Using Schmid-Leiman Solution with higher-order constructs in marketing research Piyush Sharma, Bharadhwaj Sivakumaran, Geetha Mohan Purpose – This paper introduces the Schmid-Leiman Solution (SLS) as a useful tool to interpret the results of higher-order factor analyses in marketing research irrespective of the type of higher order factor structure used (formative or reflective).

Design/methodology/approach – Two studies, one with retail shoppers in India and another with undergraduate students in Hong Kong, are used to compare different types of higher-order factor structures in order to test the utility of SLS.

Findings – We show that whether a reflective or a formative model is used to operationalize a higher order construct, using SLS as an additional analysis gives useful insights into the factor structure at different levels and helps isolate their unique contributions to the explained variance.

Research limitations/implications – We test higher-order models for store environment and consumer impulsiveness with data from retail shoppers and undergraduate students in two Asian countries, which may restrict the generalizability of our findings. Future research may try to replicate our findings with other higher-order constructs and consumers in other countries.

Practical implications – We offer a checklist that can be used by future researchers to evaluate alternate higher-order factor structures and choose the appropriate one for their research context.

Originality/value – We show that using SLS is especially useful when there is a lack of clarity on the nature of relationships between the factors at different levels or about the independent contribution of the factors at different levels, in a higher-order factor structure.

Keywords - Factor structure; formative; higher order; reflective; Schmid-Leiman

Paper type – Research paper

Introduction

Structural equation modeling (SEM) has become a well-established analytical tool in marketing research with many articles published during the last couple of decades offering specific advice on how to use SEM and its pros and cons (e.g.,). With the growing popularity of SEM, researchers are also increasingly using second-order factor models with inter-correlated first-order factors that are supposed to be driven by a "super factor" (i.e., a second-order factor). Second-order factor models are generally considered superior to first-order factor models because these may provide a better theoretical explanation than the inter-correlated first-order factors. However, there is also a growing debate about whether to choose a reflective or formative second-order factors 'reflecting' the second-order factor whereas a formative second-order factor model has the first-order factors 'reflecting' the second-order factor, while the first-order factor model has the first-order factors 'forming' the second-order factor, while the first-order factors may also be either reflective or formative on their own (Jarvis *et al.*, 2003, p.205).

Many studies use reflective second-order factors (e.g., Cheung *et al.*, 2020; Harrigan *et al.*, 2021; Park *et al.*, 2010) despite criticism that "higher-order reflective constructs are, at worst, misleading, and at best meaningless. Researchers should, therefore, avoid the use of higher-order reflective constructs" (Lee and Cadogan, 2013, p.244). Thus, it is not surprising to see the growing use of formative second-order factor structure as a more appropriate choice for many constructs in marketing research, such as customer-based brand equity (Wang and Finn, 2013), objective environmental knowledge (Fernando *et al.*, 2016), consumer innovativeness (Persaud *et al.*, 2017), perceived justice (Cambra-Fierro and Melero-Polo, 2017), and value cocreation (Harrigan *et al.*, 2021). However, studies with formative second-order factors do not directly compare these with reflective second-order factor models; hence it is not clear which of these

structures provide a better representation of the construct being studied. Researchers have also raised concerns about the use of formative second-order factors due to 'interpretational confounding' (Howell *et al.*, 2007) or problems with their use as endogenous variables (Cadogan and Lee, 2013). Others criticize formative measures because they use "conceptions of constructs, measures, and causality that are difficult to defend, the presumed viability of formative measurement is a fallacy, and the objectives of formative measurement may also be achieved using alternative models with reflective measures" (Edwards, 2011).

To address this ambiguity about how and when to choose reflective or formative structures for second-order factors, we propose the Schmid-Leiman Solution - SLS (Schmid and Leiman, 1957), a bi-factor structure, as an additional analysis when using either reflective or formative second-order factor models to provide additional insights into the factor structure at different levels and help isolate their unique contributions to the explained variance (Eggers *et al.*, 2020). Using SLS might provide useful diagnostic information by allowing researchers to assess the variance explained by the different levels of latent variables in a hierarchical model (Keeling *et al.*, 2020). This may be especially useful when there is a lack of clarity about the nature of relationships between the factors or about the individual contributions of the lower-order factors in a higher-order factor model (Eggers *et al.*, 2020; Keeling *et al.*, 2020).

In this paper, we extend the sparse literature on the usage of SLS in the domain of marketing research and its utility in analyzing higher order factor structures. We first review the literature on reflective versus formative higher order factor structures to highlight the difficulty in conceptualizing and operationalizing any given higher order construct as either reflective or formative. We then review prior research using SLS and present it as an additional test to help provide unique insights into the structure of higher order factors and the inter-relationships

among higher and lower order factors. Next, we demonstrate the utility of SLS by evaluating both reflective and formative second-order factor structures with data from two empirical studies - a mall survey with retail shoppers in India investigating the impact of store environment on impulse buying behavior, and an experimental study with undergraduate business students in Hong Kong exploring the role of consumer impulsiveness in self-regulatory failure.

Literature review and conceptual framework

Reflective vs. formative higher order factors

Despite the growing popularity of higher order factors in marketing research, past research on the debate between reflective versus formative structures focused on the first-order factors (e.g., Edwards, 2011; Howell *et al.*, 2007; Wilcox *et al.*, 2008). However, unlike first-order factors, a second-order factor is not a direct manifestation of indicator variables, which means that there are no direct measures for the second-order factors. Thus, a second-order factor could be reflective or formative, based on how it relates with its underlying first-order factors (Jarvis *et al.*, 2003). However, others have criticized the use of higher-order reflective constructs as "misleading and needless" because according to them, if the measures are really reflective, a first-order model should account for the variance in all the items (Lee and Cadogan, 2013).

For example, satisfaction is used as a reflective second-order factor driving perceptions about three first-order factors (price/quality, gastronomy and atmosphere) in a food service setting (Correia *et al.*, 2008). However, one may argue that perceptions of price/quality, gastronomy and atmosphere may drive satisfaction, and hence it would be more appropriate to conceptualize satisfaction as a formative second-order factor. Likewise, Dorai et al. (2021) conceptualize relationship quality as a formative second-order factor with the first order factors being

satisfaction, trust and affective commitment. However, one may also make the case that if for a consumer, relationship quality with a firm is good, satisfaction, trust and affective commitment would follow. In other words, a reflective second order model may also be deemed appropriate. Thus, there is ambiguity on the use of reflective versus formative second order models. In this paper, we offer SLS, a higher-order factor analysis method (Schmid and Leiman, 1957), as a tool to examine the higher order constructs and explore the independent effects of the lower as well as higher-level factors on the other constructs in the model.

Schmid-Leiman Solution (SLS)

SLS is a higher order bifactor model in which the indicator variables are assumed to 'reflect' both, group level factors and a general factor, which are usually known as first-order and higher order factors in a standard reflective or formative structure (Schmid and Leiman, 1957). SLS provides additional insights beyond those from the standard reflective and formative higher order models because it allows the study of independent effects of both first-order and higher order factors on a set of variables. SLS orthogonalizes the first-order and higher order factors to allow the interpretation of their relative impact, which is quite useful in theory and scale development (Eggers *et al.*, 2020; Keeling *et al.*, 2020). Thus, SLS helps gain additional insights into the relationship between variables and factors as well as interpret factors at different levels by providing the independent influence of first-order and higher order factors on a set of primary variables (Wolff and Preising, 2005). Figures 1A, 1B and 1C show typical reflective, formative and Schmid-Leiman higher-order factor structures.

< Insert Figures 1A, 1B & 1C about here >

SLS generally gives a solution with independent contributions of factors of different levels, where one variable loads on its original lower-level factor as well as a higher-level general

factor, although both these factors are uncorrelated. Therefore, factor loadings in SLS represent independent influences of the lower level as well as higher-level factors on each variable, and their relative strength provides further information about a variable. In other words, the lower order factor loadings in SLS are merely the partial correlations between the lower-order factors and their indicators, with the influence of the higher-order factors partialed out. In higher order factor analysis, the explanatory power of first-order factors depends upon the inter-correlations of primary variables (indicators) with each other and the explanatory power of higher-level factors is derived from the correlation between factors of the lower level. Hence, the first-order factors explain x% of the correlation between variables (indicators), and second-order factors explain y% of the correlations between first-order factors. In contrast, SLS partitions the variance explained by each level into non-overlapping contributions, so each factor explains z% of the correlation between variables (indicators), irrespective of its level.

This ability of SLS to provide insights into the relative contribution of different levels to explain the total variance has important theoretical implications, because it helps clarify the tradeoffs between accuracy and generality at different levels of analysis. For instance, if higher order factors explain a high percentage of total variance (say 40-50%), the lower order factors may be of little theoretical interest, thus increasing generality at a little expense of accuracy. In contrast, if higher order factors have little explanatory power, lower order factors may be of greater theoretical importance. However, despite the popularity of SLS in the field of psychology there is hardly any research employing this useful tool in the marketing area. We address this important research gap in this paper using two empirical studies on impulse buying behavior.

Study 1

Sivakumaran and Sharma (2005) show that store environment affects impulse buying

positively. Mohan et al. (2013) too found that store environment influences impulse buying positively. This relationship was mediated by positive affect and urge to buy impulsively. Mattila and Wirtz (2001) found that aspects of a store's environment like lighting and music drive impulse buying. A recent meta-analysis (Iyer *et al.*, 2020) too found that a store's ambience played a key role in determining impulse buying. In this study, we consider the effect of store environment and two individual characteristics (impulse buying tendency and shopping enjoyment) on impulse buying through two contextual factors as mediators (positive and negative affect) based on prior research (e.g., Mohan *et al.*, 2013).

Model 1 - Store environment as a reflective second-order construct

In our first model, we conceptualize store environment as a second-order reflective construct, 'reflected' by four first-order factors – music and lighting (ambient), layout (design) and employees (social). According to this model, shoppers first form an overall perception about the store environment as a whole and this is in turn reflected by their perceptions about its various elements (i.e., music, lighting, layout and employees).

Model 2 - Store environment as a formative second-order construct

To clarify the use of reflective vs. formative factor models for store environment, we need to clarify if it is 'reflected' or 'formed' by the ambient, social and design factors? For example, a shopper may evaluate a store's ambient factors (e.g., music), social factors (e.g., employees) and design factors (e.g., layout) and based on these form an 'overall' impression of the store's environment. In such situations, Jarvis et al. (2003, pp. 203) recommend using formative indicators. Accordingly, Model 2 has store environment as a formative second-order factor with four reflective first-order factors (music, lighting, layout and employees).

Model 3 - Store environment using Schmid-Leiman Solution

As described earlier, SLS is a higher-order factor analysis method that helps clarify the hierarchical structure of the studied phenomena (Schmid and Leiman, 1957). Moreover, it allows us to explore the independent effects of the lower (ambient, social and design) as well as higher level (store environment) factors on the other constructs (positive and negative affect, and urge to buy impulsively) in the model. Hence, Model 3 with SLS has the store environment as well as the ambient, social and design factors reflecting the indicator variables.

Sample and procedure

In study 1, we collected data from India as it is one of the fastest growing economies in the world and has a retail industry worth almost USD 1 trillion (Berman *et al.*, 2018; pp. 5-6). In addition, with a wide variety of retailers, including small mom and pop stores, large organized retailers, and hypermarkets, Indian consumers are increasingly buying more impulsively (e.g. Bandyopadhyay, 2016, Upadhye *et al.*, 2021). Hence, India is an appropriate setting for this study. Following prior studies on impulse buying (e.g., Mohan *et al.*, 2013) we used a mall-intercept survey to collect data from shoppers at 44 outlets of a leading Indian supermarket chain in Chennai, South India. All these outlets have similar standardized design and layout, employee profiles as well as management practices; hence the responses collected from these outlets are comparable to each other. We chose locations across the city for a fair representation of the different segments of shoppers and approached 1478 shoppers, out of which 733 agreed to participate in the study. Of the 733 responses collected, 40 were removed from analysis due to incompleteness and excessive missing values, giving us a usable sample of 693 (47% response). We adapted scales from past research (e.g., Sharma *et al.*, 2010a) to measure the other constructs and used a pretest with 30 shoppers to test the questionnaire.

Data analysis and results

Following the two-step approach (Anderson and Gerbing, 1988), we tested the measurement models followed by the structural models. We began by testing a baseline first-order model (Model 0) with the four first-order factors (music, lighting, layout and employees) along with shopping enjoyment and impulse buying tendency as the predictors and impulse buying as the outcome variable with positive and negative affect and buying urge as mediators. The measurement model for Model 0 shows a poor fit ($\chi^2 = 879.70$, p < .001, df = 361, $\chi^2/df = 2.44$; NFI = .88; CFI = .92; RMSEA = .048; SRMR = .064) compared to the cut-off values of fit indices (NFI > .90, CFI > .95, RMSEA < .06, SRMR < .08) by Hu and Bentler (1999). Next, Model 1 with store environment as a reflective second-order factor shows an even poorer fit ($\chi^2 = 1047.49$, p < .001, df = 381, $\chi^2/df = 2.75$; NFI = .85; CFI = .90; RMSEA = .059; SRMR = .072).

For Model 2, we added two reflective indicators (R1 and R2, tapping satisfaction with the store environment) to the formative second-order factor, for the measurement model to be identified and found a closer fit ($\chi^2 = 676.98$, p < .001, df = 361; $\chi^2/df = 1.88$; NFI = .92; CFI = .96; RMSEA = .042; SRMR = .054) compared to the first two models. However, Model 1 and 2 are non-nested as neither of these models can be derived from the other through suitable parameter restrictions; hence we employed non-nested tests with indices such as Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and Expected Cross-Validation Index (ECVI) to compare their fit with each other (Kumar and Sharma, 1999). All these indices show lower values for the formative (AIC = 388.42, BIC = 473.19, ECVI = 1.94) than the reflective model (AIC = 459.87, BIC = 686.32, ECVI = 2.69). Hence, store environment seems to be a formative second-order construct 'formed' by its first-order factors. Next, Model 3 with Schmid-Leiman structure also shows a close fit ($\chi^2 = 585.56$, p < .001, df = 343, $\chi^2/df =$

1.71, NFI = .91; CFI = .95; RMSEA = .044, SRMR = .056). Finally, we found all the sub-scales to be reliable with composite reliabilities ranging from .75 to .88.

Next, we examined the unique variance explained by the overall store environment factor as well as the erstwhile first-order factors (ambient, social and design factors) and their independent influences on the other constructs in the model. In this context, it is important to remember that the variance of a reflective construct is the sum of the common variance of its measures, whereas the variance of a formative construct includes the total variance of its measures. Therefore, we calculated the sum of its squared loadings and divided it by the sum of squared loadings for all the factors at each level, albeit only for the reflective and SL models, which gives the percentage of variance explained by a factor or factor level respectively.

Model 0 with the four first-order factors (music, lighting, layout and employees) explains 45.3% variance, whereas Model 1 with store environment as a reflective second-order factor explains 46.8% variance, most of which (93.0%) comes from the four first-order factors. However, Model 2 with store environment as a formative second-order factor explains 49.2% variance. Hence, the formative model (Model 2) explains greater variance in the data (+2.4%) than the reflective model (Model 1) as expected, so it seems that a formative second-order model provides a better operationalization of the store environment construct, compared to a reflective second-order factors and the higher order factor for the formative model; therefore, we next looked at variance explained by the SLS model.

Model 3 (SLS) explains the highest amount of variance (60.4%) in the data, with the four first-level factors (51.4%) and the second-level factor (48.6%) explaining almost similar amount of variance. This finding indicates that besides being a higher order construct 'formed' by the

first-order factors, store environment may also act as a 'general' factor and have its unique influence apart from the first-order (or, group-level) factors, as suggested by the first two models. Hence, SLS is a useful method to assess the independent influence of lower and higher level factors. In addition, unlike conventional higher-order factor analysis, SLS also helps clarify the total variance explained by the primary variables (indicators). For example, the three indicators of the first-order factor 'Music' explain 27.2% variance in the reflective model; yet their total contribution to the lower and higher level factors in SLS drops to only 19.5%. A similar result is observed for 'Employees' with its contribution dropping from 26.5% to 23.2%. In contrast, for the other two first-order factors, namely 'Light' and 'Layout', the total contribution in SLS is higher than that for the other two models (28.8% vs. 17.7% for 'Light' and 28.5% vs. 21.6% for 'Layout'). Hence, light and layout may have a greater 'direct' influence on the store environment compared to music and employees. The regular higher-order factor analysis cannot provide such nuanced insights into the impact of individual components.

Finally, we tested all the four structural models and found all the hypothesized paths significant and in the expected direction. We also replicated a similar pattern of results as for the measurement models, wherein the structural model with store environment as a formative construct (Model 2) shows the best fit among all four models. To conclude, we found that store environment as a general factor explains much higher variance (48.6%) compared to its lower-level factors, music (14.3%), light (9.8%), layout (12.4%) and employees (15.0%). Next, we replicated these findings using a different sample and a context in which a reflective second-order model may be conceptually more appropriate than a formative one.

Study 2

Consumer impulsiveness (CI) is a relatively stable consumer trait related mainly with

impulse buying behavior and conceptualized as a one or two-dimensional construct (e.g., Sharma *et al.*, 2010b). This study conceptualizes CI as a global consumer trait consisting of three dimensions – cognitive (imprudence), affective (self-indulgence), and behavioral (lack of self-control), which are all important aspects of impulsive consumer behaviors (Sharma *et al.*, 2011). Prior research defines *imprudence* as the inability to think clearly, plan in advance, and solve complex problems; *self-indulgence* as the tendency to spend money on oneself, to buy things for own pleasure and to enjoy life all the time; and *lack of self-control* as the inability to control oneself, regulate emotions, manage performance, maintain self-discipline, and to quit bad habits (Sharma *et al.*, 2011). Thus, 'consumer impulsiveness' seems to satisfy all the conditions for a reflective second-order factor, as specified by Jarvis et al. (2003), with three reflective first-order factors (imprudence, self-indulgence, and lack of self-control) as Model 1. To be consistent with Study 1, we tested two other models, a formative second-order model and an SLS model.

Sample and procedure

Study 2 uses a sample of 300 undergraduate business students at a major university in Hong Kong (52% females, 20.3 years). We chose Hong Kong as the setting for this study as it is quite different from India in terms of socio-economic and cultural composition. Moreover, its well-developed retail sector provides an excellent context to study impulse buying by shoppers. Besides the new 12-item consumer impulsiveness scale (Sharma *et al.*, 2011), the questionnaire included two other scales, seven-item "ability to modify self-presentation" self-monitoring subscale (Lennox and Wolfe, 1984) and change seeking index (CSI) short form (Steenkamp and Baumgartner, 1995), with seven-point Likert scale (1 = strongly disagree, 7 = strongly agree). All the participants completed the scales in a single session at the beginning of a new semester while signing up for experimental studies later in the semester. Table 1 shows the results.

< Insert Table 1 about here >

Data analysis and results

Using a similar approach to the first study, we first tested a first-order measurement model (Model 0) and found a relatively poor fit ($\chi^2 = 643.68$, df = 310, p < .001; $\chi^2/df = 2.08$; NFI = .88; CFI = .92; RMSEA = .052; SRMR = .068) based on the cut-off values (NFI > .90, CFI > .95, RMSEA < .06, SRMR < .08) recommended by Hu and Bentler (1999). Next, Model 1 with a reflective second-order factor for consumer impulsiveness shows a better fit ($\chi^2 = 557.84$, df = 314, p < .001; $\chi^2/df = 1.78$; NFI = .92; CFI = .96; RMSEA = .044; SRMR = .056), whereas Model 2 with consumer impulsiveness as a formative second-order construct shows a poorer fit ($\chi^2 = 786.62$, df = 307, $\chi^2/df = 2.56$; NFI = .85; CFI = .90; RMSEA = .058; SRMR = .074) compared to the other two models. All the relevant fit indices for the non-nested models are also lower for the reflective model (AIC = 446.13, BIC = 633.47, ECVI = 1.76) compared to the formative model (AIC = 592.36, BIC = 766.28, ECVI = 2.48). Hence, consumer impulsiveness seems to be a reflective second-order construct with three underlying dimensions (imprudence, self-indulgence, and lack of self-control) rather than a formative second-order construct.

Next, Model 3 with SLS shows the best fit among all the models ($\chi^2 = 511.26$, df = 295, p < .001; $\chi^2/df = 1.73$; NFI = .93; CFI = .97; RMSEA = .042; SRMR = .054). Thus, consumer impulsiveness seems to explain unique variance in the data as a general factor and also have independent influence on all the indicators. To explore this further, we examined the standardized factor loadings and the variance explained by each factor. We also found all the sub-scales to be reliable with their composite reliabilities ranging from .78 to .85.

< Insert Table 2 about here >

As shown in Table 2, Model 1 with consumer impulsiveness as a reflective second-order factor explains 49.5% variance in the data, most of which (88.1%) is explained by the three first-order factors. In contrast, the second model with consumer impulsiveness as a formative second-order factor explains 45.5% variance in the data, which is 4.0% less than the reflective model. Hence, a reflective second-order model for consumer impulsiveness provides a better fit to the data and judgment its conceptualization as a reflective second-order construct. Moreover, similar to first study, Model 3 (SLS) explains the highest amount of variance (62.6%) in the data, with the four first-level factors (52.1%) and the second-level factor (47.9%) explaining almost similar amount of variance. Hence, consumer impulsiveness may exist as a broad construct 'reflected' by the individual indicators and may not fully depend upon the three first-order factors (imprudence, self-indulgence and lack of self-control) as suggested by other two models.

We also found differences in the variance explained by the indicators of the lower-level factors. For example, the indicators for 'Self-indulgence' (35.5% vs. 30.9%) and 'Lack of self-control' (34.5% vs. 28.9%) explain greater variance in SLS compared to the reflective model. In contrast, the indicators of 'Imprudence' explain similar amount of variance in SLS (30.0%) as well as the reflective model (28.3%). These findings suggest that self-indulgence and lack of self-control may reflect a greater 'direct' influence of consumer impulsiveness compared to imprudence. Finally, we also tested all the four structural models and found all the hypothesized paths significant and in expected directions. More importantly, the structural model with consumer impulsiveness as a reflective construct (Model 1) shows the best fit among all four models, which supports our hypothesized factor structure for this construct.

Construct validity

In both our studies, we found high Cronbach's α and composite reliability for all the scales

higher than 0.75, showing adequate reliability (Hair *et al.*, 2016). Next, all the average variance extracted (AVE) values exceed the cut-off value of 0.50, which shows convergent validity (Hair *et al.*, 2016). Finally, the square roots of AVE values for all the construct are higher than their correlations with the other constructs, which confirms discriminant validity. Next, we used the method prescribed by Sarstedt et al. (2019) to assess the validity of higher-order constructs. First, we found path coefficients higher than 0.70 for the redundancy analysis in both studies, showing convergent validity of the higher-order constructs. Next, all the variance inflation factor (VIF) values are less than 3, showing that all the dimensions are distinct. Finally, high values of outer weights and significance of the dimensions confirmed the validity of higher-order constructs.

Common Method Variance (CMV)

As both the studies use the predictor and criterion variables from the same source in a single survey, we took several precautions to minimize the impact of common method variance (CMV). Specifically, we did not collect any personal information from the participants to reduce socially desirable responding and evaluation apprehension by ensuring the anonymity of the responses. The survey also used a Likert format for the independent variables and directly calculated the value of the dependent variable, reducing "method bias due to the commonalities in scale endpoints and anchoring effects" (Podsakoff *et al.*, 2003). Next, we used the 'single-commonmethod-factor' approach to estimate the method biases at the measurement level and to control the measurement error by comparing the fit indices between our original measurement model and one in which all the items loaded on a latent CMV factor besides their theoretical constructs. This method allows the partitioning of the variance of responses to a specific measure into three components: trait, method, and random error. The models with the CMV factor showed a poorer fit and a significantly higher χ^2 value compared to the original measurement models. Hence, most of the variance is explained by the individual constructs and common method variance is not a significant concern in both our studies (Podsakoff *et al.*, 2003).

General discussion

This research extends the growing literature on the ongoing debate between the use of reflective vs. formative indicators by showing that either one of these may be appropriate in a given context as long as it is justified by its conceptual and theoretical background (Harrigan et al., 2021). Moreover, this paper demonstrates that it is important to not only make the right choice with first-order models but also with higher order models that use multi-dimensional constructs. Thus, we provide a useful direction for marketing researchers who use second-order factor models, to not only help them improve the fits by choosing between either the reflective or formative second-order factors but also compare both options and share their results to lend credibility to their findings and conclusions. In this context, incorrect specification of a scale as reflective can change the meaning of the construct and lead to underestimation of parameters. Moreover, structural equation models can have good fit statistics despite model misspecification. Therefore, incorrect specification can possibly give wrong answers to research questions, hamper theory development and lead future research to a wrong direction. Moreover, it is also quite likely that researchers may find a poor fit for their incorrectly specified measurement model and wrongly conclude that there is something wrong with their methodology or the quality of their data. In such a case it would be useful to test alternative models and build a case for different conceptualization for the concerned constructs. Based on an extensive review of the literature on higher order factor structures and using the findings reported in this paper, we propose a checklist with the following questions that researchers may ask themselves, to help them identify the most appropriate measurement model for their specific research context:

- Is the use of the second-order factor model appropriate? If there are inter-correlations
 amongst the first-order factors, or there is a common conceptual basis for the existence of
 the first-order factors, the answer would be yes. If not, then use a first-order factor model.
- If a first-order factor model is to be used, is a reflective or a formative structure more suitable? If the flow of the directionality is from the first-order factor to the indicators, a reflective first-order factor model is the right choice; otherwise a formative first-order factor structure would be more appropriate (Jarvis *et al.*, 2003).
- 3. If a second-order factor model is to be used, is a reflective or a formative structure more appropriate? If the flow of the directionality is from the second-order factor to the first-order ones, a reflective second-order factor model should be used; otherwise a formative second-order factor model would be the right choice.
- 4. Is it conceptually accurate to consider the higher-level construct as a 'General' factor independent from the lower-level constructs, even if they are driven by a common set of variables (indicators)? If yes, then a Schmid-Leiman structure may help the researchers examine the independent influence of both lower and higher level factors.
- 5. In a SLS structure, is greater variance explained by the lower level factors? If yes, then it indicates that the higher-level general factor may not be useful, hence it would be better to revert to a reflective or formative higher order factor model. If not, then SLS structure may be retained with the lower and higher level factors as orthogonal to each other.
- 6. Is there a reason to expect the lower-order and higher-order factors to be uncorrelated with each other? In other words, is there a reason to expect that these factors have independent influence? If yes, then SLS can provide useful insights by orthogonalizing

these factors and allowing the interpretation of their relative impact.

In most cases, researchers may be able to choose the appropriate factor structure for their measurement models by answering the first three questions. However, in some cases there may be some ambiguity on whether reflective or formative models may be more appropriate. We consider a few examples from published research in the business discipline and make the case for applying SLS factor structures. For example, Correia et al. (2008) conceptualize customer satisfaction with food service as a reflective second-order factor that drives perceptions about three first-order factors (price/quality, gastronomy and atmosphere) but one may argue that these perceptions may actually drive satisfaction, and hence it would probably be more appropriate to conceptualize satisfaction as a formative second-order factor.

Next, there is still some ambiguity on whether the use of reflective/formative models is appropriate in all the above cases. In addition, both reflective (Lee and Cadogan, 2013) and formative second-order factor models (Howell *et al.*, 2007) have attracted substantial criticism. Researchers caught in such a situation (where there is some uncertainty on which one is more appropriate: reflective or formative second-order models) may ask themselves the last three questions in our proposed checklist in order to decide the proper course of action. They can also use SLS to gain deeper insights into the factor structures of their higher order constructs and the relationships among the factors at different levels.

To conclude, SLS is not necessarily a substitute to other higher order factor analyses; instead, it may supplement the information from higher order factor analysis by providing a direct link between the higher order factors and primary variables (indicators). Moreover, it helps determine the independent contribution of each factor level by transforming the factor loadings and the variance explained. All these unique features provide additional insights into the factor structure,

help interpret the factors at different levels, evaluate the contribution of factors to variables, and assess the theoretical relevance of factor levels (Wolff and Preising, 2005).

Contributions and implications

This paper makes several important contributions. From a substantive standpoint, we add to the literature on the use of relative versus formative models for higher order constructs. While there is considerable work on reflective vs. formative indicators for first-order factors (Jarvis *et al.*, 2003), there is growing use of formative second-order factor models in contexts where it seems to be more appropriate (e.g. Cambra-Fierro and Melero-Polo, 2017; Fernando *et al.*, 2016; Harrigan *et al.*, 2021; Persaud *et al.*, 2017; Wang and Finn, 2013). This paper extends this research stream by showing that researchers may use either a formative or reflective second-order factor to operationalize a higher-order construct depending upon how it is conceptualized.

Specifically, we use both reflective and formative second-order factor models for two different constructs in two different empirical settings to show that one of these models may be more appropriate in either situation. We also show that in addition to using reflective/formative structures, one may also consider the use of SLS factor structures to provide additional insights about the unique contribution of the lower as well as higher-level factors. Recent literature promoting the use of SEM in Marketing (e.g., Cambra-Fierro and Melero-Polo, 2017; Fernando *et al.*, 2016; Harrigan *et al.*, 2021; Persaud *et al.*, 2017; Wang and Finn, 2013) does not cover the issues surrounding the use of reflective, formative or SLS for higher-order factor models. We address this important gap in this paper by demonstrating this empirically.

This paper also adds to the SLS literature in two ways. First, it introduces SLS into marketing research. Marketing researchers can use this useful yet simple tool to seek additional insights into the higher-order factor models used by them. Second, this paper extends the SLS literature

by clarifying the conditions under which it may be appropriate to use the SLS factor structure on its own or to use it to augment the analysis of formative or reflective second-order models. We also provide a checklist with specific questions to help researchers how to choose the most appropriate higher order factor structure for their multi-dimensional constructs. Finally, past research on SLS compared it with reflective second-order models and ignores formative secondorder models. We address this gap by comparing SLS with formative as well as reflective second-order models for both our studies.

Both our studies also have useful managerial implications. Managers may work on elements of store environment, like lighting and music, and this will then enhance impulse buying. Retailers may also target shoppers who are by nature impulsive and enjoy shopping, as these consumers are more likely to buy on impulse. Study 2 shows that consumer impulsiveness leads to self-regulatory failures. Hence, policy makers may alert consumers that ae high on this trait with messages to avoid falling into problems on this account. Finally, SEM is "fast becoming a popular technique" and is being used extensively by market research companies (Malhotra and Dash, 2016, p. 702). Hence, our checklist may help these researchers identify the most appropriate measurement model when dealing with higher order constructs.

Limitations and future research

We used different constructs (store environment and consumer impulsiveness), methods (mall survey and lab experiment), samples (retail shoppers and undergraduate students) and cultural settings (India and Hong Kong) to test the generalizability of our findings, but future research could use other constructs, methods, contexts and cultural settings. Second, future research could also use variance-covariance matrices of other existing studies in order to reanalyze the existing findings and further explore the utility of Schmid-Leiman Solution.

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Figure 1A – Reflective First-order and Reflective Second-order Model

Figure 1B – Reflective First-order and Formative Second-order Model



Figure 1C – Schmid-Leiman Factor Model



		Model 0	Model 1 (Reflective 2 nd Order)	Model 2 (Formative 2 nd Order)	Model 3 (SLS)	
		(First- order)			Group Factors	General Factor
	M1	0.90	0.96	0.98	0.90	0.44
Music	M2	0.78	0.83	0.81	0.78	0.48
	<i>M3</i>	0.49	0.53	0.55	0.49	0.42
Variance Explained		27.4%	27.2%	NA	14.3%	5.2%
	т 1	0.71	0.72	0.72	0.71	0.72
T • 1 /		0./1	0.73	0.72	0./1	0.72
Light		0.66	0.69	0.70	0.66	0.89
<i>L3</i> Variance Explained		0.45 18.9%	0.48 17.7%	0.48 NA	0.44 9.8%	0.95 19.1%
ľ						
	LO1	0.70	0.72	0.75	0.71	0.73
Layout	LO2	0.81	0.84	0.80	0.80	0.82
	LO3	0.52	0.55	0.54	0.54	0.81
Variance Explained		23.4%	21.6%	NA	12.4%	16.1%
	E1	0.68	0.68	0.70	0.65	0.58
Employees	E2	0.84	0.84	0.86	0.82	0.61
	E3	0.82	0.82	0.84	0.80	0.50
Variance Explained		30.4%	26.5%	NA	15.0%	8.3%
Variance explained by lower (Group) level factors		100.0%	93.0%	NA	<u>51.4%</u>	
	Music	NA	0.53	0.39	NA	NA
Store	Light	NA	0.18	0.58	NA	NA
Environment	Layout	NA	0.21	0.56	NA	NA
	Employees	NA	0.36	0.61	NA	NA
Variance explained by higher level (General) factor		NA	7.0%	NA	<u>48.6%</u>	
Total Variance explained		45.3%	46.8%	49.2%	<u>60.4%</u>	

 Table 1 - Confirmatory Factor Analysis (Study 1)

Note: All the figures are standardized factor loadings except the %ages. All the items in *italics* had factor loadings below 0.50 and these were removed in final analysis.

		Model 0 (First- order)	Model 1 (Reflective)	Model 2 (Formative)	Model 3 (SLS)	
					Group Factors	General Factor
			. = .	~ 		
	IMPI	0.73	0.78	0.75	0.70	0.65
Imprudence	IMP2	0.75	0.80	0.78	0.75	0.68
	IMP3	0.78	0.81	0.80	0.78	0.60
	IMP4	0.74	0.79	0.76	0.73	0.66
Variance explained		32.0%	28.3%	NA	17.0%	13.0%
	SIN1	0.81	0.85	0.82	0.77	0.75
	SIN2	0.78	0.82	0.80	0.75	0.72
Self-Indulgence	SIN3	0.80	0.84	0.81	0.78	0.74
	SIN4	0.77	0.81	0.78	0.76	0.78
Variance explained		35.6%	30.9%	NA	18.1%	17.3%
	I SC1	0.74	0.78	0.75	0.71	0.73
Look of Colf		0.74	0.78	0.73	0.71	0.75
Lack of Self-	LSC2	0.77	0.01	0.80	0.75	0.77
control	LSC3	0.75	0.00	0.77	0.74	0.75
LSC4 Variance explained		0.78 32.4%	0.82 28.9%	0.78 NA	0.76 17.0%	0.76 17.6%
·		-			,	
Variance explained by lower (Group) level factors		100.0%	88.1%	NA	<u>52.1%</u>	
C	IMP	NA	0.54	0.26	NA	NA
Consumer	SIN	NA	0.58	0.29	NA	NA
Impuisiveness	LSC	NA	0.66	0.32	NA	NA
Variance explained by higher (General) factor		NA	11.4%	NA	<u>47.9%</u>	
Total Variance explained		42.8%	49.5%	45.5%	<u>62.6%</u>	

 Table 2 - Confirmatory Factor Analysis (Study 2)

Note: All the figures are standardized factor loadings except the %ages.