite justify the retention of AT2 as a measurement item. Given that the AVE surpasses the 0.5 threshold, we can confidently conclude that the composites exhibit convergent validity.

Structural Model Analysis

Table 8 presents the results of the model fit tests and parameter estimates obtained through composite-based Structural Equation Modeling (SEM), employing both Partial Least Squares (PLS) and Generalized Structured Component Analysis (GSCA) estimators. These results indicate that both approaches yield similar and closely aligned outcomes. Notably, the issue of multicollinearity does not exert a detrimental influence on the interpretation of the findings, as evidenced by the Variance Inflation Factor (VIF) values being consistently below 3 for all composites.

Effect size measurements shed light on the extent to which various composites contribute to the variance observed in the model. In this regard, it is noteworthy that perceived value (PV) exhibits the most substantial influence on satisfaction (SAT), while SAT, in turn, has the most pronounced impact on both revisit intentions (RI) and word-of-mouth (WOM).

Moreover, the analysis of generalizability, as depicted in Table 9, corroborates the model’s commendable predictive power. The positive values of Q-squared for all indicators and the consistently lower Root Mean Square Error (RMSE) of the target model, in comparison to the benchmark model, across all measurement items, underscore the model’s robustness and its applicability to new data.

| Table 6 Out-of-Sample Predictive Power Test for Generalizability |
|------------------|------------------|------------------|------------------|
| Indicator | RMSE target | RMSE Benchmark | Q-sq Predict |
| SAT1     | 0.4783        | 0.4975          | 0.2943          |
| SAT2     | 0.4561        | 0.4788          | 0.3309          |
| SAT3     | 0.4802        | 0.4960          | 0.3004          |
| RI1      | 0.5660        | 0.6016          | 0.1933          |
| RI2      | 0.5648        | 0.6059          | 0.1996          |
| WoM1     | 0.5058        | 0.5334          | 0.2270          |
| WoM2     | 0.4895        | 0.5266          | 0.2129          |
### Table 7 Confirmatory Composite Analysis

<table>
<thead>
<tr>
<th>Type</th>
<th>Construct</th>
<th>Indicator</th>
<th>PLS</th>
<th>GSCA</th>
<th>CI(\hat{w}_i)</th>
<th>AVE</th>
<th>Alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>Composite</td>
<td>AT</td>
<td>AT1</td>
<td>0.5091</td>
<td>0.5077</td>
<td>0.3363; 0.6512</td>
<td>0.7146</td>
<td>0.8639</td>
</tr>
<tr>
<td></td>
<td>AT2</td>
<td>-0.0429</td>
<td>-0.0443</td>
<td>-0.2447; 0.1541</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>AT3</td>
<td>0.5366</td>
<td>0.5377</td>
<td>0.3606; 0.7123</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>AT4</td>
<td>0.1476</td>
<td>0.1497</td>
<td>0.0072; 0.2966</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Composite</td>
<td>SQ</td>
<td>SQ1</td>
<td>0.4839</td>
<td>0.4823</td>
<td>0.3250; 0.6256</td>
<td>0.8162</td>
<td>0.8873</td>
</tr>
<tr>
<td></td>
<td>SQ2</td>
<td>0.2766</td>
<td>0.2833</td>
<td>0.1287; 0.4534</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SQ3</td>
<td>0.3458</td>
<td>0.3406</td>
<td>0.1746; 0.4894</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Composite</td>
<td>PV</td>
<td>PV1</td>
<td>0.4357</td>
<td>0.4409</td>
<td>0.2567; 0.5886</td>
<td>0.7334</td>
<td>0.8182</td>
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<tr>
<td></td>
<td>PV2</td>
<td>0.5370</td>
<td>0.5145</td>
<td>0.3595; 0.6623</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>PV2</td>
<td>0.1826</td>
<td>0.2029</td>
<td>0.0373; 0.3714</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Composite</td>
<td>SAT</td>
<td>SAT1</td>
<td>0.2869</td>
<td>0.2231</td>
<td>0.0954; 0.3551</td>
<td>0.8084</td>
<td>0.8819</td>
</tr>
<tr>
<td></td>
<td>SAT2</td>
<td>0.3841</td>
<td>0.3861</td>
<td>0.2405; 0.5563</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SAT3</td>
<td>0.4384</td>
<td>0.4954</td>
<td>0.3035; 0.6372</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Composite</td>
<td>RI</td>
<td>RI1</td>
<td>0.4925</td>
<td>0.4375</td>
<td>0.2306; 0.6783</td>
<td>0.8872</td>
<td>0.8730</td>
</tr>
<tr>
<td></td>
<td>RI2</td>
<td>0.5688</td>
<td>0.6221</td>
<td>0.3758; 0.8088</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Composite</td>
<td>WoM</td>
<td>WoM1</td>
<td>0.5861</td>
<td>0.5282</td>
<td>0.3800; 0.7123</td>
<td>0.8236</td>
<td>0.7858</td>
</tr>
<tr>
<td></td>
<td>WoM2</td>
<td>0.5153</td>
<td>0.5735</td>
<td>0.3871; 0.7056</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note.* SRMR(PLS/GSCA) = .0236/.0248, Critical value 95% SRMR(PLS/GSCA) = .0253/.0258, \(\hat{w}_i\) = Composite weight

### Table 8 Results of Structural Model Analysis Using GSCA

<table>
<thead>
<tr>
<th>Relationship</th>
<th>Std. Path</th>
<th>PLS</th>
<th>GSCA</th>
<th>CI Percentile 95%</th>
<th>VIF</th>
<th>Effect Sizes</th>
<th>Adj R-sq</th>
</tr>
</thead>
<tbody>
<tr>
<td>AT =&gt; SAT</td>
<td>0.2106</td>
<td>0.2093</td>
<td>0.1229; 0.3308</td>
<td>1.6551</td>
<td>0.0447</td>
<td>0.4030</td>
<td></td>
</tr>
<tr>
<td>SQ =&gt; SAT</td>
<td>0.2168</td>
<td>0.2391</td>
<td>0.0827; 0.3625</td>
<td>1.8729</td>
<td>0.0515</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PV =&gt; RI</td>
<td>0.3125</td>
<td>0.3133</td>
<td>0.2135; 0.4284</td>
<td>1.5355</td>
<td>0.1079</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SQ =&gt; RI</td>
<td>0.2461</td>
<td>0.2444</td>
<td>0.1546; 0.3493</td>
<td>1.4186</td>
<td>0.0619</td>
<td>0.3166</td>
<td></td>
</tr>
<tr>
<td>SAT =&gt; RI</td>
<td>0.3937</td>
<td>0.3943</td>
<td>0.2956; 0.4845</td>
<td>1.4186</td>
<td>0.1612</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PV =&gt; WoM</td>
<td>0.0994</td>
<td>0.0922</td>
<td>-0.0126; 0.1914</td>
<td>1.4501</td>
<td>0.0115</td>
<td>0.4840</td>
<td></td>
</tr>
<tr>
<td>SAT =&gt; WoM</td>
<td>0.4788</td>
<td>0.4818</td>
<td>0.3669; 0.5999</td>
<td>1.7315</td>
<td>0.2617</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RI =&gt; WoM</td>
<td>0.2401</td>
<td>0.2423</td>
<td>0.1414; 0.3344</td>
<td>1.4034</td>
<td>0.0817</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note.* SRMR (PLS/GSCA) = .0325/.0533, Critical value 95% SRMR(PLS/GSCA) = .0344/.0667

### Table 9 Out-of-Sample Predictive Power Test for Generalizability

<table>
<thead>
<tr>
<th>Indicator</th>
<th>RMSE target</th>
<th>RMSE Benchmark</th>
<th>Q-sq Predict</th>
</tr>
</thead>
<tbody>
<tr>
<td>SAT1</td>
<td>0.4779</td>
<td>0.4998</td>
<td>0.2983</td>
</tr>
<tr>
<td>SAT2</td>
<td>0.4558</td>
<td>0.4743</td>
<td>0.3300</td>
</tr>
<tr>
<td>SAT3</td>
<td>0.4820</td>
<td>0.4932</td>
<td>0.2949</td>
</tr>
<tr>
<td>RI1</td>
<td>0.5671</td>
<td>0.5942</td>
<td>0.1929</td>
</tr>
<tr>
<td>RI2</td>
<td>0.5693</td>
<td>0.5976</td>
<td>0.1917</td>
</tr>
<tr>
<td>WoM1</td>
<td>0.5066</td>
<td>0.5336</td>
<td>0.2264</td>
</tr>
<tr>
<td>WoM2</td>
<td>0.4938</td>
<td>0.5236</td>
<td>0.2008</td>
</tr>
</tbody>
</table>
CONCLUSION

In the field of academic tourism marketing, Structural Equation Modeling (SEM) has gained significant popularity, both in Thai and international journals. As evident in this article, the utilization of composite-based SEM has seen a notable increase. However, one crucial issue frequently overlooked by researchers is a failure to specify the nature of constructs as either factors or composites.

This distinction is paramount because composite-based SEM, such as Partial Least Squares (PLS), should not be employed for factor analysis, especially Confirmatory Factor Analysis (CFA). Analysis of this nature is better suited to factor-based SEM. Neglecting this aspect can lead to bias, with biases arising from using factor-based SEM to analyze composite models being more pronounced than those from employing composite-based SEM to analyze factor models.

Consequently, we advocate good practice, involving the selection of composite-based SEM for analyzing composite models and factor-based SEM for analyzing factor models. Nevertheless, contemporary research models often incorporate a blend of both factors and composites. In such complex scenarios, techniques such as PLS and IGSCA-SEM prove suitable for analysis.

Although this article does not explicitly address mixed models, we provide an example of analysis using the case of hotels in Khung Bang Kachao. We have identified hypothetical constructs in both factor and composite forms. It is essential to emphasize that researchers should not hastily categorize hypothetical constructs as either factors or composites based solely on their names. In general, we tend to categorize constructs as factors when dealing with behavioral constructs characterized by conceptual unity. Conversely, constructs created by humans, often referred to as emergent variables, should be identified as composites.

In the first case, this study undertakes a comparative analysis of factor-based Structural Equation Modeling (SEM) alongside composite-based SEM using PLS and GSCA estimators, all of which are considered unbiased estimators. Researchers are cautioned against employing PLS or GSCA for factor analysis, as it can introduce bias into the parameter estimates. The analysis commences with an examination of the measurement model, assessing fit indices such as SRMR (less than 0.08), Cronbach’s alpha (between 0.7 and 0.95), and Average Variance Extracted (AVE, exceeding 0.5). In cases where the AVE falls below 0.5, researchers should investigate factors such as individual factor loadings below 0.7. Typically, item deletion is feasible within a factor model since the questions are often interchangeable. Regarding discriminant validity, researchers should consider the HTMT ratio (not exceeding 0.85) or conduct CI-CFA analysis. When interpreting the results of the structural model, vigilance is required concerning multicollinearity, which can be checked using the VIF (Variance Inflation Factor, less than 3).

One significant aspect that researchers often neglect is the generalizability of the model. Frequently, researchers focus on achieving model fit through extensive adjustments, resulting in overfitting or even perfect fit scenarios. However, models of this nature may not be applicable beyond the dataset used for analysis, rendering them less practical. Therefore, it is recommended to collect two sets of data: one for training (405 observations in this case) and one for testing (100 observations). Criteria for decision-making can be based on positive Q-squared values and targeted RMSE exceeding benchmarked RMSE for all predicted indicators.

In the second scenario, we assume that the indices are designed to measure hypothetical constructs from a composite perspective entirely, rendering factor-based SEM inappropriate. Instead, PLS and GSCA were utilized, both of which are unbiased estimators. A key distinction from the first scenario is the use of CCA (Composite Component Analysis) in place of CFA (Confirmatory Factor Analysis). CCA nomenclature can be perplexing for researchers, as it has been used in the context of assessing the quality of a measurement model with PLS, whereas the CCA employed
in the second scenario is akin to CFA, utilizing PLS and GSCA estimators. Model fit tests are conducted, focusing on the significance level of SRMR compared to the critical value at 95%. The results indicate that, theoretically, the composite model aligns excellently with the empirical data. Another differentiating factor from the first scenario is the emphasis on composite weights rather than loadings during presentation. If the indicators used to construct composites have been well-considered, it is not required for researchers to omit indicators when no statistical significance is found, as the meaning of composites is immediately changed by such an action. The multicollinearity of composites can be indirectly assessed through the Variance Inflation Factor (VIF). Furthermore, we introduce an additional assumption that the research’s objective is prediction and the extension of findings to other samples. Therefore, analyzing out-of-sample predictive power is of paramount importance and carries significant weight in the model assessment. This differs from the first scenario where the research primarily aimed at testing theory, with emphasis placed on model fit analysis.

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