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The Measurement of Endogenous Higher-Order Formative Composite Variables in PLS-SEM: An Empirical Application from CRM System Development

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***Abstract*—**In recent methodological articles related to structural equation modeling (SEM), the question of how to measure endogenous formative variables has been raised as an urgent, unresolved issue. This research presents an empirical application from the CRM system development context to test a recently developed technique, which makes it possible to measure endogenous formative constructs in structural models. PLS path modeling is used to demonstrate the feasibility of measuring antecedent relationships at the formative indicator level, not the formative construct level. Empirical results show that this technique is a promising approach to measure antecedent relationships of formative constructs in SEM.

***Keywords*—**CRM system development, formative measures, PLS path modeling, research methodology.

I. Introduction

STRUCTURAL equation modeling (SEM) has become the leading analytical approach in contemporary IS research. SEM owes its popularity to the fact it allows researchers to examine multiple causal relationships simultaneously. Thus, SEM accommodates research that aims to unravel complex phenomena and inter-relationships between concepts in complete theoretical models.

Historically, covariance-based SEM (CB-SEM) [24] has been the standard analysis method in IS research as well as behavioral sciences in general. It is parameter-based and the underlying assumption of the traditional CB-SEM is that the indicators used to measure latent variables are reflective in nature [8]. Partial Least Squares SEM (PLS-SEM) [39] has challenged CB-SEM has emerged as a complementary analysis method in recent years. Unlike CB-SEM, PLS modeling aims to maximize the explained variance of the dependent endogenous variables in the structural model [19]. In addition to reflective latent variables, PLS is also well-equipped to estimate formative latent variables. As this paper focuses on formative measurement, PLS-SEM was chosen as the most appropriate analysis method [20].

Compared to reflective models, the use of formative models in empirical studies remains scarce [11]. The lack of popularity of formative models in IS research and other related disciplines has probably been influenced by the lack of practical guidelines how to create, estimate and validate formative models, in sharp contrast to standardized development procedures that have been developed for reflective measures over the years [11], [33]. Publications that have addressed these issues have appeared only fairly recently, with arguably the most notable contributions coming from [12]-[14], [23], [29], [36], respectively.

The scarcity of empirical models with formative structures may also be due to the fact that choice of measurement perspective is still often ignored by researchers [10], despite increasing evidence in literature about the undesirable consequences of model misspecification [13], [23]. In recent years, though, scholars have begun to challenge the "blind adherence" to the reflective approach with its strict emphasis on exploratory factor analysis and internal consistency [9]. Indeed, formative measurement models have been increasingly applied by IS researchers (for a list of examples, see [33]).

In addition to the issues related to formative measurement model assessment, structural models with formative measures pose a particular type of problem, which has remained largely unsolved to date. Reference [9] voiced their concerns about "the conceptual plausibility of formatively-measured constructs occupying endogenous positions in structural models", and stressed the urgency of finding a solution to this dilemma. This is a challenge with endogenous formative constructs due to different nomological networks of antecedents and consequences [23]. As a response, Cadogan & Lee [5] demonstrated the inappropriateness of developing theory about antecedents to endogenous formative constructs at the aggregate level (i.e. path relationships between latent variables). Rather, antecedents' relationships to the dependent formative construct should be assessed at the formative indicator level (i.e. path relationships from latent variable to indicator), which would be unorthodox in SEM. *The purpose of this paper is to discuss and empirically test the feasibility of Cadogan & Lee's [5] conceptual solution in the measurement of endogenous 2nd order formative constructs.*

II. Measuring Endogenous Formative Composite Variables

Cadogan & Lee [5] presented a conceptual solution to measure endogenous 2nd order formative constructs. As their novel approach has been neither discussed nor tested in other

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published articles, the following discourse is largely based on their article unless stated otherwise.

They [5] identified two important issues, which provide support for assessing the relationships between antecedents and formative indicators, not the formative construct. The first issue is related to the conceptual distinction between formative latent variable and formative composite variable. Theoretically, the relationship between antecedents and formative latent variable can be assessed at the formative construct level. However, a formative latent variable requires a census of all possible causes, which is usually empirically unrealistic. Thus, in most cases the construct is not a formative latent variable but in fact a formative composite variable. A formative composite variable is merely a collection, not a census of formative indicators. In the case of a formative component variable, antecedents can be only assessed based on their correlations with the specific set of formative indicators proposed to form the formative composite variable. Unfortunately, there is no generalizability in such results. Consequently, the solution is to assess relationships between antecedents and formative indicators.

The second issue is related to the different nomological networks of formative indicators' antecedents. In other words, formative indicators may be influenced by common antecedents in different magnitudes, or they may have different antecedents altogether. Thus, examining the relationships from antecedents to a formative composite variable may conceal significant relationships or display non-existent relationships. As a result, empirical findings regarding antecedent relationships would be ambiguous at best. In a similar vein with the first issue, the solution is to assess relationships between antecedents and formative indicators, not the formative composite variable.

Cadogan & Lee [5] argued further that any variation in a formative construct must occur either due to variation in one or more formative indicators, and/or due to variation in unknown indicators (error term). While this ambiguity is inherent to a formative latent variable, a formative composite variable allows parameters to be explicitly estimated in the absence of the error term [10]. Thus, hypothesized antecedent relationships and indicator weights can only be empirically tested with a formative composite variable. On the other hand, results related to endogenous formative composite variables cannot be extended to endogenous formative latent variables, which cannot be tested empirically under any circumstances [5].

As the formative indicators have an important role in assessing the relationships in the structural model, it is important to be able to estimate their measurement error. A type II 2nd order measurement model [23], namely, a 1st order reflective 2nd order formative model, does not suffer from this problem concerning the lack of estimation of item-level measurement error with formative constructs [10].

Estimating measurement error is more problematic with endogenous 1st order formative measures. Reference [15] introduced a "spurious model" with multiple common causes, which represents a conceptual example of an attempt to tackle the issue of measurement error estimation with formative measurement models. Latent variables are intentionally included to enable the estimation of measurement error at the indicator level. This is achieved by assigning each formative indicator a single reflective indicator of its respective latent variable. Its conceptual justification is questionable, though [10]-[11].

In summary, the appropriate approach is to test antecedent-endogenous formative composite variable relationships at the formative indicator level. As reference [5] put it, "if the items (formative indicators) are logically formative, then … item level modeling is most appropriate". With regard to the constructs adopted in this study, this is the case from a theoretical viewpoint as well as from an empirical viewpoint. The conceptualization of an endogenous 2nd order formative composite variable with antecedent relationships measured at the formative indicator level is presented in Fig. 1.

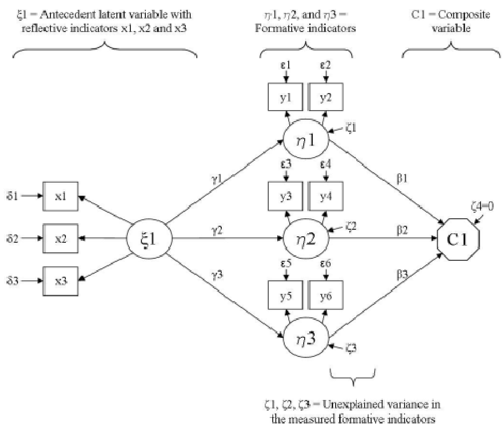

Fig. 1 Endogenous 2nd order formative composite variable with antecedent relationships at the formative indicator level (adopted from [5])

In Fig. 1, C1 represents the endogenous formative composite variable (error term ξ4=0), which is shaped like a hexagon to distinguish it from a formative latent variable. The exogenous reflective antecedent variable (ξ1) with three indicators influences C1 only through reflective LVs η1, η2 and η3, which act as C1's formative indicators. Therefore, path coefficients (γ1-3) and measurement error (ξ1-3) are estimated at the formative indicator level. Indicator weights (β1-3) represent the contributions of the formative indicators to the composite variable. We will test this solution with an empirical study in the CRM system development context.

III. Empirical Study

The research model was developed based on an extensive review of all relevant academic literature related to CRM system development. Due to the interdisciplinary nature of the phenomena under investigation, the theoretical review covered relevant theories within marketing and IS research. More specifically, two research streams in marketing, namely, CRM/ SFA adoption studies in sales management and CRM-performance literature in marketing, were reviewed to identify factors related to CRM system development. Distinct areas of IS research - risk and project management theory, IT innovation research, and IT capability literature – were also reviewed to develop a higher-order formative measure of CRM system development, its antecedents and consequences, which is presented in Fig. 2.

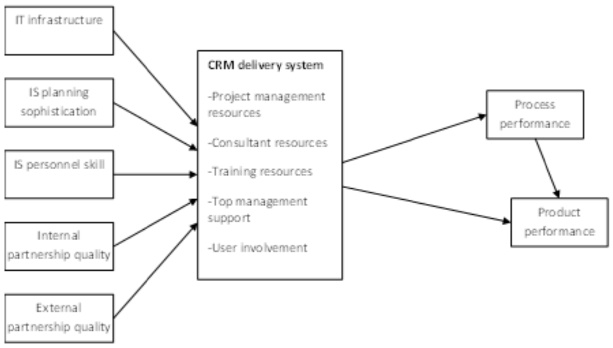

Fig. 2 Research model

Based on a review of IT capability studies in IS research, IT resources including technological, human, and relationship resources [35], are expected to be antecedents of functional IT capabilities such as the firm's capability to deliver CRM systems. More specifically, we adopted operational measures from [34], which included IT infrastructure (INF), IS planning sophistication (ISP), IS personnel skill (PS), internal partnership quality (IPQ), and external partnership quality (EPQ).

We developed the formative measure CRM delivery system (CRMDS), which is theoretically derived from the innovation delivery system concept [27] in innovation diffusion theory literature. According to reference [16], effective delivery systems are characterized by organizational factors such as top management support, training, links to consulting services; and process model factors ensuring fit with the particular technology and organization. Reference [25] developed the concept ERP (enterprise resource planning) delivery system, which included project management resources (PMR), consultant resources (CR), training resources (TR) and top management support (TMS). Based on a review of marketing studies [7], [17], [40] and industry expert interviews, we added user involvement (UI) as a fifth dimension into a new concept CRM delivery system (CRMDS).

We conceptualized the CRMDS as a 1st order reflective, 2nd order formative construct. Although the five dimensions of CRMDS do not represent an exhaustive list of components, they have received the most theoretical support to justify their inclusion into the formative CRMDS construct. As the dimensions were not identified through a census, they form a formative composite variable, not a formative latent variable. Following reference [23], CRMDS is clearly formative in nature: its dimensions will not necessarily co-vary, the causality flows from the dimensions to the construct, and the dimensions are not interchangeable as the meaning of CRMDS would change. Consequently, the formative 2nd order composite variable is a coherent description which depicts the multidimensional nature of CRMDS.

This construct responds to recent calls to develop new holistic operationalizations, representing combinations of factors affecting IS development, by academics in risk and project management literature [18], IT innovation research [16], and IT capability literature [26]. In this view, different IT resources in CRM system development projects do not work in isolation but rather in combinations. Based on resource complementarity arguments, a higher-order conceptualization would better reflect reality than stand-alone IT resources [25]. Such an operational measure has been lacking in the CRM context.

Based on theoretical review, we expect CRMDS to directly influence the well-established IT project performance measures [31], which include process performance (SPP), i.e. meeting budget and schedule estimates; and product performance (SPD), i.e. CRM system quality [37]. Furthermore, we expect SPP to influence SPD [3].

IV. Sample and Measurement Model

The population under investigation was client firms (at SBU level) in Finland using CRM technology, excluding small businesses. The population sample consisted of 526 organizations. The final sample size after screening was 161 usable responses, which met the minimum requirement criteria for PLS-SEM suggested by [2].

Reflective measures were subject to rigorous reliability and validity testing, which showed satisfactory results. Formative measurement model assessment was based on the recommendations by [4], [30], who provided guidelines to address multicollinearity, model identification, and reliability and validity assessment. Based on these tests, CRMDS proved to be robust construct. As the next step, structural model assessment was performed with PLS-SEM, which allowed us to estimate the feasibility of Cadogan & Lee's [5] technique.

V. Results and Discussion

The primary criteria for structural model assessment in PLS-SEM are the explained variances of endogenous constructs (R^2 values), and the strength of standardized path coefficients (β) coupled with significance testing (t-values) [20-21].

The key construct CRMDS was in an endogenous position, which is problematic with formative constructs due to different nomological networks of antecedents [23]. To overcome this issue, we adopted the solution suggested by Cadogan and Lee [5] for testing antecedent relationships of a formative composite variable at the indicator level instead of the construct level. These relationships could be estimated by adopting a technique known as the hierarchical component model [28], [39].

Following these guidelines, we tested antecedent relationships to the CRMDS construct (in grey) at 1st order construct level (PMR, CR, TR, TMS, UI), which resulted in a total of twenty-five antecedent paths. While the formative composite has an error term fixed at zero, measurement error can also be estimated at formative indicator level in a Type II higher-order construct. For demonstrative purposes, the final model, including significant paths only, is presented in Fig. 3.

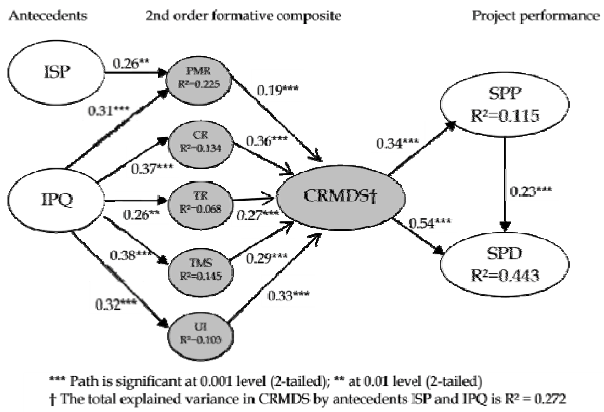

Fig. 3 Final structural model

The antecedent relationships show that IPQ and ISP had significant paths to CRMDS through its formative indicators. Furthermore, the total explained variance in CRM delivery system quality (R^2=0.272) could be calculated in the PLS path model by conceptualizing CRMDS as a 1st order construct representing all five project-level IT resources PMR, CR, TR, TMS and UI.

The Type II higher-order construct CRMDS importantly allowed for parameter estimation at the formative indicator level. The parameters for the 1st order reflective measurement models, which represented the formative indicators of the 2nd order formative construct, remained stable in various empirical tests. Cadogan & Lee's [5] conceptualization also proved to be useful in measuring the antecedent relationships of each formative indicator, and their contribution to the formative construct as indicator weights. These measurements also remained stable across different structural model scenarios. Based on these considerations, this study provides empirical support for the functionality of the solution suggested by [5], following which the antecedent relationships of formative variables are measured at the formative indicator level, not the formative construct level.

However, Cadogan & Lee's [5] model is subject to the general limitations associated with formative measurement. Formative indicator weights vary across different empirical data sets and research contexts, leading to limitations regarding the generalizability of empirical findings [1].

Reflective measures are thus considered more useful from a theory development perspective [22]. Based on theoretical rationale, however, CRM system development is clearly a formative, multidimensional construct. Under these circumstances and based on this empirical study, Cadogan & Lee's [5] recommended technique is currently the most fruitful approach to investigate formative variables, Type II in particular, occupying endogenous positions in structural equation models.

In order to improve the generalizability of the formative composite variable CRMDS, future studies could also test CRMDS with predetermined indicator weights. These weights could be predetermined as equal weightings [5] or based on theoretical considerations [22], for example.

In conclusion, it is important to find a solution to measure antecedent relationships of higher-order formative constructs. Model parsimony, when theoretically justifiable, has been supported by scholars [6]. According to reference [32], a higher-order construct can more parsimoniously explain the single cumulative effect, as opposed to multiple distinct effects of individual facets, on outcome measures. Therefore, the development of higher-order constructs in IS development is desirable. Arguably many of these constructs are likely to be formative in nature: IS development is an inherently multidimensional phenomenon. Consequently, techniques that allow for estimation of factors affecting higher-order conceptualizations of IS development should also be available for future studies.

In this particular empirical example, theory suggests that CRMDS dimensions are inherently intertwined and should not be assessed in isolation; therefore, the composite variable is theoretically justified [26]. CRMDS incorporates the multidimensional phenomenon of CRM delivery system from five separate constructs into a single construct. Although the different facets that constitute CRMDS may vary in importance from one CRM project to another, it would arguably be difficult to achieve CRM system development success in the absence of any given dimension identified in existing literature. The solution suggested by Cadogan & Lee [5] represents a novel approach, which has the potential to increase our knowledge regarding factors affecting formative composite variables, such as CRMDS in this study.

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