

Partial least squares structural equation modeling (PLS-SEM): A useful tool for family business researchers



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ABSTRACT

Structural equation modeling (SEM) has become a mainstream method in many fields of business research, but its use in family business research remains in its infancy. This lag in SEM's application holds especially true for partial least squares SEM (PLS-SEM), an alternative to covariance-based SEM, which provides researchers with more flexibility in terms of data requirements, model complexity and relationship specification. This article draws attention to PLS-SEM as an opportunity to advance the development and testing of theory in family business research by providing a non-technical introduction into the basic concepts and issues of PLS-SEM, bearing the needs of potential users in mind. To this end, a systematic procedure for PLS-SEM results evaluation is presented and applied to an annotated example. The article also illustrates the analysis of mediating effects, which researchers are increasingly testing in their models.

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1. Introduction

Analytical rigour and sophistication in research methods are important to innovation in theory building in business research (Bird, Welsch, Astrachan, & Pistrui, 2002; Chandler & Lyon, 2001). However, the value of such new methods depends on scholars' willingness to learn, adopt and embrace these methods and think strategically about the research process (Zahra & Sharma, 2004). As far back as the early 1990s, Wortman (1994) noted that empirical studies in family business research used only rudimentary statistical techniques. Similarly, Bird et al.'s (2002) review of 148 family business research articles showed that only 35 (23.65%) used some type of multivariate analysis (e.g., analysis of variance, regression, or factor analysis), whereas the majority of studies relied on descriptive and bivariate (e.g., correlation) analyses or did not perform any statistical analysis. However, Bird et al. (2002) also show that more recent research places much greater emphasis on statistical modeling and analysis, concluding that "family business

research is increasing in sophistication" (Bird et al., 2002, p. 346). Wilson et al. (2014) recently further substantiated this finding in their review of 30 years of research methods used by family business researchers. Other important fields of business research have undergone similar developments. For example, several decades ago, the top marketing journals contained articles that were virtually free of multivariate data analysis. Today, however, scholarly marketing journals are filled with articles describing and using sophisticated, quantitative methodologies (e.g., Babin, Hair, & Boles, 2008).

One of the most salient methods in this respect is structural equation modeling (SEM; e.g., Rigdon, 1998), which enables researchers to simultaneously examine a series of interrelated dependence relationships between a set of constructs, represented by several variables (e.g., scales), while accounting for measurement error. SEM's ability to simultaneously test relationships incorporated into an integrated model has contributed to its widespread application. However, although SEM has become a mainstream method in many fields of business research (e.g., Babin et al., 2008), its use in family business research remains at an early stage of development (Wilson et al., 2014). This condition holds especially true for partial least squares SEM (PLS-SEM), an alternative to covariance-based SEM (CB-SEM) for estimating theoretically established cause–effect relationship models, whose

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use has recently gained momentum in a variety of fields (Hair, Sarstedt, Pieper, & Ringle, 2012; Hair, Sarstedt, Ringle, & Mena, 2012; Ringle, Sarstedt, & Straub, 2012).

The PLS-SEM method has been designed as a prediction-oriented approach to SEM that relaxes the demands on data and specification of relationships set by CB-SEM (Dijkstra, 2010; Jöreskog & Wold, 1982; Rigdon, 2012). For example, PLS-SEM is able to reliably estimate very complex models using only few observations without imposing distributional assumptions on the data. In a nutshell, its statistical properties make PLS-SEM particularly useful for exploratory research settings that are “simultaneously data-rich and theory-primitive” (Wold, 1985, p. 589). However, its capabilities also support its use for theory testing (Hair, Ringle, & Sarstedt, 2011). As such, PLS-SEM meets the challenges faced by family business researchers who are confronted with an increasing complexity of theories and cause–effect models, over-surveyed respondents and decreasing response rates (Benavides-Velasco, Quintana-García, & Guzmán-Parra, 2013; Gedajlovic, Carney, Chrisman, & Kellermanns, 2012; Rogelberg & Stanton, 2007; Wright & Kellermanns, 2011).

Against this background, this article draws attention to PLS-SEM as an opportunity to advance the development and testing of theory in family business research. We first provide an overview of PLS-SEM compared to CB-SEM, highlighting not just its strengths but also its weaknesses. We then explain the stages involved in the evaluation of PLS-SEM results. The article then presents a family business research-related example of how to apply PLS-SEM and concludes with a discussion of further research avenues that warrant greater attention.

2. Partial least squares structural equation modeling (PLS-SEM)

2.1. What is structural equation modeling?

To start with, we briefly explain the fundamentals of SEM in accordance with Hair, Hult, Ringle, and Sarstedt (2014). The SEM

method allows researchers to model, simultaneously estimate and test complex theories with empirical data. Fig. 1 presents an example of a potential structural equation model in the family business context. The structural model represents the underlying theory or concept with its constructs (i.e., variables that are not directly measured), which are represented in structural equation models as circles or ovals (Y_1 to Y_6), and hypothesized cause–effect relationships. When latent variables serve only as independent variables (i.e., single-headed arrows are going only out of them), they are called *exogenous latent variables* (Y_1 , Y_2 and Y_3). Moreover, when latent variables serve only as dependent variables (i.e., single-headed arrows are only going into them), such as Y_6 , or as both independent and dependent variables (i.e., single-headed arrows are going both into and out of them), such as Y_4 and Y_5 , they are called *endogenous latent variables*.

In the structural equation model example in the family business context displayed in Fig. 1, the exogenous latent variables—often seen in family business research (Astrachan, Klein, & Smyrnios, 2002)—Family Power, Family Culture and Family Experience explain the endogenous latent variables Strategic Information Sharing and Innovation. The latter two constructs explain the final target construct Relationships Value. Because the purpose of this article is to demonstrate the application of PLS-SEM in the context of family business research, we do not provide detailed theoretical support for the model, which otherwise would be necessary. After the model estimation, the researcher obtains, among others, the relative strength of the cause–effect relationships between the constructs in the structural equation model. Moreover, the R^2 value of endogenous latent variables reveals how well other constructs in the model explain these constructs.

In SEM, the latent variables must be measured by observed variables (also often called indicators, items or manifest variables). The rectangles (x_1 to x_{30}) in Fig. 1 represent the raw data that, for example, stem from responses to a questionnaire. Measurement theory determines the relationships between the latent variables and their indicators. More precisely, each construct has a measurement model (also referred to as the outer model in

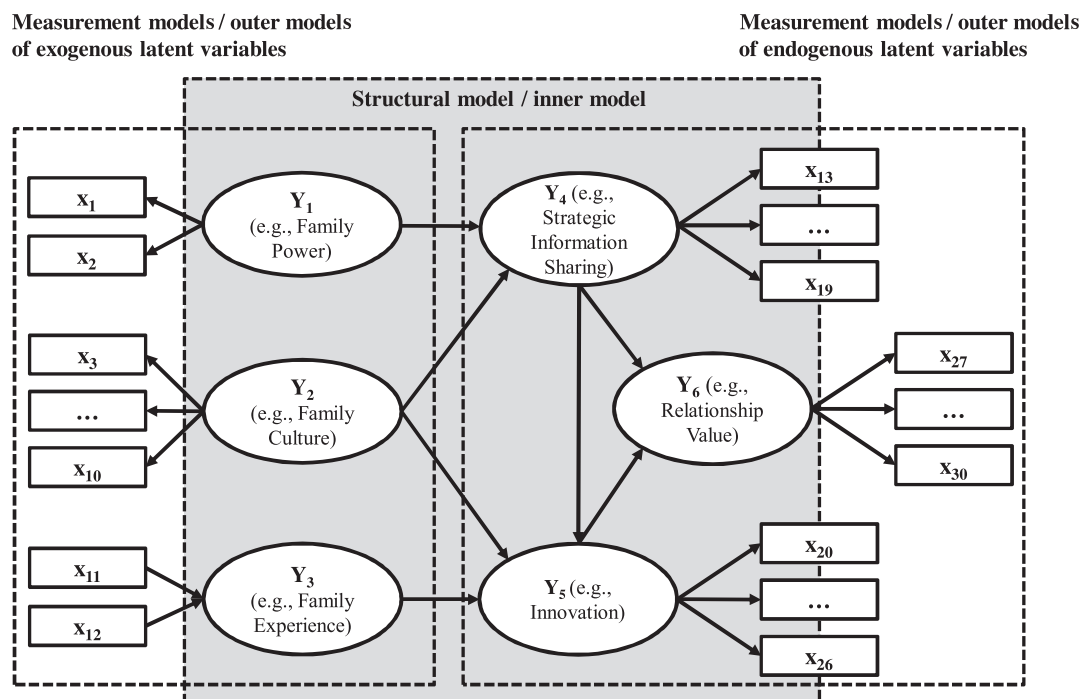


Fig. 1. A structural equations model in the family business context.

PLS-SEM) that specifies the relationship between each construct (circle) and its indicator variables (rectangles). Generally, there are two different ways to measure latent (unobserved) variables (Diamantopoulos & Sigauw, 2006; Gudergan, Ringle, Wende, & Will, 2008). One approach with relationships (single-headed arrows) from the construct to the indicators is referred to as a reflective measurement. In Fig. 1, latent variables Y_1 , Y_2 , Y_4 , Y_5 and Y_6 have reflective measurement models. The other approach with relationships (single-headed arrows) from the indicators to the construct is called formative measurement. Construct Y_3 in Fig. 1 builds on a formative measurement model.

Reflective indicators are caused by the construct (more precisely, their covariance), with the measures reflecting some phenomenon such as a family firm's reputation (Binz, Hair, Pieper, & Baldauf, 2013), image (Zellweger, Kellermanns, Eddleston, & Memili, 2012), or organizational identity (Zellweger, Eddleston, & Kellermanns, 2010). On the contrary, formative measurement represents instances in which the indicators cause the construct. Specifically, with formative measurement the phenomenon of interest does not occur naturally but is instead “formed” by the presence of underlying measures (Jarvis, MacKenzie, & Podsakoff, 2003). Examples of formatively measured constructs in family business research include entrepreneurial orientation in Casillas, Moreno, and Barbero (2010) or family ownership in Chua, Chrisman, and Sharma (1999). Although choosing the “correct” measurement specification has triggered significant debate across a variety of disciplines in recent decades (e.g., Bollen, 2011; Bollen & Lennox, 1991; Diamantopoulos, Riefler, & Roth, 2008; Gudergan et al., 2008), it is important to note that constructs are not inherently reflective or formative in nature. Rather, the type of measurement depends on the construct conceptualization, the aim of the research and the role of the construct in the model—Hair, Hult, et al. (2014) provide guidelines for choosing the appropriate measurement specification.

2.2. Why is partial least squares useful for the estimation of structural equation models?

CB-SEM (Jöreskog, 1978, 1982) and PLS-SEM (e.g. Lohmöller, 1989; Wold, 1982) are the two primary techniques for estimating structural equation models (e.g. Dijkstra, 1983; Jöreskog & Wold, 1982). Whereas CB-SEM has been the predominant approach, in recent years, PLS-SEM has been increasingly disseminated in a variety of disciplines. Fig. 2 shows the growth trend of PLS-SEM use across the strategic management (Hair, Sarstedt, Pieper, et al., 2012), marketing (Hair, Sarstedt, Ringle, et al., 2012; Henseler, Ringle, & Sinkovics, 2009) and management information systems disciplines (Ringle et al., 2012). As can be seen, PLS-SEM use has recently gained momentum in all three fields. In family business research, however, very few applications of PLS-SEM may be found. For example, Segaro, Larimo, and Jones (2014) and Wold (1985)

use the method to examine organizational culture in family businesses, while Farsi, Rezazadeh, and Najmabadi (2013) apply PLS-SEM to research entrepreneurial orientation in Middle Eastern family business firms. Further examples include studies by Chua et al. (1999), Vallejo (2009) and Casillas and Acedo (2005).

Both approaches to SEM have distinct features that make them suitable for different research purposes. CB-SEM is primarily used to confirm (or reject) theories (i.e., a set of systematic relationships between multiple variables that can be tested empirically). This approach does so by determining how well a proposed theoretical model is able to estimate the covariance matrix for a sample dataset. In contrast, the variance-based PLS-SEM approach is primarily used to develop theories in exploratory research. This approach does so by focusing on explaining the variance in the dependent variables when examining the model.

Much of the increased use of PLS-SEM may be credited to the method's ability to manage problematic modeling issues that routinely occur in the social sciences (e.g. Hair, Ringle, & Sarstedt, 2013; Robins, 2012), many of which are also typical of family business research. For example, PLS-SEM works efficiently when used to estimate path models comprising many constructs (typically more than five), several structural path relationships and/or many indicators per construct (typically more than six). This characteristic holds especially true when small sample sizes are used, which makes PLS-SEM particularly useful for family business research where populations being researched are often limited in size, putting natural restrictions on sample sizes. In these situations, PLS-SEM generally achieves higher levels of statistical power and reaches convergence much more often than CB-SEM (Henseler, 2010; Reinartz, Haenlein, & Henseler, 2009). However, it is important to note that PLS-SEM is not immune to the need for an adequate sample size and that researchers—just like with any other statistical technique—should rely on power analyses to determine an adequate sample size (e.g. Marcoulides & Chin, 2013).

Furthermore, PLS-SEM allows for a flexible handling of more advanced model elements such as moderator variables, nonlinear relationships or hierarchical component models (e.g., Becker, Klein, & Wetzels, 2012; Henseler & Chin, 2010; Henseler, Fassott, Dijkstra, & Wilson, 2012).¹ With theories in family business research becoming more elaborate, these advanced model elements are likely to experience increasing dissemination in family business research (e.g. Bird et al., 2002), making PLS-SEM the method of choice.

In contrast to CB-SEM, PLS-SEM also enables researchers to more flexibly specify the relationships between items and constructs, whether measurement is reflective or formative (Hair, Hult, et al., 2014). Whereas PLS-SEM is generally considered the “natural approach” to formative measurement as it avoids identification problems that routinely occur when CB-SEM is being applied, it should not be considered a *carte blanche* in this respect. Researchers must be aware of the fact that the evaluation of formatively measured constructs relies on a totally different set of criteria compared to their reflective counterparts. Prior PLS-SEM review studies (e.g. Hair, Sarstedt, Pieper, et al., 2012; Hair, Sarstedt, Ringle, et al., 2012) have criticized the careless handling of formative indicators, and researchers should acquaint themselves with the most recent set of evaluation criteria when examining the validity of formatively measured constructs (Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014).

¹ Hierarchical component models are higher-order structures that involve a more abstract higher-order component (mostly second-order), related to two or more lower-order components in a reflective or formative way. Hair et al. (2014a) give more detailed explanations on hierarchical component models; recent examples of hierarchical component models in family business research are provided by Barbera and Hasso (2013) or Spriggs, Yu, Deeds, and Sorenson (2013).

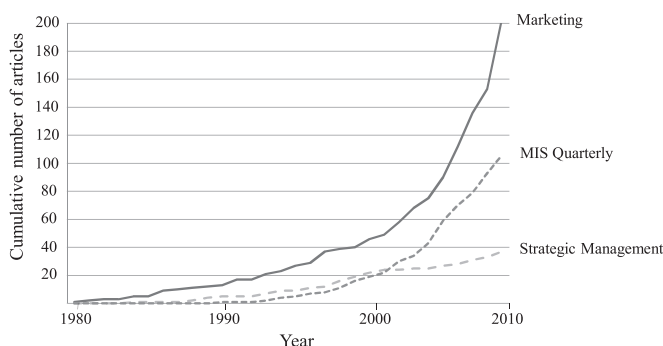


Fig. 2. PLS-SEM use in different management disciplines.

Table 1
Research settings that favour PLS-SEM use.

<i>Research goal</i>
<ul style="list-style-type: none"> • The research goal is to predict one or more key target construct(s) or to identify the most important antecedents of the target construct(s). • The research goal is primarily exploratory in nature (i.e., development of a new or extension of an existing theory).
<i>Model set-up</i>
<ul style="list-style-type: none"> • The model comprises many constructs (typically more than five), many path relationships and/or many indicators per construct (typically more than 6 per construct). • The model includes advanced model elements such as moderator variables or hierarchical component models. • The model comprises formatively measured constructs. • The plan is to use latent variable scores in subsequent analyses.
<i>Data characteristics</i>
<ul style="list-style-type: none"> • The data are non-normal. • The analysis draws on secondary data.

Finally, in terms of data characteristics, PLS-SEM makes practically no assumptions about the underlying data (e.g., in terms of data distributions), making it particularly useful for handling data collected for family business studies, which like other social science disciplines often fails to follow a multivariate normal distribution (Bird et al., 2002). In the age of big data, researchers increasingly encounter datasets that hold the promise of yielding insights about research questions but which were collected by organizations without a theoretical framework and for a purpose other than SEM (Rigdon, 2013). PLS-SEM is the primary choice for analysing such secondary data, as it does not emphasize model fit, as defined in the context of CB-SEM (Henseler & Sarstedt, 2013), but considers explained variance as a meaningful and sufficient measure of fit.

To summarize, PLS constitutes a very versatile approach to SEM (e.g., Hair, Ringle, & Sarstedt, 2012; Henseler et al., 2014) that is capable of handling modeling and data issues that routinely occur in family business research. Drawing on Hair, Hult, et al. (2014) and Hair et al. (2011), Table 1 summarizes the previous discussion, highlighting research settings that favour the use of PLS-SEM.

3. Evaluation of PLS-SEM results

Evaluating PLS-SEM results involves completing two stages, which we illustrate in Fig. 3. Stage 1 examines the measurement models, with the analysis varying depending upon whether the model includes reflective measures (Stage 1.1), formative measures (Stage 1.2) or both. If the measurement model evaluation provides satisfactory results, the researcher moves on to Stage 2, which involves evaluating the structural model (Hair, Hult, et al., 2014). In short, Stage 1 examines the measurement theory, whereas Stage 2 covers the structural theory, which includes determining whether the structural relationships are significant and meaningful, and testing hypotheses.

As with other methods of analysis, PLS-SEM relies upon rules of thumb to evaluate the results of the model estimation (Chin, 2010; Götz, Liehr-Gobbers, & Krafft, 2010; Hair, Hult, et al., 2014; Henseler et al., 2009). These rules follow guidelines based upon whether the model includes reflective measures, formative measures, or both. Following is a discussion of each of these criteria.

3.1. Stage 1.1: reflective measurement model assessment

In the case of reflectively measured constructs, a researcher begins Stage 1 by examining the indicator loadings. Loadings above 0.70 indicate that the construct explains over 50% of the indicator's variance.

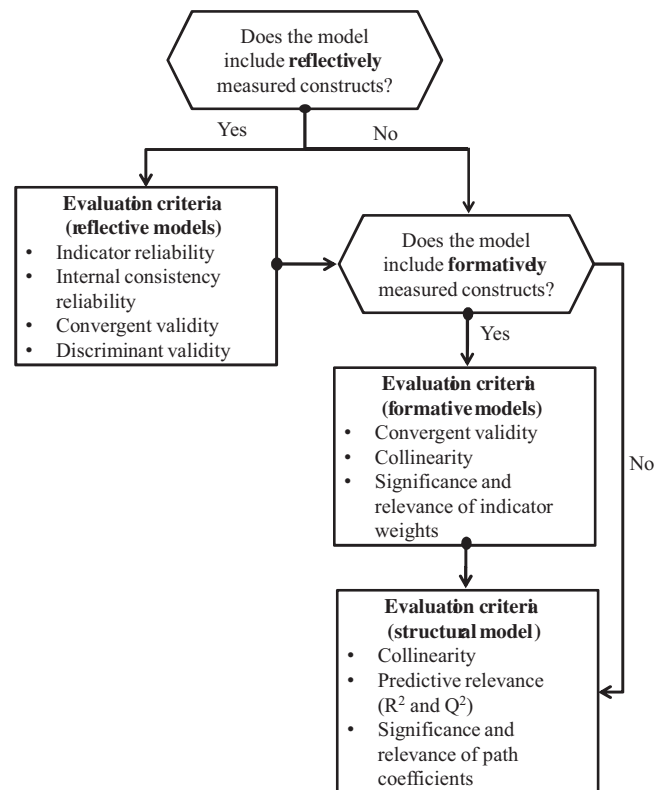


Fig. 3. PLS-SEM evaluation stages.

The next step involves the assessment of the constructs' internal consistency reliability. When using PLS-SEM, internal consistency reliability is typically evaluated using Jöreskog's (1971) composite reliability ρ_c . In assessing reliability, higher values indicate higher levels of reliability. Values between 0.60 and 0.70 are considered "acceptable in exploratory research", whereas values between 0.70 and 0.95 are considered "satisfactory to good" (Hair, Hult, et al., 2014, pp. 101–102). Values higher than 0.95 are considered problematic, as they indicate that the items are redundant, leading to issues such as undesirable response patterns (e.g., straight lining), and inflated correlations among indicator error terms (Drolet & Morrison, 2001).

Next, the convergent validity of the reflectively measured constructs is examined. Convergent validity measures the extent to which a construct converges in its indicators by explaining the items' variance. Convergent validity is assessed by the average variance extracted (AVE) for all items associated with each construct. The AVE value is calculated as the mean of the squared loadings for all indicators associated with a construct. An acceptable AVE is 0.50 or higher, as it indicates that on average, the construct explains over 50% of the variance of its items.

Once the reliability and convergent validity of reflective constructs are successfully established, the next step is to assess the discriminant validity of the constructs. Discriminant validity determines the extent to which a construct is empirically distinct from other constructs in the path model, both in terms of how much it correlates with other constructs and in terms of how distinctly the indicators represent only this single construct. The most conservative criterion recommended to evaluate discriminant validity is the Fornell and Larcker (1981) criterion. The method compares each construct's AVE value with the squared interconstruct correlation (a measure of shared variance) of that construct with all other constructs in the structural model. The recommended guideline is that a construct should not exhibit

shared variance with any other construct that is greater than its AVE value.

A less rigorous approach to assessing discriminant validity is to examine the cross loadings. The recommended guideline for this approach is that an indicator variable should exhibit a higher loading on its own construct than on any other construct included in the structural model (Hair, Hult, et al., 2014). If the loadings of the indicators are consistently highest on the construct with which they are associated, then the construct exhibits discriminant validity.

Discriminant validity should also be assessed qualitatively. Specifically, post hoc face validity should be assessed using a panel of experts as a final approach to concluding that discriminant validity is evident.

3.2. Stage 1.2: formative measurement model assessment

Formatively measured constructs are evaluated differently from reflectively measured constructs. The evaluation of formatively measured constructs involves the examination of (1) convergent validity, (2) collinearity and (3) statistical significance and the relevance of the indicator weights (Hair, Hult, et al., 2014).

Convergent validity of formatively measured constructs is determined based on the extent to which the formatively measured construct correlates with a reflectively measured (or single-item) construct that has the same meaning as the formatively measured construct. Hair, Hult, et al. (2014) suggest that the formatively measured construct should explain at least 65% of the variance of the reflectively measured item(s), which is indicated by a path coefficient of approximately 0.80. In most cases, however, a path coefficient of 0.70 (which translates into a shared variance of about 50%) would also be considered acceptable. Accordingly, researchers must plan for the assessment of convergent validity in the research design stage by including a reflectively measured construct or single-item measure of the formatively measured construct in the final questionnaire. Note that one should generally avoid using single items for construct measurement. Single items exhibit significantly lower levels of predictive validity compared to multi-item scales (Diamantopoulos, Sarstedt, Fuchs, Wilczynski, & Kaiser, 2012), which may be particularly problematic when using a variance-based analysis technique such as PLS-SEM. In the context of convergent validity assessment as described above, however, the aim is not to fully capture the entire content domain of the target construct but rather to have a measure that summarizes the essence of the construct that the formative indicators purport to measure (Sarstedt, Wilczynski, & Melewar, 2012).

To assess the level of collinearity among the formative indicators, the researcher should compute each item's variance inflation factor (VIF). For this purpose, the researcher must run a multiple regression of each indicator of the formatively measured construct on all the other measurement items of the same construct. The R^2 values of the i th regression facilitates the computation of the VIF for the i th indicator, using the following formula:

$$VIF_i = \frac{1}{1 - R_i^2}$$

Higher R^2 values in the i th regression imply that the variance of the i th item may be explained by the other items, which indicates collinearity issues. Correspondingly, a higher VIF implies a greater level of collinearity. As a rule of thumb, VIF values above five are indicative of collinearity among the indicators.

The third step in assessing formatively measured constructs is examining the significance and relevance of the indicators. In

contrast to multiple regression, PLS-SEM does not make any distributional assumptions regarding the indicators or error terms that would facilitate the immediate testing of the weights' significance based on, for example, the normal distribution. Instead, the researcher must run a bootstrapping routine, a resampling technique that draws a large number of subsamples (typically 5000) from the original data (with replacement) and re-estimates the model for each subsample. Using these subsamples, the researcher may compute bootstrap standard errors, which allow for the computation of t -values (and p -values) for each indicator weight. Based on the t -values, the significance of the weights may be determined to make the following decisions:

- If the weight is statistically significant, the indicator is retained.
- If the weight is non-significant but the indicator's loading is 0.50 or higher, the indicator is still retained, provided that theory and expert judgement support its inclusion.
- If the weight is non-significant and the loading is low (i.e., below 0.50), the indicator should be deleted from the measurement model.

However, researchers should be cautious in deleting formative indicators based on statistical outcomes for at least two reasons. First, the weight is a function of the number of indicators used to measure a construct: a higher number of indicators implies a lower average weight. In other words, formative measurement has an inherent limit to the number of indicators able to retain a statistically significant weight. When indicators are assumed to be uncorrelated, the maximum possible weight is $1/\sqrt{n}$, where n is the number of indicators. As each indicator's significance is positively related to the weight, an increase in the number of indicators will therefore reduce their significance. Second, eliminating formative indicators from the model should generally be the exception, as formative measurement theory requires that the measures fully capture the entire domain of a construct. Unlike their reflective counterparts, formative indicators are not interchangeable. Therefore, deleting an indicator may have adverse consequences for the content validity of the measurement model (Hair, Hult, et al., 2014). In terms of relevance, indicator weights are standardized to values between -1 and $+1$, with weights closer to $+1$ representing strong positive relationships and weights closer to -1 indicating strong negative relationships.

3.3. Stage 2: structural model assessment

Provided that the measurement model assessment indicates that the measurement model quality is satisfactory, the researcher moves to Stage 2 of the PLS-SEM evaluation process (Fig. 3), which involves the assessment of the structural model. Different from CB-SEM, PLS-SEM does not have a standard goodness-of-fit statistic, and efforts to establishing a corresponding statistic have proven highly problematic (Henseler & Sarstedt, 2013). Instead, the assessment of the model's quality is based on its ability to predict the endogenous constructs. The following criteria facilitate this assessment: coefficient of determination (R^2), cross-validated redundancy (Q^2) and the path coefficients. Prior to this assessment, the researcher must test the structural model for potential collinearity between the predictor constructs.

The computation of the path coefficients linking the constructs rests on a series of regression analyses. Therefore, the researcher must ascertain that the regression results are not biased by collinearity issues. This step is analogous to the formative measurement model assessment, with the difference being that the scores of the exogenous latent variables serve as input for the VIF assessments.

The next step involves reviewing the R^2 value of each endogenous construct. The R^2 is a measure of the variance explained in each of the endogenous constructs and is thus a measure of the model's predictive accuracy (in terms of in-sample prediction). The R^2 ranges from 0 to 1, with higher levels indicating a greater degree of predictive accuracy. As a "rough" rule of thumb, R^2 values of 0.75, 0.50 and 0.25 may be considered substantial, moderate and weak, respectively (Hair et al., 2011; Henseler et al., 2009).² Generally, however, the researcher should interpret the R^2 in the context of the study at hand by considering R^2 values from related studies.

Another means to assess the model's predictive relevance is the Q^2 (also called blindfolding). The Q^2 builds on the blindfolding procedure, which omits a part of the data matrix, estimates the model parameters and predicts the omitted part using the previously computed estimates. The smaller the difference between predicted and original values the greater the Q^2 and thus the model's predictive accuracy. As such, Q^2 is considered as a measure of out-of sample prediction (Rigdon, 2014; Sarstedt, Ringle, Henseler, & Hair, 2014). As a rule of thumb, Q^2 values larger than zero for a particular endogenous construct indicate that the path model's predictive accuracy is acceptable for that particular construct. Note that there are two approaches to calculating Q^2 , one is referred to as cross-validated redundancy and the other cross-validated communality. Hair, Hult, et al. (2014) recommend cross-validated redundancy as the best approach.

Next, the strength and significance of the path coefficients is evaluated for the relationships (structural paths) hypothesized between the constructs. Analogous to the assessment of formative indicator weights, the significance assessment builds on bootstrapping standard errors as a basis for calculating t -values for the path coefficients. In terms of relevance, path coefficient values are standardized on a range from -1 to $+1$, with coefficients closer to $+1$ representing strong positive relationships and coefficients closer to -1 indicating strong negative relationships. The determination of whether the size of the coefficient is meaningful must be interpreted in light of the context of the research.

Finally, the assessment of structural model relationships should not be restricted to direct effects but, if applicable, also consider total effects, which is the sum of the direct effect and the indirect effect between an exogenous and an endogenous construct in the structural model. The consideration of total effects allows for the examination of an exogenous construct's influence on a target construct via all mediating constructs and thus provides a richer picture of the relationships in the structural model.

4. Family business PLS-SEM example

To further demonstrate the opportunities for the usage of the PLS-SEM method to family business research, we illustrate its application to examine the influence of family business characteristics on strategic information sharing and innovation, and, ultimately, the perceived value of a relationship with a strategic vendor. This research defines a family as "... a group of persons including those who are offspring of a couple (no matter what generation) and their in-laws as well as their legally adopted children" (Astrachan et al., 2002, p. 55). All 125 participants were senior executives or owners of family businesses in the U.S. retail and services sector. As part of the data collection, they were screened and identified as key informants because they managed strategic partnerships in their organization. Respondents were asked to complete the survey as it related to their "major strategic partner", which was defined as their most important vendor/

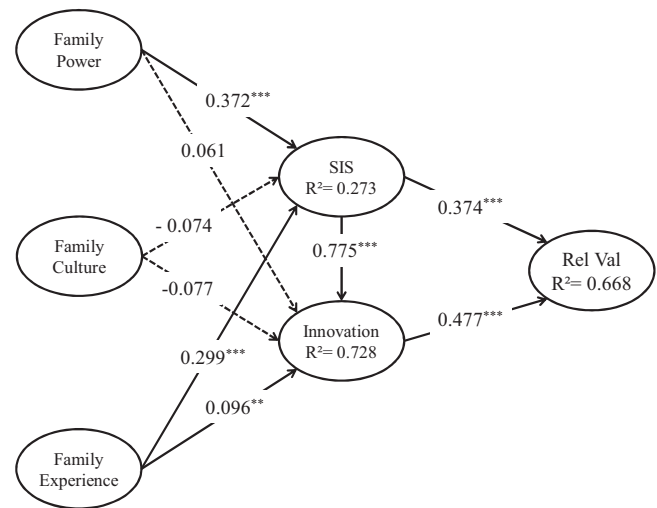


Fig. 4. Path model and PLS-SEM estimates. Notes: *** $p \leq 0.01$; ** $p \leq 0.05$; * $p \leq 0.10$; dashed lines represent non-significant relationships. SIS = Strategic Information Sharing; Rel Val = Relationship Value.

supplier helping them to achieve a higher level of competitiveness in the next 3–5 years. A professional marketing research firm was hired to recruit qualified panellists and administer the online questionnaire during May/June 2012. The survey instrument was designed to prevent common method bias. Expert judgement was used to examine each case for straight-lining (Dillman, Smyth, & Christian, 2009; Podsakoff, MacKenzie, Podsakoff, & Lee, 2003).

The structural model for our family business research example is shown in Fig. 4. Examination of this theoretical model involved six constructs measured at three levels of structural relationships. The three exogenous variables Family Power, Experience and Culture are derived from Astrachan et al.'s (2002) F-PEC scale. Strategic Information Sharing and Innovation mediate the relationship between the three exogenous constructs and the final target construct, Relationship Value. All constructs draw on a reflective measurement model set-up, except for Family Experience, which is measured formatively.³ The initial measurement models draw on a total of 33 items (31 reflective and 2 formative).

To test the model, this study draws on SmartPLS 2.0 (Ringle, Wende, & Will, 2005), applying the path weighting scheme. The bootstrapping procedure draws 125 cases and 5,000 samples, using the no sign change option. In evaluating and reporting the results, we followed recent guidelines for PLS-SEM, for example, given by Hair, Hult, et al. (2014), Hair et al. (2011), Hair, Sarstedt, Pieper, et al. (2012), and assessed the measurement models before evaluating the structural model.

4.1. Measurement model assessment

First, reflective measurement models were assessed for their reliability and validity. In the course of indicator reliability assessment, three indicators were removed from the initial model because they exhibited loadings clearly below 0.70 (Table A1) and thus have adverse effects on the construct measures' convergent validity and internal consistency reliability. The first indicator of Family Power was retained despite its loading of 0.614 because otherwise the construct would have been measured with a single item, which has adverse effects on the construct measures' predictive validity (Diamantopoulos et al., 2012; Sarstedt & Wilczynski, 2009). All other indicators were retained, as they had loadings above 0.70 or slightly lower. Table A1 provides an

² It is important to note, however, that in some research contexts, such as when predicting stock returns, R^2 values of 0.10 are considered satisfactory (e.g., Raitchel, Sarstedt, Scharf, & Schwaiger, 2012).

³ Note that in their construction and validation of the F-PEC scale, Klein et al. (2005) do not broach the issue of measurement specification.

Table 2

AVE values and Fornell–Larcker test of discriminant validity.

	Family Culture	Family Experience	Family Power	Innovation	Relationship Value	Strategic Information Sharing
Family Culture	0.631					
Family Experience	0.078	Formative				
Family Power	0.058	0.034	0.657			
Innovation	0.020	0.184	0.143	0.704		
Relationship Value	0.010	0.118	0.076	0.627	0.690	
Strategic Information Sharing	0.005	0.150	0.168	0.701	0.602	0.720

Note: AVE values are on the diagonal (in bold).

overview of the final set of items used. The AVE values for this model exceeded 0.50 for the reflective constructs (Hair, Sarstedt, Ringle, et al., 2012), thus indicating convergent validity for all constructs. Composite reliabilities for the five reflectively measured constructs ranged from 0.78 to 0.95, exceeding the minimum requirement of 0.70. Furthermore, the Fornell and Larcker (1981) criterion demonstrated that all AVE values for the reflective constructs were higher than the squared interconstruct correlations, indicating discriminant validity. Similarly, all indicator loadings were higher than their respective cross loadings, providing further evidence of discriminant validity. Table 2 shows the AVE values on the diagonal and the squared interconstruct correlations off the diagonal.

The next step is to evaluate the formative construct in the path model—Family Experience. For convergent validity assessment, we used a single item as an alternative measurement of Family Experience and correlated it with the formative measurement of this construct. This analysis yielded a path coefficient of 0.81, thus providing support for the formative construct's convergent validity (Hair, Hult, et al., 2014). Collinearity assessment by means of the VIF yielded a value of 1.050, which is well below the threshold value of 5. Both indicator weights are high (0.844 and 0.382) and significant ($p \leq 0.05$), as evidenced by the bootstrapping results.

4.2. Structural model assessment

After the construct measures have been confirmed as reliable and valid, the next step is to assess the structural model results. Before interpreting the path coefficients, we examined the structural model for collinearity, which is important because the estimation of the path coefficients is based on ordinary least squares regressions (Mooi & Sarstedt, 2011). The results of these analyses may be biased if collinearity is present (Hair, Hult, et al., 2014). The first step was to examine the collinearity between the Family Culture, Experience and Power constructs, as these serve as exogenous constructs in the prediction on both Innovation and Strategic Information Sharing. The second step was to examine the collinearity between Strategic Information Sharing and Innovation, as these serve as predictors of Relationship Value. VIF values of these analyses ranged between 1.144 (Family Power) and 3.448 (Strategic Information Sharing and Innovation), providing confidence that the structural model results are not negatively affected by collinearity.

The examination of the endogenous constructs' predictive power (Fig. 4) shows that Relationship Value, the primary outcome measure of the model, has a substantial R^2 value 0.668. Prediction of Innovation is higher with an R^2 value of 0.728, whereas the prediction of Strategic Information Sharing is comparably weak ($R^2 = 0.268$). However, considering the multitude of potential antecedents of strategic information sharing activities, this construct's R^2 value is satisfactory.

Blindfolding was used to evaluate the model's predictive relevance for each of the endogenous constructs. Running the blindfolding procedure with an omission distance of seven yielded

cross-validated redundancy values for all three endogenous constructs well above zero (Strategic Information Sharing: 0.513; Innovation: 0.460; Relationship Value: 0.194), providing support for the model's predictive relevance.

The final step of the structural model analysis considers the significance and relevance of the structural model relationships. Results from the bootstrapping procedure (125 cases, 5000 samples, no sign changes option) reveals that six of nine structural relationships are significant ($p \leq 0.05$). The results in Fig. 4 highlight the important role of Family Power and Experience in driving Strategic Information Sharing with path coefficients of 0.372 and 0.299, respectively. In addition, Family Experience has a significant effect on Innovation; however, with a path coefficient of 0.096, this effect is rather weak. Surprisingly, Family Culture has no significant effect on either Strategic Information Sharing or Innovation. Further analysis shows that Innovation has a stronger direct effect on Relationship Value than Strategic Information Sharing (0.477 vs. 0.374).

A different picture emerges when also considering the indirect effect of Strategic Information Sharing on Relationship Value via the mediator Innovation. The corresponding total effect is given by the following equation:

$$\begin{aligned} \text{Total effect} &= \text{direct effect} + \text{indirect effect} \\ &= 0.374 + 0.775 \cdot 0.477 = 0.744 \end{aligned}$$

As is shown, this total effect is much stronger than the direct (total) effect of Innovation on Relationship Value (0.477), underlining the important role of information sharing activities. In addition, these results suggest that Innovation mediates the relationship between Strategic Information Sharing and Relationship Value—this issue is further broached in the following section. Table 3 provides an overview of all total effects and their significance.

4.3. Mediation analysis

As the results from the analysis of total effects suggest that Innovation mediates the relationship between Strategic Information Sharing and Relationship Value, it is worthwhile to explicitly test for this potential mediating effect. To do so, our analysis draws on Hair, Hult, et al. (2014) by answering the following three research questions:

Table 3

Total effects.

Relationship	Total effect
Family Power → Innovation	0.350***
Family Culture → Innovation	−0.134
Family Experience → Innovation	0.328***
Family Power → Relationship Value	0.306***
Family Culture → Relationship Value	−0.092
Family Experience → Relationship Value	0.268***
Strategic Information Sharing → Relationship Value	0.744***

*** $p < .01$.

- (1) Is the direct effect between Strategic Information Sharing and Relationship Value significant when the mediator variable is excluded from the path model,
- (2) Is the indirect effect via the mediator variable significant after Innovation has been included in the path model and
- (3) How much of the direct effect does the indirect effect via the mediator absorb?

To answer the first question, we exclude Innovation from the path model and run the bootstrapping routine with the previously described specifications. As a result, the direct effect between Strategic Information Sharing and Relationship Value is 0.776 and significant at $p \leq 0.01$. Answering the second question requires re-estimating the full model (i.e., with the mediator included) and testing the indirect effect's significance. The corresponding bootstrapping results indicate that the indirect effect of 0.370 is significant at $p \leq 0.01$. Finally, we compute the variance accounted for (VAF) using the following formula:

$$\text{VAF} = \frac{\text{indirect effect}}{\text{total effect}}$$

The results of this final analysis step yield a VAF value of 0.497, which, according to Hair, Hult, et al. (2014), suggests that Innovation partially mediates the relationship between Strategic Information Sharing and Relationship Value. The mediation analysis procedures in PLS-SEM may also be applied to multiple mediators in a PLS path model—see Klarner, Sarstedt, Höck, and Ringle (2013) for an example.

4.4. Summary of findings

The objective of the data analysis was to determine the effect of Family Influence on Strategic Information Sharing and Innovation and, finally, on the target construct, Relationship Value. The results showed that both Family Experience and Family Power were significant drivers of Strategic Information Sharing. Family Experience had a significant effect on Innovation. Family Culture had no effect on either construct. Family Power and Family Experience had pronounced and significant total effects on Relationship Value (see Table 3). In this model, Family Power and Family Experience impacted both marketing and performance constructs. It is important to recognize the vital role of Strategic Information Sharing as a driver of Relationship Value through Innovation and the important role that Innovation plays in family business retailer-vendor strategic partnerships.

5. Discussion

As theories in family business research become more nuanced, it becomes more necessary to have methods capable of handling more complex model structures. PLS-SEM proves particularly beneficial in this respect, as it allows estimating models with many constructs, structural model relationships and many indicators per construct, situations which generally hinder the use of classical approaches to SEM. Furthermore, PLS-SEM is capable of handling data inadequacies such as non-normal data and accommodates formatively measured constructs, the latter of which have recently gained increasing prominence in a variety of disciplines (e.g., Diamantopoulos et al., 2008; Gudergan et al., 2008; MacKenzie, Podsakoff, & Podsakoff, 2011).

Our example illustrates how a researcher may utilize PLS-SEM to investigate the interrelationships between family business theories and theories in other disciplines, such as marketing or strategy. Although the F-PEC scales (Astrachan et al., 2002; Klein, Astrachan, & Smyrniotis, 2005) had been tested, the other three constructs based on previously tested scales had not been

examined from this particular family business context. The research was exploratory rather than confirmatory, justifying the use of PLS-SEM (Hair, Hult, et al., 2014). Furthermore, the use of PLS-SEM enabled us to review all of the constructs' conceptualizations and specify them as formative or reflective (Hair, Sarstedt, et al., 2014), avoiding misspecification of the model (Jarvis et al., 2003). In addition, the analysis of the mediating relationships in the PLS path model augmented our insight of the relationships between the constructs because it delved deeper into the cause and effect of these relationships, indicating the strength of direct and indirect effects. These rich findings may lead to the refinement or development of new models or theories in family business and related disciplines.

Whereas our initial analyses illustrated the use of PLS-SEM and provided important insights into the functioning of strategic partnerships with vendors, researchers may make use of more advanced modeling and estimating techniques to shed further light on the proposed relationships. Recently, research has brought forward a variety of complementary analysis techniques and procedures, which extend the methodological toolbox of researchers working with the method.

One of the most prominent streams of research addresses the issue of unobserved heterogeneity. Although the analysis on the aggregate data level may provide insight into the complex relationships between, for example, family business characteristics, behavioural constructs and, ultimately, relationship value, this type of analysis still makes the simplifying assumption that all observations come from a single, homogeneous population. However, individuals may be heterogeneous in their perceptions and evaluations of unobserved phenomena, which might account for distinct group-specific structural model path coefficients. This heterogeneity especially holds for this study, as the data may be viewed as a hierarchical system of companies operating in different sectors within the retailing and services industry, defined at separate levels of this hierarchical system. More often than not, such heterogeneous data structures cannot be attributed to observable characteristics such as demographics (Sarstedt, Henseler, & Ringle, 2011) but have their roots in unobservable background factors.

To ensure that the aggregate data results are not biased by such unobserved heterogeneity, research has brought forward a variety of latent class techniques that allow researchers the identification and treatment of heterogeneous data structures. Available approaches generalize, for example, finite mixture (Hahn, Johnson, Herrmann, & Huber, 2002; Sarstedt, Becker, Ringle, & Schwaiger, 2011) genetic algorithms (Ringle, Sarstedt, & Schlittgen, 2014; Ringle, Sarstedt, Schlittgen, & Taylor, 2013) or hill-climbing approaches (Becker, Rai, Ringle, & Völckner, 2013; Esposito Vinzi, Trinchera, Squillacioti, & Tenenhaus, 2008) to PLS-SEM. Sarstedt (2008) provides an early review of latent class techniques. Considering the pronounced biases that result when heterogeneity is not considered (Rigdon, Ringle, Sarstedt, & Gudergan, 2011; Ringle, Sarstedt, & Mooi, 2010; Sarstedt & Ringle, 2010; Sarstedt, Schwaiger, & Ringle, 2009), researchers should routinely apply latent class techniques to ascertain that their results are not affected by heterogeneity.

Another stream of methodological research on PLS-SEM deals with complex constructs that are operationalized at higher levels of abstraction. For example, in this study, Family Power, Experience and Culture may constitute three lower-order dimensions of the higher-order construct Family Influence. Instead of modeling these three dimensions on a single construct layer (as done in the empirical example), researchers could also summarize them as three lower-order components related to a single multidimensional higher-order construct. Fig. 5 illustrates the conceptual model if the three F-PEC were modelled as a

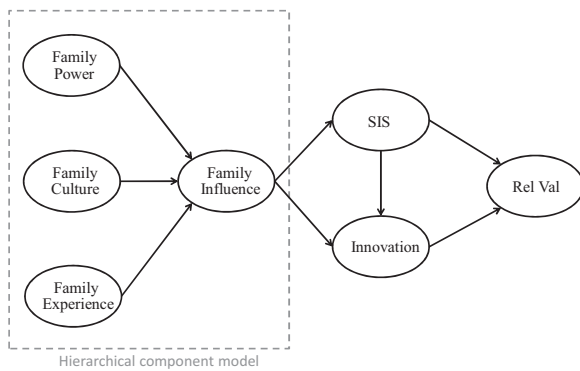


Fig. 5. Path model with hierarchical component structure.

hierarchical component model (Jarvis et al., 2003). This modeling approach leads to more theoretical parsimony, reduces model complexity and may avert confounding effects in multidimensional model structures, such as multicollinearity (Kuppelwieser & Sarstedt, 2014; Wilson & Henseler, 2007).

Finally, PLS-SEM applications should consider the usefulness of the importance-performance matrix analysis (IPMA) for drawing conclusions from the analysis (Hair, Hult, et al., 2014; Höck, Ringle, & Sarstedt, 2010; Rigdon et al., 2011; Völckner, Sattler, Hennig-Thurau, & Ringle, 2010). When focusing on a certain target construct (e.g., Relationship Value), the estimated total effects (i.e., the sum of the direct and indirect effects in the PLS path model) reveal how important the other constructs are for the target construct's explanation. The IPMA adds another important dimension to these PLS-SEM results by also taking the performance of each construct into account. A construct's performance is determined by the weighted average of its indicators (e.g., the actual responses on a scale from 1 to 11). In that way, researchers and practitioners obtain a two dimensional representation of PLS-SEM results for a selected target construct in the form of an

importance-performance matrix. The x-axis displays the importance (i.e., total effects) of the other constructs on the selected target construct, whereas the y-axis shows their performance (e.g., re-scaled from 0 to 100). As a result, the IPMA allows identifying constructs with a comparatively low performance and a relatively high importance for the target construct. Such constructs have the highest relevance and priority for practitioners because activities to improve their performance result in a strong effect on the selected target construct and, subsequently, in its performance improvements.

The technical details of the IPMA are explained, for example, by Hair, Hult, et al. (2014); IPMA examples are provided in Höck et al. (2010) and Völckner et al. (2010). We believe that PLS-SEM in combination with the IPMA will be particularly valuable for family business studies.

PLS-SEM is a very valuable method for developing and testing theories in family business research (Henseler et al., 2014). Furthermore, the manifold methodological extensions and complementary analysis techniques further increase the technique's versatility, allowing researchers to test more complex model relationships (e.g., moderation, nonlinear relationships, hierarchical component models) and handle data inadequacies that threaten the validity of standard analyses (e.g., unobserved heterogeneity). Family firm research is at a crossroads and needs sophisticated research methods to bridge theoretical and empirical findings (Benavides-Velasco et al., 2013; Gedajlovic et al., 2012). The complexity of family business research lends itself to model building, exemplified by the framework for future family firm research proposed by Wright and Kellermanns (2011). To move from "adolescence" to the next level, family business scholars should consider research methods that will provide them with tools for rigorous exploratory research and actionable results for managerial practice (Gedajlovic et al., 2012, p. 1010; Schulze & Gedajlovic, 2010; Wright & Kellermanns, 2011). PLS-SEM demonstrates this and family business researchers should exploit recent advances to run more nuanced analyses of their existing and future models.

Appendix A

Table A1

Construct measures and indicator loadings/weights.

Measures ^a	Loadings/weights ^b	Sources
<i>Family Power (reflective)</i>		
Senior management strongly wants the business to stay in the family.	0.614	Holt, Rutherford, and Kuratko (2010)
The next generation is strongly committed to long-term business ownership.	0.972	
<i>Family Culture (reflective)</i>		
The owning family members and the business share similar values.	0.684	Astrachan et al. (2002)
The owning family members are willing to put in a great deal of effort beyond that normally expected to help the family business to be successful.	0.812	
I support the family business in discussions with friends, employees and other family members.	0.872	
My values are compatible with those of the business.	0.873	
I agree with the family business goals, plans and policies.	0.811	
I really care about the fate of the family business.	0.729	
Deciding to be involved with the family business has a positive influence on my life.	0.794	
I support the owning family's decisions regarding the future of the family business.	0.761	
<i>Family Experience (formative)</i>		
Which generation has the largest proportion of share ownership held by family members?	0.844	Astrachan et al. (2002)
Which generation(s) serve(s) on the Board of Directors/Advisory Board?	0.382	
<i>Relationship Value (reflective)</i>		
Our company and my major Strategic Partner have compatible goals.	0.809	Vázquez, Iglesias, and Álvarez-González (2005) Kumar, Scheer, and Steenkamp (1995)
The relationship with my major Strategic Partner is mainly based on having similar points of view as to how to do business.	0.882	
It would be difficult for our firm to replace the sales and profits generated from this major Strategic Partner.	0.792	
There are other vendors who could provide us with comparable product lines.	0.836	

Appendix A (Continued)

Measures ^a	Loadings/weights ^b	Sources
<i>Innovation (reflective)</i>		
We continuously develop new products/services with our major Strategic Partner.	0.878	Jenssen and Nybakk (2009)
As a result of this Strategic Partnership, we introduce new products/services more often than similar firms.	0.837	
As a result of this Strategic Partnership, we are more innovative than our rivals in developing cost-saving processes.	0.877	
As a result of this Strategic Partnership, we are more innovative than our rivals in exploiting information technology in our business.	0.839	
As a result of this Strategic Partnership, we have entered new market segments more often than our rivals.	0.877	
As a result of this Strategic Partnership, we have entered market segments that are new to our sector.	0.857	
As a result of this Strategic Partnership, we are able to deliver a higher level of value to our customers.	0.693	
<i>Strategic Information Sharing (reflective)</i>		
We frequently discuss strategic issues with my major Strategic Partner.	0.847	Cannon and Homburg (2001)
Performance metrics are shared across the supply chain.	0.870	Patnayakuni (2008)
My organization shares best practices with my major Strategic Partner.	0.862	Lages, Lages, and Lages (2005)
We collaborate on arriving at demand forecasts.	0.871	
We have created formal arrangements for information exchange with my major Strategic Partner.	0.829	
We have created informal arrangements for information exchange with my major Strategic Partner.	0.821	
Team members have continuous interaction with this major Strategic Partner.	0.830	

^a Innovation, Strategic Information Sharing, Relationship Value and Family Culture were measured on 11-point Likert scales (0 = strongly disagree; 1 = strongly agree); Family Power was measured with an 11-point scale with the endpoints “not at all” (0) and “to a large extent” (10).

^b Numbers show loadings for all constructs except the formatively measured construct Family Experience where weights are shown.

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