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PLS-SEM Approach to Second-order Factor of Deviant Behaviour: Constructing Perceived Behavioural Control

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Abstract

Partial least square structural equation modelling (PLS-SEM) provides researchers with a predictive tool for theory building. In an attempt to understand deviant behaviour which can potentially become a criminal offence, PLS-SEM opens up a valuable mean to analyse latent constructs are designed from a composite of indicators. At its basic, this is called a first-order variable. Using the first-order variable in a basic predictor-criterion research model illuminates in-depth structure on how each component of these variables affects each other. However, as an analysis moves to a more complex level, the first-order variable poses a great challenge to the researchers. This is especially true when the main focus of a study is to look at a general predisposition of a group of related first-order variables with the criterion. Nevertheless, driven by sufficient theories and validated by appropriate statistical tests, related first-order latent variables can be funnelled into a higher-order latent construct. This in turn, helps to reduce complexity of the overall research model allowing more interpretable output and concise discussions.

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1. Introduction

Often researchers are presented with a construct composing multiple unobserved variables. These unobserved (latent) variables are measured via their manifest variables which are referred as indicators. In an attempt to decipher

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deviant behaviour which can result in substantial loss to an organisation or compromise its information system assets, latent constructs are commonly used. At its basic, a composite of question-statement become indicators for a construct of a first-order variable. Using the first-order variable in a basic predictor-criterion research model illuminates in-depth structure on how each component of these variables affects each other. However, as an analysis moves to a more complex upper level, using the first-order variable poses a great challenge to the researchers to devise a set of appropriate tests for the variables of interest. This is particular true when the main focus of a study is to look at a general predisposition of a group of related first-order variables with the criterion. Nevertheless, driven by sufficient theories and validated by appropriate statistical tests, related first-order latent variables can be funnelled into a higher-order latent construct. This in turn, helps to reduce complexity of the overall research model and assist in an interpretation of statistical analyses, hence discussions that follow.

A higher-order construct can represent a hypothesis that apparently distinct, yet related, lower-order latent variables (Chen, Sousa, & West, 2005). A construct can be measured at any level of abstraction (Hair, Black, Babin, & Anderson, 2010). A latent construct with multiple indicators allows researchers to run statistical tests to support or reject hypotheses. Multiple latent constructs can also converge at a higher level predicting a common trait simplifying a complex model and interpretation of the statistical outputs. A good illustration on this topic is illustrated in the case of *theory of planned behaviour* (TPB: see Ajzen, 1991, 2002; Trafimow, Sheeran, Conner, & Finlay, 2002; Zolait, 2011). Apart from predictor variables subjective norms and attitude, TPB postulates that behaviour is affected directly by perceived behaviour control (PBC) and indirectly through intention. PBC on the other hand, is argued to be two discernable latent constructs which prompt Ajzen (2002) to conclude that PBC is unitary at its higher-order level.

The use of a higher-order in a structural equation modelling (SEM), particularly covariance-based SEM, results in more parsimonious model and thus performs better on goodness of fit indices (Hair et al., 2010). With the higher-order factor included in a model, this factor consumes less degree of freedom which contributes to a better model fit. On these advantages, a higher order factor becomes a magnet attracting the researchers to 're-specify' their research model. However, without sound theoretical backings and less-than-accepted statistical parameters to support an aggregation of the first-order to higher-order factors, this advantage can result in misleading results. Using theory of planned behaviour, we illustrate in this paper how PBC are populated into a single second-order factor which forms a basis for other statistical tests.

2. Theory Validation

Variations and freedom to operationalise latent constructs at different level of abstraction necessitate a thorough examination of theories underpinning the level at which the constructs are aggregated. If the theory supports only first-order level, then a higher-order factor should not be used in a study. Hair, et al. (2010) emphasise the theory validation as a superior criterion to decide whether a higher-order factor is appropriate in a given study. This is regardless of statistical viabilities and adequacy to perform SEM analysis using such model.

In the case of theory of planned behaviour where controversies arises from a notion that perceived behaviour control (PBC) is a two-component factor, this study illustrates a working example how the factor structure can be determined both at lower- and higher-order levels. Trafimow, et al. (2002) argue that PBC reflects both internal and external locus of controls which is partly influenced by the concept of self-efficacy by Bandura (1978). Based on this notion, 2 first-order latent variables for PBC (i.e. Outcome to reflect control perception on outcome of behaviour, and Resource to reflect perception of control over resources to engage in behaviour) can be assessed on their theoretical validity to be aggregated at a higher-order level. This is consistent with Ajzen (2002) that PBC "...can be considered as unitary latent variable in a hierarchical factor model" (Ajzen, 2002, p. 665).

The reflective or formative nature of first and second order factors is also required to be determined. A wrong specification of the latent constructs can undermine the construct content validity, misrepresent a structural model, and result in less useful theories for both researchers and practitioners (Coltman, Devinney, Midgley, & Veniak, 2008). A construct is said to be reflective when its indicators are results of changes in the construct. This means causality flows from the construct to the indicators. For example, if production efficiency is measured using a latent construct, indicators such as reduction in wastage, spoilage and reduction in production cycle time support the notion of a reflective construct because these indicators are the results of an efficient production.

On the other hand, a causality flow from indicators to the construct indicates it is formative. In the example of production efficiency measurement above, when employee's motivation and job satisfaction are used as indicators,

production efficiency is now a formative latent variable. This is because, production efficiency is achieved when the employees are motivated and well satisfied with their job.

Theoretical ground and statistical approach can also be used to determine whether a construct is reflective or formative. This is assessed through the theory underpinning each latent variable (Bagozzi, 2007; Chin, 1998) and validity by means of Cronbach's alpha and average variance extracted (AVE) (Coltman, et al., 2008). Additionally, the indicator-construct causality flow can also be checked using weight-loading sign (WLS). A negative WLS indicates a causality issue which means the indicator-construct link is impossible or reverse (Kock, 2013; Wagner, 1982), a tale-tale sign of a Simpson paradox instance (Kock, 2015). In this study, Cronbach's alpha for the constructs is between .84 to .96, and AVE is between .76 to .96 which demonstrate a satisfactory constructs' validity. This is further supported by positive WLS indicating that all constructs are free from possible Simpson paradox.

3. Methodology

The latent constructs of theory of planned behaviour (TPB) were measured using instruments adapted from those developed by Ajzen (n.d.-b), Ajzen (n.d.-a), Chatterjee (2008), Venkatesh, Morris, Gordon, and Davis (2003), and Thompson, Higgins, and Howell (1991) These are five questions designed to capture intention (INTENT), three for subjective norm (SN), two for attitude (ATT) and five for perceived behaviour control (PBC). PBC 5-item questions were measured at its lower-order factors with two measuring perceived control over the outcome of behaviour (Outcome) and three measuring control over resources to perform behaviour (Resource).

A total of 1380 surveys were sent to middle managers of medium size companies in Malaysia. 387 responses were later collected and used for the analysis. This represented 28% response rate which was acceptable in a survey-based study (see Baruch & Holtom, 2008; Taskin, 2011).

Later, a two-stage procedure (Anderson & Gerbing, 1988; Mohamadali, 2012) for structural equation modelling approach was used in the analysis. The first stage was an assessment on the measurement model to see if the model can be used for later analyses. In the second stage of the analysis a full structural model can be analysed. In the interest of this study which is to illustrate a working example of constructing a second-order factor, the structural model is not discussed. The software used in this example is WarpPLS version 4.

4. Statistical Validation

At each stage of scale development, each latent variable has to be assessed for their discriminant and convergent validity. Theoretically, an item is said to have sufficient convergent validity when the item measures a latent construct for which it is designed for. In order to support such notion, convergent validity for the items in this study was assessed through their factor loadings. Items having high loading ($> .5$) on its parent construct (Hair, et al., 2010; Kline, 2010; Schumacker & Lomax, 2012) with low cross-loading on other factors supported good convergent validity. Kock (2013) and Schumacker and Lomax (2012) also propose these loadings should also be assessed for their statistical significance (p -values $\leq .05$) because the p -values are used as validation parameters in a confirmatory factor analysis. In addition to these parameter estimates, the result of the analysis shows that average variance extracted (AVE) for each construct exceeds the minimum threshold of .50 (Hair, et al., 2010; Urbach & Ahlemann, 2010) which further supporting convergent validity.

In order to assess discriminant validity of a construct, AVE was used. Fornell and Larcker (1981) suggest that, for good discriminant validity, square-root of AVE of a construct has to be higher than the construct's correlations with other constructs. The current study shows that this criteria was met at the first-order factor structure as shown in Table 1.

Table 1. Construct correlation matrix and average variance extracted (AVE) for first-order factor.

	ATT	SN	Outcome	Resource	INTENT	VIF
ATT	(.975)					3.070
SN	.772	(.954)				3.291
Outcome	.642	.681	(.980)			3.595
Resource	.574	.636	.806	(.872)		2.996
INTENT	.770	.772	.711	.643	(.924)	3.433

Square-root of AVE is in brackets () on the diagonal
VIF = Variance inflation factor

Table 1 also shows Outcome and Resource correlation is relatively high (.81). Consistent with an approach by Greene and D'Arcy (2010), variance inflation factor (VIF) was further checked to determine if Outcome and Resource were two distinct constructs at their first-order level. VIF of 10 or lower is considered acceptable (Hair, et al., 2010), while a conservative estimate is 5 or lower (Kock & Lynn, 2012). As shown in Table 1, VIF for all constructs were below the conservative estimate.

Hair, Black, Babin, Anderson, and Tatham (2006) suggest that a higher-order construct to be assessed in a similar manner as in the lower-order construct structure. As such, apart from the theoretical assessment outlined in section 2.1 above, statistical validations for validity and reliability used at the first-order level are also applicable when the second-order construct is assessed. At this stage, Outcome and Resource become two indicators for perceived behavior control (PBC). Indicators for PBC were created using factor scores of Outcome and Resource generated by WarpPLS.

The output shows that Outcome and Resource had significant loading on PBC (loading = .95, $p < .001$) with positive WLS, and AVE of PBC was .90. The reliability of PBC was confirmed with Cronbach's alpha of .89. Table 2 further supports discriminant validity of PBC with the square-root of AVE that was higher than the maximum shared variance among the constructs.

Table 2. Construct correlation matrix and average variance extracted (AVE) for second-order factor.

	ATT	SN	PBC	INTENT	VIF
ATT	(.975)				3.058
SN	.772	(.954)			3.291
PBC	.640	.693	(.950)		2.273
INTENT	.770	.772	.712	(.924)	3.406

5. Discussions and Conclusion

As latent variables can be measured at various levels of abstraction, researchers are presented with a flexibility to refine a research model for further analysis. However, without sound theoretical backings and sufficient statistical tests to support the level at which the latent variables are used, the validity and usefulness of resulting findings are questionable. In the case of behavioural science, particularly in measuring malpractices that amount to criminal offences, establishing a good second-order latent construct is paramount to reduce model complexity and assist the interpretation of the results. In this paper, perceived behavioural control (PBC) was highlighted as being two components which can be aggregated at a second-order level. Statistical tests following the theories were made to see if the second-order factor was appropriate.

Despite the flexibility and the model simplification, a higher-order factor also has a disadvantage. A higher-order factor in general, overshadows what could otherwise be illuminated at a lower level factor (Hair et al., 2006). If a research interest is to find which of the two components of PBC significantly affects other variables and how the effect is laid upon, the inclusion of a second-order factor may place a limitation for further discussion. The researcher has to fall back to the first-order factor for that purpose. However, in the interest of this paper, the primary objective to form a second-order factor is to investigate how PBC, measured as a higher-order composite can influence other

variables in the model. For this reason, a well-defined higher-order factor supported by both theoretical underpinning and statistical evidence was used. In conclusion therefore, it is impetus for a researcher to define the boundary of which his or her research is and the interest for which the formation of a higher-order factor to be used.

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