SEM is dead ... long live SEM

Scott MacLean

About our speaker:

Scott MacLean has over 30 years economic, social and market research experience, and over the last nine years has worked in Australia, Germany and the UK for Research International, most recently as Marketing Science & Research Director.

He holds B. Sc. (hons) and M. App. Sc. degrees in mathematics, statistics and modelling.

He has recently joined Melbourne-based Lewers Research, where he is jointly responsible (with Lisa Lewers) for direction of quantitative projects, as well as leading the company's strategic modelling and analytical activities.

Contact details:
Mob 0419 504 588
Eml scott@lewers.com.au

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Lewers Research

1. INTRODUCTION

Nearly 10 years ago, Kevin Gray and I presented a paper at the (then) MRSA Annual Conference, introducing the benefits of Structural Equation Modelling (SEM) and its application to what practising market researchers do on a daily basis. That is, on the basis of things we can measure, we attempt to make predictions of things we cannot measure.

We explained that for market research, SEM provides an opportunity (in fact, a requirement) to *hypothesise* models of market behaviour, and to test or *confirm* these models statistically.

JARGON ALERT !!

Technically, SEM estimates the unknown coefficients in a set of linear structural equations. Variables in the equation system are usually directly observed variables, plus unmeasured latent variables, or constructs, that are not observed, but which relate to observed variables.

SEM assumes there is a causal structure among a set of latent constructs, and that the observed variables are indicators of those latent constructs. The latent constructs may appear as linear combinations of other latent constructs, or they may be intervening variables in a causal chain.

More specifically, SEM generally involves the specification of an underpinning linear regression-type model (incorporating the structural relationships or equations between the latent constructs) together with a number of observed (measured/indicator) variables. By examining the *co-variation* between the observed variables, it is possible to:

- estimate the values of the coefficients in the underpinning linear model that describes the structural relationship;
- statistically test the adequacy of the model to adequately represent the process(es) being studied; and
- if the model is adequate, conclude that the postulated relationships are plausible (or, more correctly, that they are not inconsistent with the data).

Given that the discussion above is a pretty good model of obfuscation – lots of big words and lots of technical jargon - I feel that it may be best to start with a brief re-interpretation of some of what was presented in our earlier paper. Those who are already familiar with SEM can skip to Section 3.

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2. SOME BASIC CONCEPTS

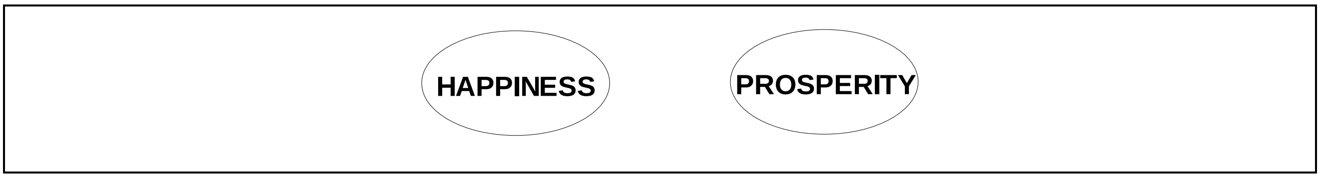
A Structural Equation Model in its most general form involves the specification of a number of components which, when pictured in full detail, can be more than daunting, and it is therefore instructive to examine the various elements of SEM, one by one.

Latent Variables

Unobserved or unmeasured, latent constructs are those which represent abstract concepts or theoretical constructs which cannot be directly measured. Such variables are often referred to as 'factors' or 'common factors'. That is, they are presumed to underlie what can be observed, in the sense that the latent constructs directly influence the outcome or values taken by the observed variables.

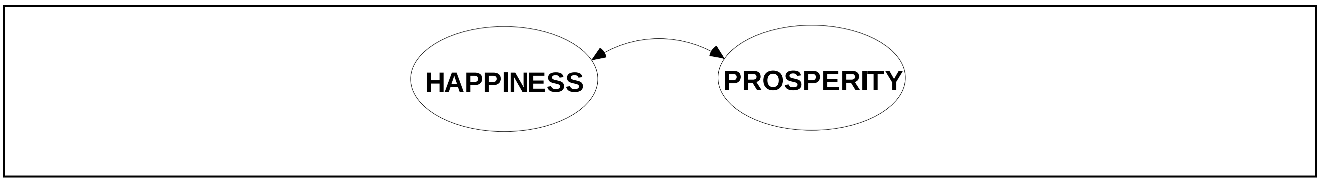
In pictorial form, latent constructs are usually represented as ellipses, as shown in Figure 1.

FIGURE 1



Latent constructs can be correlated with each other, as represented by the double-headed arrow in Figure 2.

FIGURE 2



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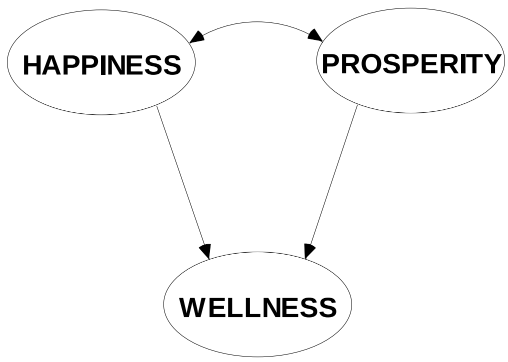
Latent constructs can also influence other latent constructs directly, via a regression-type relationship, as represented by the single-headed arrows in Figure 3. . Instead of the term 'regression coefficient', however, we use the term 'path coefficient' to describe the degree of influence that each variable has on each other variable.

FIGURE 3



Observed Variables

Because latent constructs are, by definition, unobservable, their measurement must be obtained indirectly.

This is done by linking one or more observed variables to each construct. In fact, it is effectively what most of us do on a day-to-day basis as we prepare questionnaires. *The difference, however, lies in how we analyse the information we collect.*

With SEM, the linking of observed (or indicator) variables with latent (or unobserved) constructs is the first step in a formal statistically valid procedure. In contrast, with our day-to-day work the linking procedure is oftentimes implicit - in other words, if we feel that a particular measured variable makes a good indicator of some underlying construct, then we simply use it !

In pictorial form, observed or indicator variables can be represented as rectangles, as shown in Figure 4.

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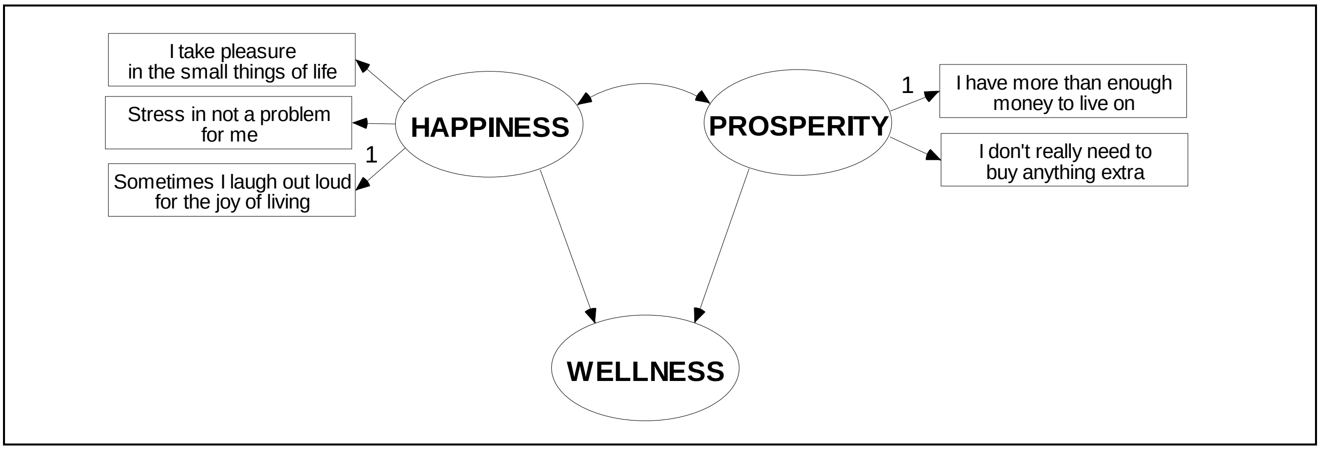
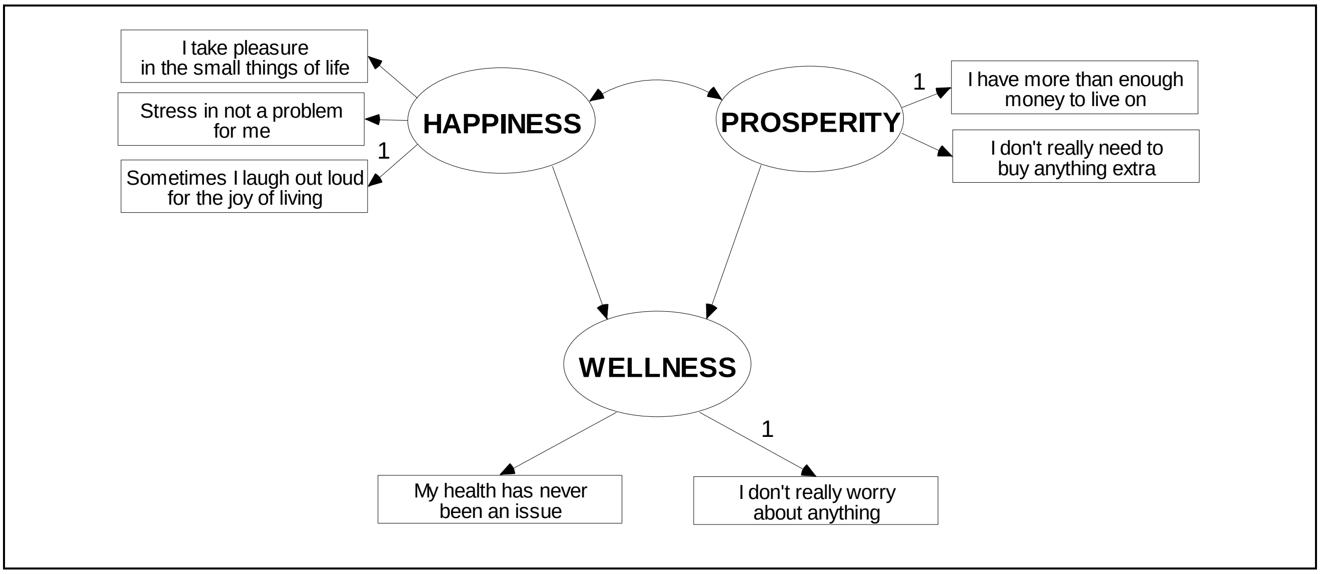
FIGURE 4



In this diagram, the single-headed arrows connecting the latent constructs and observed variables indicate that the latent constructs directly influence the outcome or values taken by the observed variables, again through a regression-type relationship. Again, instead of the term 'regression coefficient', we use the term 'path coefficient'.

We can go still further, in terms of identifying observed variables for the completely endogenous latent construct labelled as "Wellness", as illustrated in Figure 5.

FIGURE 5



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Still More Variables

Apart from the latent and observed variables, there are *residual* and *error* terms associated with each of these which also form a key part of the overall model. For simplicity, however we omit these from the discussion for the time being.

Suffice it to say that a fully specified Structural Equation Model is potentially a complex interplay between a large number of observed and unobserved variables, and residual and error terms.

3. MODEL CALIBRATION

The central thesis of SEM model calibration is twofold:

- the statistical relationship between the observed variables (in fact, the estimated covariances between them) can be used to provide estimates of the regression coefficients which link the unobserved, latent constructs; and
- the adequacy, or goodness-of-fit, of the hypothesised structural model can be statistically tested using methods closely aligned with conventional chi-square goodness-of-fit approaches.

It is, however, not quite that simple.

Whilst computer packages such as AMOS, LISREL® and EQS in principle make the calibration process 'easy', there are many traps for the tyro modeller.

Not the least significant of these is the issue of *identification*.

Paraphrasing Garson (2007), we can explain just one of the many aspects of identification as follows[1]:

> *The variance of the latent constructs and the regression (path) coefficients associated with them depend on the units with which the variables are measured, but initially this is unknown.*

---

1 Garson's 'Statnotes' are a goldmine of information for the statistical modeller. For SEM in particular, see http://www2.chass.ncsu.edu/garson/pa765/structur.htm

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> *For each latent construct and also for the unknown error terms, it is necessary to assign an arbitrary value to a regression weight associated with the latent variable or error term. Once this is done, the remaining coefficients can be estimated for the remaining paths in the model.*
>
> *Therefore, for each latent variable, one of the paths leading away from it toward one of its indicator measures has to be set to 1 by the researcher. This sets the measurement scale of each latent variable, whereas without this the scale would be indeterminate. Likewise, the paths from each error term to each indicator variable are set at 1. With these constraints, the model is usually identified.*

Not only that, lack of identification can lead to the program issuing an error message (eg. failure to converge), generate non-sensical estimates (eg. negative error variances), display very large standard errors for one or more path coefficients, yield unusually high correlation estimates (eg. over 0.9) among the estimated path coefficients, and/or even stall or crash.

In my experience, this can happen not infrequently, and it is not always obvious that it has happened. For example, it can be a little tricky to detect an error variance that is just very slightly less than zero unless you are looking for it.

There is in fact a whole host of issues associated with 'conventional' SEM that can conspire to make rubbish out of your most careful attempts to model a structural system.

There is also a whole host of statistical measures of fit that you can use to determine if your model is good enough (or, better put, not too bad) and it is not always clear which should be used. Again, Garson (2007) has an extremely good discussion of these.

It's all sooooo confusing. So is there a way out ?

The answer is 'yes'.

But the answer is not what you might think it is.

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4. FORMATIVE VERSUS REFLECTIVE SEM

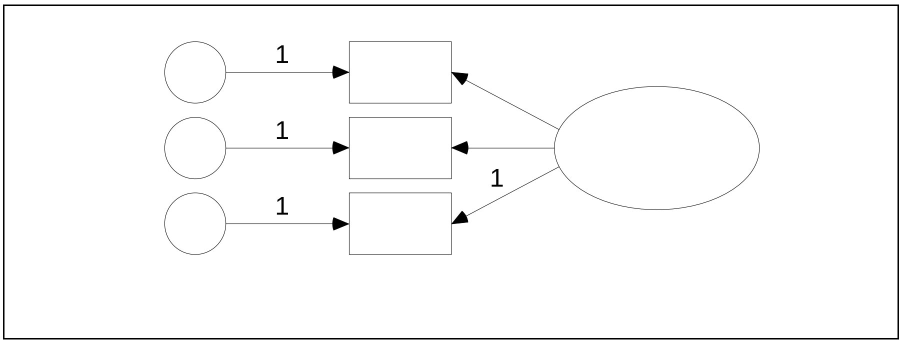
SEM invariably assumes that the variation in scores on measures of a latent construct is a function of both the true score (ie. what the construct itself measures) and an error, or unique score component.

For example, Customer Loyalty, as a construct, might be measured by items such as:

- Likelihood of recommending supplier to others
- Likelihood of purchasing from supplier again
- Likelihood of increasing expenditure with supplier in the future.

This is the classic Confirmatory Factor Analysis model, and adapting the diagrammatic language introduced earlier, it would look like the outline shown in Figure 6 (this time showing the error, or unique, variables):

FIGURE 6

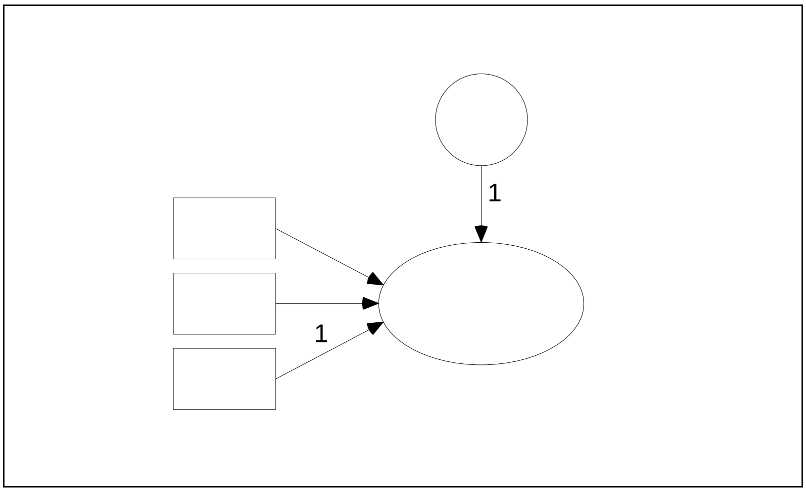


[Note that to ensure identification, one of the path coefficients has been fixed to equal unity.]

They key point in this path diagram to note is that the arrows go <u>from</u> the latent construct <u>to</u> the measured variables, because the construct is assumed (partially) to <u>cause</u> ("influence" might be a better word) the result observed for each of the measured variables.

However, in some circumstances, it makes more sense to assume that causality/influence actually flows <u>from</u> the measured variables <u>to</u> the construct. For example, the construct may actually perform more as an *index* than as an underlying factor, in which case the arrows in the above path diagram would go in the reverse direction, as shown in Figure 7.

FIGURE 7



In this case, the measured variables have become *formative* indicators. Note an important difference between the two diagrams; with the former, the error or unique terms are associated with the measured variables, whereas with the latter there is only one error term and this is associated with the construct.

In fact, formative indicators have several other properties that distinguish them from reflective indicators (Diamantopoulos and Winklhofer (2001)):

1. Reflective indicators are essentially inter-changeable, and the removal of an item does not change the essential nature of the underlying construct. With formative indicators, in contrast, omitting an indicator is to omit a part of the construct itself.

2. The correlations among formative indicators are effectively independent of any other consideration, and it is more problematic than in the case of reflective indicators to assess their validity.

3. There is no reason that a specific pattern of signs should be expected with the correlations among formative indicators of a given construct – in fact, two items might be negatively correlated but still serve as meaningful indicators of the construct.

In relation to the last of these points, note that multicollinearity among measured variables can be a significant problem for calibration (ie. estimation of coefficients) when the indicators are formative (because the underlying model is effectively a Multiple Regression) but a positive virtue when the measured variables perform the function of reflective indicators (where the underlying model is a Confirmatory Factor Analysis).

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Jarvis *et al* (2003) go further and advise that a construct should be modelled as having formative indicators if all of a number of conditions hold, eg.:

- The indicators are viewed as defining characteristics of the construct
- Changes in the indicators are expected to cause changes in the construct
- Changes in the construct are not expected to cause changes in the indicators
- The indicators do not necessarily share a common theme
- Eliminating an indicator may alter the conceptual domain of the construct
- A change in the value of one of the indicators is not necessarily expected to be associated with a change in all of the other indicators (see the comment concerning multicollinearity immediately above).

An example of a formative indicator model (Jarvis et al (2003) and Singh (1988)) would be based around customer complaints, where the indicators might be:

- Frequency of complaining to store manager
- Incidence of telling friends and relatives about a bad service experience
- Likelihood of reporting the supplier to a consumer complaints agency
- Likelihood of pursuing legal action against the supplier
- etc.

Note that in this case, a high score on one particular item would certainly influence the level of the latent construct, but would not necessarily have an effect on the other items.

What is the significance for us as researchers? Well, in terms of the implications for modelling and calibration of a relationship, taken in isolation a simple formative indicator measurement model is statistically under-identified, regardless of the number of indicators – that is, the relationship cannot be calibrated using packages such as AMOS, which take a covariance fitting approach. In contrast, a simple reflective (factor) model is identified if it has at least three indicators.

So, just considering each of the path diagrams above, the first *reflective* factor model is identified and able to be calibrated, whilst the second *formative* model is not.

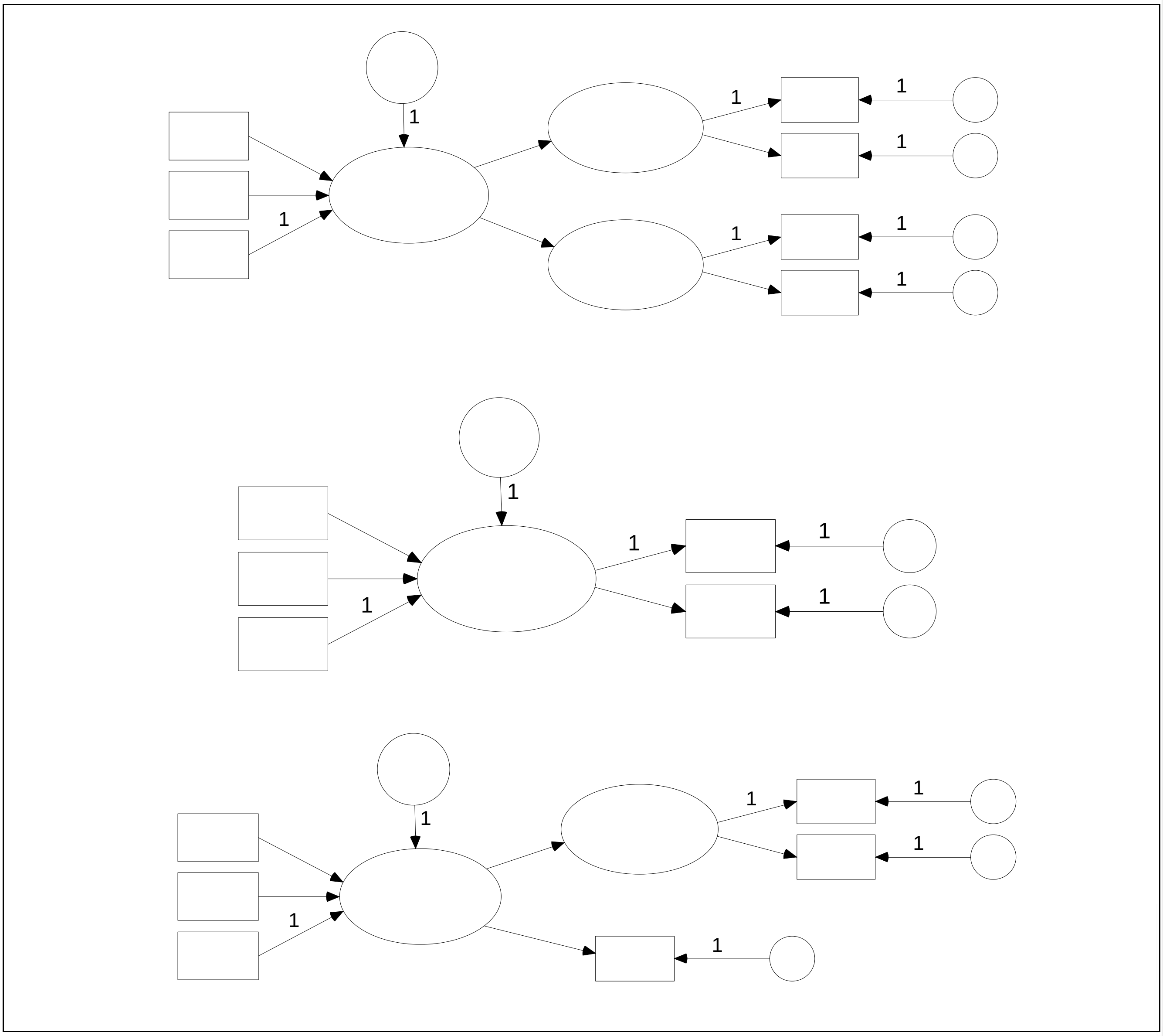
How do we get around this ?

It turns out that formative factor models **will** be identified (and able to be calibrated using covariance fitting approaches) if each formative construct emits paths to:

1. at least two unrelated latent constructs with reflective indicators, <u>or</u>
2. at least two (theoretically appropriate) reflective indicators, <u>or</u>
3. at least one reflective indicator and at least one latent construct with reflective indicators.

In other words, our outline formative model shown earlier would have to be extended to look like one of those shown in Figure 8.

FIGURE 8



5. WHAT DIFFERENCE DOES IT MAKE?

The original intention of this paper was to formulate a structural model with formative indicators and calibrate it on the basis that all indicators were reflective. The difference in results would show the ill-advisability of confusing a formative with a reflective situation.

However, when I came to undertake the work, I found that it had already been done ! Not only that, Jarvis *et al* (2003) had even undertaken a comprehensive literature review to tally published papers which relied on *reflective* SEM, but which should have included at least some element of *formative* SEM.

So probably the best I can do is tell you what they found, which is highly instructive in itself.

At the same time, I could not resist a small experiment of my own ... more of this later.

Literature Review

First, the literature review ... actually, I still can't quite believe that the authors went to this trouble, but Jarvis *et al* undertook the following steps:

- The four journals *Journal of Consumer Research (JCR)*, *Journal of Marketing (JM)*, *Journal of Marketing Research (JMR)*, and *Marketing Science (MS)* were searched for the **24-year** period from 1977 through 2000 (1982–2000 for MS) to identify all empirical applications of latent variable SEM or confirmatory factor analysis.

- Limiting themselves to methodological papers incorporating either confirmatory factor models or latent variable SEM, 178 articles containing 1,192 constructs modelled as latent factors with multiple indicators were identified.

- The classification of the constructs proceeded as follows:

    - Three independent coders (the authors, ie. Jarvis *et al* !) independently read the articles, identified those constructs with multiple measures, and determined how their measurement models were specified.

    - Next (using criteria similar to those referred to earlier), each construct was classified as formative or reflective.

    - In those cases where all three coders agreed that the construct met the criteria for either a formative or a reflective measurement model, the construct was assigned to that measurement model category.

- In instances where the coders disagreed about the extent to which the construct met the various criteria, the points of disagreement were discussed until a consensus was reached.

The upshot was as shown in the table below:

	Should have been modelled as reflective	**Should have been modelled as formative**	TOTAL
Was modelled as reflective	**810**	**336**	1,146
Was modelled as formative	**17**	**29**	46
TOTAL	827	365	1,192

Overall, 810 + 29 = 839 (of a total of 1,192) of the latent constructs with multiple measures were correctly modelled, and 336 + 17 = 353 were incorrectly modelled.

Most of those that were correctly modelled (810 out of a total of 839) were reflective constructs correctly modelled as having reflective measures, while the remainder (29 of 839) were formative constructs correctly modelled as having formative measures.

In contrast, the majority of constructs that were incorrectly modelled (336 out of a total of 353) were formative constructs incorrectly modelled as having reflective measures.

That is ... **over a 24 year period in mostly academic, refereed papers appearing in four of the world's leading market research / marketing science journals, nearly 30% (353 of 1,192) of modelled constructs were wrong.**

If the academic community can get it so wrong, then it is highly likely (in my view) that the arguably more prosaic marketing research community will also get it wrong, and probably to a greater degree.

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But the question now arises, if the modelling is done on the wrong basis, does it have any substantive impact on conclusions and findings which would otherwise have been drawn from those same studies?

Jarvis *et al* come to the rescue again.

Monte Carlo Simulation

Jarvis *et al* set out to demonstrate " ... the extent to which different types of measurement model misspecification influence the estimates of the measurement and structural model parameters", with an extremely comprehensive and rigorous experiment using simulated data.

Using pre-specified population values, raw data sets were generated of a sample size of 500 from each of two pre-specified population covariance matrices.

A total of 500 such data sets was generated for each of six population conditions. These data sets were then used to fit both correctly specified and misspecified models, generating parameter estimates and fit statistics for each replication.

The reader is invited to consult the original paper for the full details of the analysis. Suffice it to say, however, that the authors' concerns were well justified. Their conclusion was that their results ...

"... provide(d) strong evidence that measurement model misspecification of even one formatively measured construct within a typical structural equation model can have very serious consequences for the theoretical conclusions drawn from that model. ***The entire model could appear to adequately fit the data, even though the structural parameter estimates within that model exhibit very substantial biases that would result in erroneous inferences...***

More specifically ... paths emanating from a construct with a misspecified measurement model are likely to be ***substantially inflated*** *... paths leading into a construct with a misspecified measurement model are likely to be* ***deflated****."*

Enough said.

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6. PAUSE FOR REFLECTION

So far, we have established that:

- Calibration of 'conventional' reflective SEMs can be tricky, and the solution will sometimes not converge, or if it does, can give silly results
- Many reflective SEMs, or at least parts of them, should actually be modelled formatively, rather than reflectively – if not, then the results obtained will probably be misleading
- The standard covariance-fit-based packages are not always good for calibrating the latter, unless special circumstances apply.

So .... we should be doing something different when we utilise SEMs, but if we do, then we may not be able to calibrate them.

7. PLS TO THE RESCUE

The recently available Smart-PLS software[2] (Ringle *et* al, 2005) provides an alternative method for calibrating SEMs which largely circumvents these issues.

The PLS (partial least squares) approach to SEM has been around for some 15 or 20 years as a statistical method, but only with the release of this software has it become effectively usable. Lohmöller (1989) provides a very comprehensive (although difficult to read) exposition of the underpinning theory. Haenlein and Kaplan (2004) provide a simpler and very readable and informative introduction.

<u>But more importantly</u>, the PLS approach does seem to result in solutions that converge (without need for model augmentation of the type shown in Figure 8), and do not involve such monstrosities as negative variances. It will also result in a valid solution in cases where AMOS will simply implode and. additionally, seems impervious to 'identity' issues.

On this basis, the PLS approach to SEM (as embodied in the Smart-PLS software) would seem to be worthy of close attention.

Essentially (Haenlein and Kaplan, 2004) with PLS, the unobservable latent variables are estimated as exact linear combinations of their empirical indicators, or measured variables and PLS treats these estimated proxies as perfect substitutes for the latent variables. The weights used to

[2] Other PLS-based packages are also starting to emerge, eg. XLSTAT-PLSPM (see Chatelin *et al*, 2007). I exclude Wynne Chin's PLS-graph software (Chin, 2001) from these comments since, in my experience, and that of many of my colleagues, it is virtually impossible to get hold of.

determine these values are estimated so that the resulting values capture most of the variance of the independent latent variables that is useful for predicting the dependent latent variables.

8. THE BASIC PLS ALGORITHM FOR SEM

The basic PLS algorithm is not difficult, despite the seeming complexity of expositions such as that shown in Figure 9.

Essentially, a value is determined for each unobservable latent variable, simply by calculating a weighted average of its indicators/measured variables. This results in a model in which all unobservable variables are approximated by a set of case values and that can, therefore, be estimated by a set of simple, first-generation, ordinary least squares regressions.

The basic idea of PLS is therefore quite straightforward. First, the weight relations, which link the indicators to their respective unobservable variables, are estimated. Second, case values for each unobservable variable are calculated, based on a weighted average of its indicators, using the weight relations as an input. Finally, these case values are used in a set of regression equations to determine the parameters for the structural relations (Fornell & Bookstein, 1982).

Referring to Figure 10, essentially, the algorithm starts at Stage #4 by estimating a value for each latent construct *Y* as a weighted linear sum of the scores obtained for each measured variable, scaled so that the variance of the latent construct is constrained to be equal to unity. Here, the weights are represented by the *w*'s, the measured variables by the *y*'s and the scaling coefficient by the *f*'s.

In other words, regardless of whether the measured variables are being modelled formatively, or reflectively, the best guess we can make as to the value taken by the latent construct must be some 'average' of the measured variable scores.

From Stage #4 we go to Stage #1, and make a guess at the values of the path coefficients between each latent construct, as simply +1 or -1, depending on the value of the covariance between each of our initial latent construct guesses.

Stage #2 results in revised values for the latent constructs, via a regression between each latent construct and each of its driving constructs, again using our initial guesses as to the values of the predictor constructs.

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Lastly, in Stage #3:

- If we are modelling formatively, the initial sets of weights from Stage #4 are revised by undertaking a multiple regression of the actual measured value scores (the *y*'s) on the associated latent construct(s)
- If we are modelling reflectively, the initial sets of weights from Stage #4 are revised by undertaking a simple regression of each latent construct *Y* on the actual scores for the associated measured variables (the *y*'s).

Sounds crazy? It works.

FIGURE 9

Stage 1:	Iterative estimation of weights and LV scores Starting at step #4, repeat steps #1 to #4 until convergence is obtained.
#1	Inner weights $v_{ji} = \begin{cases} \text{sign}\,\text{cov}(Y_j; Y_i) & \text{if } Y_j \text{ and } Y_i \text{ are adjacent} \\ 0 & \text{otherwise} \end{cases}$
#2	Inside approximation $\tilde{Y}_j := \sum_i v_{ji} Y_i$
#3	Outer weights; solve for w_{k_j} in $\tilde{Y}_{jn} = \sum_{k_j} \tilde{w}_{k_j} y_{k_j n} + d_{jn}$ in a ModeA block $y_{k_j n} = \tilde{w}_{k_j} \tilde{Y}_{jn} + e_{k_j n}$ in a ModeB block
#4	Outside approximation $Y_{jn} := f_j \sum_{k_j} \tilde{w}_{k_j} y_{k_j n}$
Stage 2:	Estimation of path and loading coefficients
Stage 3:	Estimation of location parameters

Source: Lohmöller (1989)

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9. DRAWBACKS ?

It all sounds so fine, that one is tempted to ask: “There must be a catch ... what is it?”

In fact, there is a catch, as Haenlein and Kaplan (2004) lucidly point out. Specifically:

- Because the case values for the latent variables in PLS are aggregates of manifest variables that involve measurement error, they must be considered as inconsistent – that is they do not converge in probability to the value of the parameter being estimated as the sample size increases.

- In fact “...the path coefficients estimated through PLS converge on the parameters of the latent-variable model [only] as both the sample size and the number of indicators of each latent variable become infinite” (Here, Haenlein and Kaplan quote McDonald, 1996).

- Hence in situations in which both the number of cases in the sample and the number of indicators per latent variable will be finite, PLS tends to <u>underestimate</u> the correlations between the latent variables and <u>overestimate</u> the loadings that connect the latent variables with the measured variables.

- The immediate implication is that PLS might be better suited to situations in which covariance-based SEM tools reach their limit, namely, when the number of indicators per latent variable becomes large. [In the latter case, it is easy to show that the sample covariance matrix can easily reach a size that is difficult to handle with conventional computer systems. Haenlein and Kaplan give an example of a SEM with five latent variables, each measured by 200 indicators, which (using a conventional approach to calibration) would require the estimation of a covariance matrix with over 500,000 elements!]

On the other hand, as we have already discussed, regardless of considerations of sample size, a PLS approach <u>will</u> result in a solution to a SEM problem in which the use of covariance-based approaches will produce negative variance estimates, and correlations or r-square values greater than one.

A PLS approach will almost always work even in cases where the sample size is ludicrously small.

10. AN EXAMPLE

Data were collated from a brand equity study of airline brands in Europe. Because of the sensitivity of the information the variables involved have, unfortunately, been required to be heavily disguised. So heavily, in fact, that I gave up on the idea of using the data in their original guise (hence the need for <u>dis</u>-guisement !).

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So let's pretend that these data in fact relate to a simplified Happiness-Prosperity model, with three indicators (measured variables) for each of two latent constructs.

An initial model, entirely conventional (and fully reflective) in format, could look like that in Figure 10.

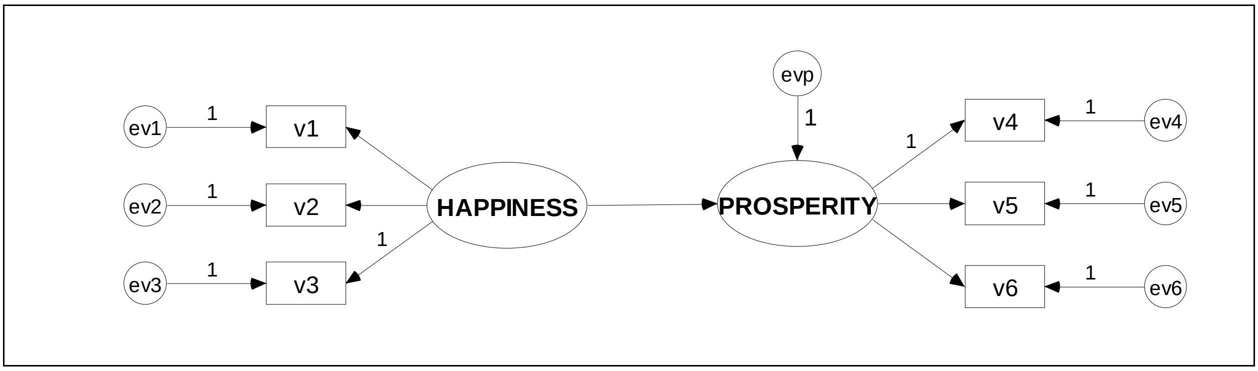
Development of a solution via AMOS results in the outputs shown in Figure 11.

What do we notice?

- The key fit indices are pretty good. In fact the Goodness of Fit (GFI) Index[3] is very high, with a value of 0.98 and the Comparative Fit Index (CFI) similarly high, with a value of 0.99.
- All factor loadings are satisfactorily high (with the possible exception of that for v1).
- BUT (and this is a big but), the Squared Multiple Correlation (essentially an r-square value) for the regression between Prosperity and Happiness is 1.01. In other words, it's larger than unity, which is impossible.
- Similarly, if we were to inspect the detailed output we would see that the variance estimate for the error term 'evp' is in fact 'slightly' negative, also impossible.

So our conventional modelling approach has not worked.

FIGURE 10



3 I am indebted to Katrina White for the notion that GFI could be alternatively expressed as a "Gut Feel Index" !

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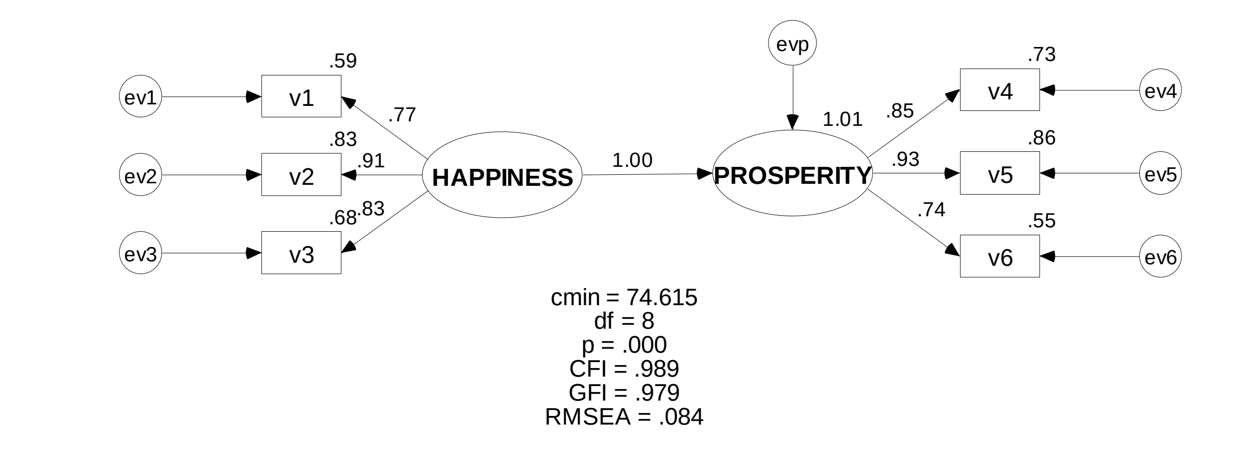
FIGURE 11



Let's try a slightly different formulation, this time with the 'Happiness' factor being modelled on a formative, rather than reflective, basis as in Figure 12.

What happens this time? Precisely nothing. Or to be more precise, the solution fails to converge, in fact fails to do anything, due to a lack of identification.

So, using our rules of thumb discussed earlier, we can introduce an additional indicator for 'Happiness', as shown in Figure 13, with calibration results shown in Figure 14.

FIGURE 12

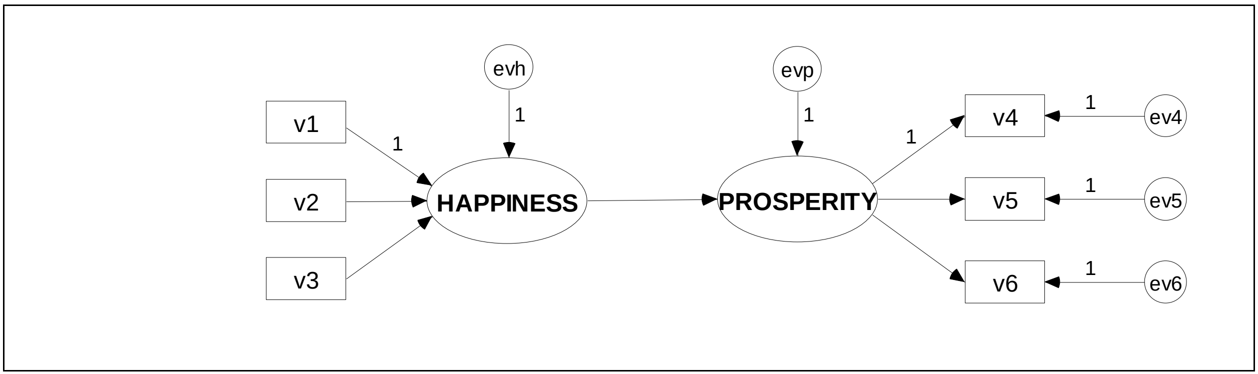


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FIGURE 13

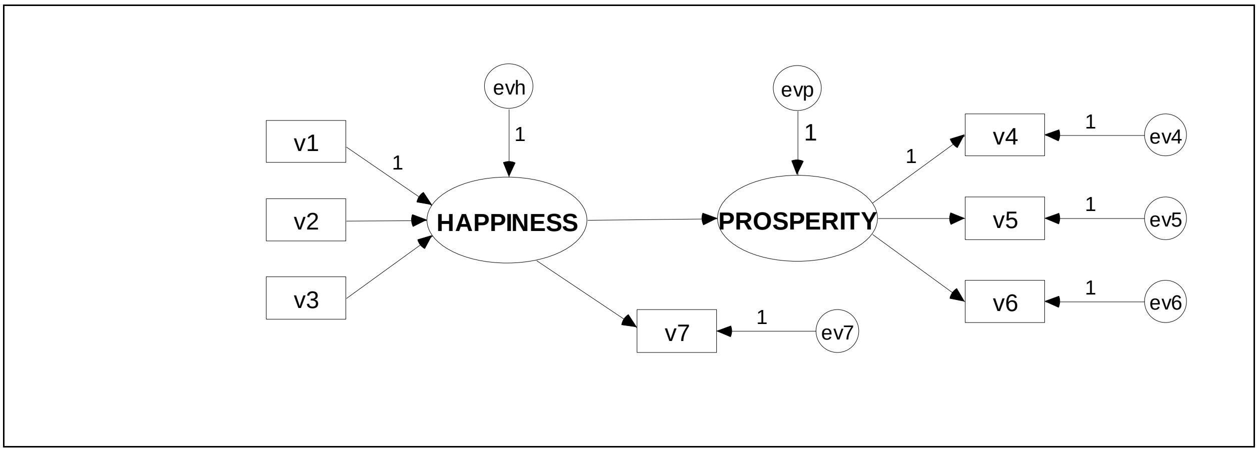
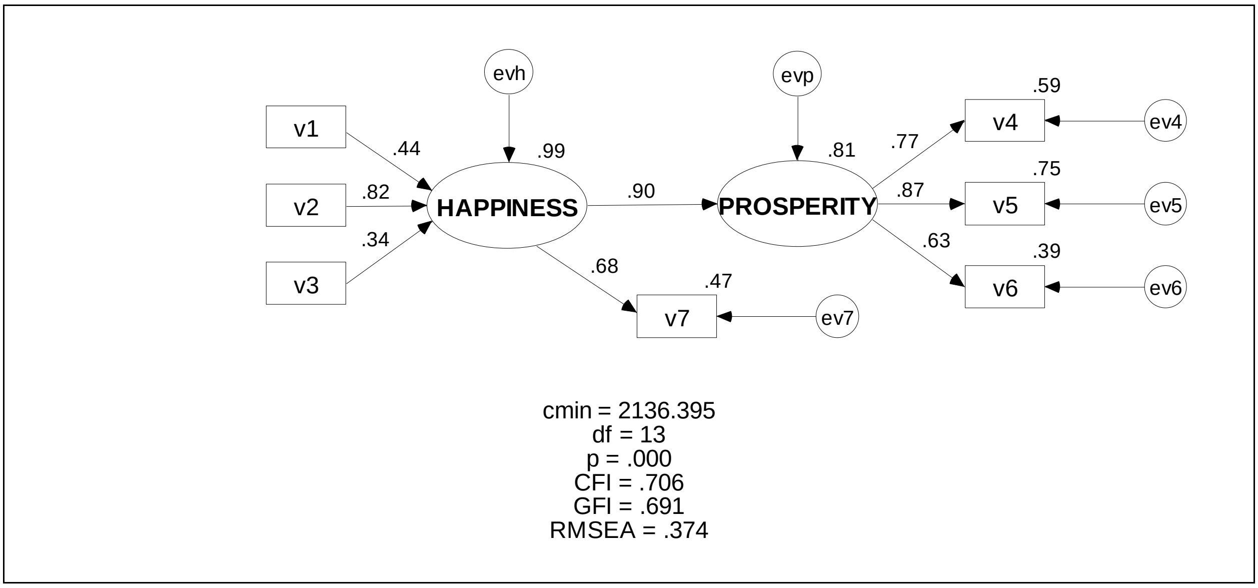


FIGURE 14



This time we achieve success, with no nasties such as negative variance estimates, although on the down side, the fit does not look too flash.

Let's now repeat the whole exercise using a PLS approach.

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Figure 15 shows the original model, as presented in Figure 10, this time formulated in a PLS format using Smart-PLS.

FIGURE 15

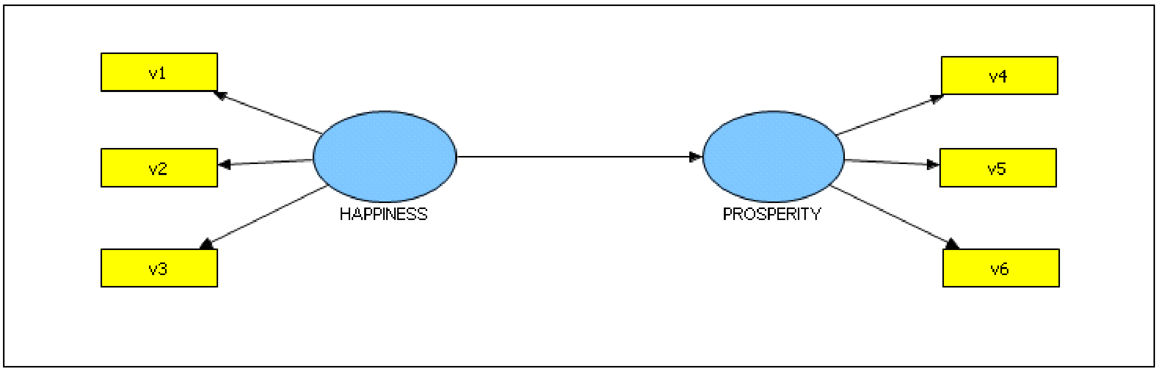
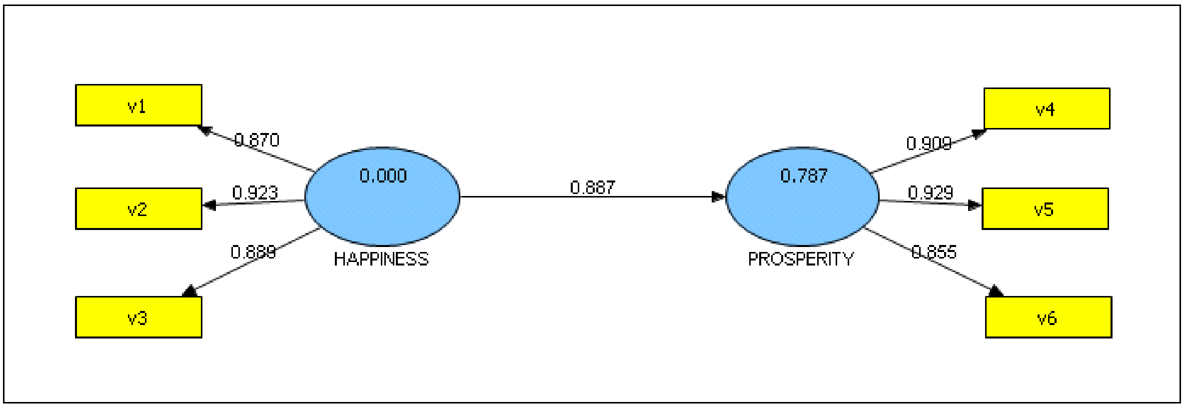


Figure 16 shows the results of calibration, using the Smart-PLS software. In contrast to the results shown in Figure 10, the r-square value for the relationship is 'sensible', at 0.79.

FIGURE 16



With 'Happiness' modelled formatively, as in Figure 17, the PLS solution also converges, unlike the covariance-based approach.

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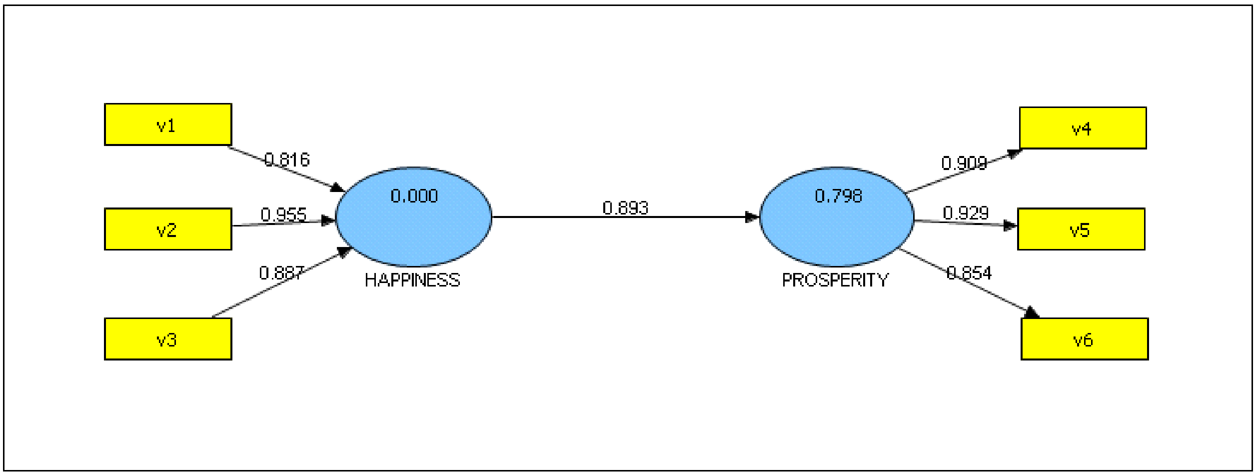
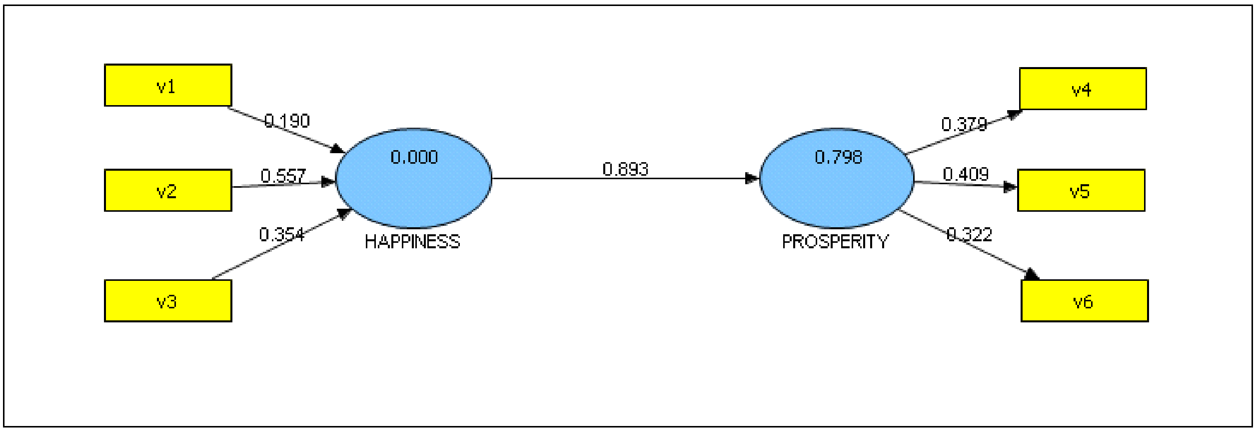
FIGURE 17



It can be seen that there is no need for the machinations of Figures 13/14 to ensure that a valid solution will be obtained.

Figure 18 shows the same model, this time with the (outer) weights shown. Note that this model is the exact equivalent of that shown in Figure 17, except the latter shows the factor loadings, rather than the outer weights.

FIGURE 18



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11. CONCLUSION

We have seen that:

- Virtually all SEM conducted in recent years has involved purely reflective factor modelling.
- In around <u>one-third</u> of cases over a 24 year period, where results were published in respected academically-oriented market research and marketing science journals, this was ***the wrong thing to do***.
- SEM can be difficult to handle at the best of times, and when formative elements are included, the conventional covariance-based approaches to calibration can easily collapse.
- The PLS approach to calibration of SEMs offers the twin advantages of (a) being robust (ie. usually always resulting in a stable solution) and (b) being able readily to deal with formative modelling.

This whole subject is difficult – much of the literature is confusing and difficult to follow (at least for the present writer !).

If you are interesting in following up some of the ideas presented in this paper, I would urge you to consult some of the references presented – most of these are available as pdf's or in other readable formats. I would, in particular, recommend Haenlein and Kaplan (2004) for a general introduction to PLS- versus covariance-based SEM modelling, Garson (2007) for a solid background to covariance-based SEM, and Diamantopoulos and Winklhofer (2001) and Jarvis *et al* (2003) for comprehensive discussions of the formative *versus* reflective issue.

********************** **FIN** ***********************

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