Multicollinearity in Marketing Models: Notes on the Application of Ridge Trace Estimation in Structural Equation Modelling

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Abstract: Multicollinearity in Structural Equation Modelling (SEM) is often overlooked by marketing scholars. This is unfortunate as multicollinearity may lead to fallacious path coefficient estimates or even bring about statistical non-significance of the parameter estimates. Previous empirical illustrations on mitigating the effects of multicollinearity are virtually non-existent in the literature. The purpose of this paper is to empirically illustrate the problem of multicollinearity in marketing models and the use of ridge trace estimation in mitigating the effects of multicollinearity in SEM, using the LISREL program. Two slightly differing ridge estimation procedures are illustrated using real data with a multicollinearity problem: Method A, in which the ridge constant is added manually to all diagonal elements of the correlation matrix of the variables in the model, and Method B, in which the ridge constant is added manually only to the diagonal elements of the correlation matrix of the exogenous and *explanatory* endogenous variables in the model. In evaluating suitable values of the ridge constant, the ridge trace method is used. It is concluded that ridge trace estimation is an effective way of mitigating the effects of multicollinearity in SEM. With same ridge constant values, both methods produce same point estimates of path coefficients, but Method B produces smaller standard errors of parameter estimates and larger squared multiple correlations than Method A.

Keywords: marketing modelling, multicollinearity; structural equation modelling; ridge trace estimation; LISREL

1. Introduction

Structural equation modelling (SEM) is particularly useful for marketing research that often deals with models consisting of unobserved theoretical constructs (e.g. benefits, attitudes, value, customer satisfaction) that may only be measured through observable indicators (Steenkamp & Baumgartner, 2000). Indeed, the advantages of SEM, such as its ability to account for measurement error and manage multiple endogenous variables, have probably contributed to its spread among marketing scholars (Steenkamp & van Trijp, 1991; Steenkamp & Baumgartner, 2000). From the 1970s to the early 1990s the use of SEM increased fairly steadily among marketing scholars (Baumgartner & Homburg, 1996). Following a clear decrease in published papers at the end of the 20th century, in the 21st century the use of SEM in marketing modelling has achieved a phase of maturity (Martinez-López et al., 2013). SEM is a commonly used tool for theory testing in marketing research. In fact, articles in which SEM is used appear frequently in most major marketing and consumer behaviour journals (Baumgartner & Homburg, 1996; Steenkamp & Baumgartner, 2000; Martinez-López et al. 2013).

Extensive use of SEM has naturally also led to the appearance of articles addressing problem areas and suggesting improvements for future modelling (e.g. Baumgartner & Homburg, 1996; Hulland et al., 1996; Grewal et al., 2004). Regardless of its maturity, application of SEM in marketing research has a need for improvement (Martinez-López et al., 2013). As Baumgartner and Homburg (1996) have stated, SEM may be a dangerous tool in the hands of inexperienced users. The quality of marketing knowledge generated based on marketing research using SEM is dependent on how well researchers apply this methodology (Martinez-López et al., 2013). One of the possible issues encountered in using SEM is multicollinearity, that is, high correlations between the latent exogenous variables. This is one of the potential problems that marketing science models in general suffer from (Leeflang, 2011). Overall, correlation between exogenous variables is a fact of life in survey research (Grapentine, 2000) and in marketing models these explanatory variables are often highly correlated with each other (Mahajan et al., 1977, see also Grewal et al., 2004).

Unfortunately, multicollinearity is frequently overlooked by marketing scholars. To prove this point Grewal et al. (2004) reviewed 42 articles using either confirmatory factor analysis or SEM that had been published in the 1999 and 2000 issues of the Journal of Marketing, Journal of Marketing Research and Journal of the Academy of Marketing Science. They found that although potential multicollinearity problems could be assessed for 31

Reference this paper as: Niemelä-Nyrhinen J and Leskinen E. "Multicollinearity in Marketing Models: Notes on the Application of Ridge Trace Estimation in Structural Equation Modelling" *The Electronic Journal of Business Research Methods, Volume 12 Issue 1 2014 (pp 3-15),* available online at www.ejbrm.com

of the studies through the published correlation matrix, not a single article discussed how multicollinearity might have affected the results.

Grewal et al. (2004) speculate on the reasons behind this unfortunate dismissal of multicollinearity by marketing researchers and suggest that one basic cause might be an assumption that multicollinearity does not pose a problem in SEM. However, this is a severe misconception. As in other econometric models, in SEM the reliability of one's results may suffer due to multicollinearity (Jagpal, 1982). Multicollinearity may lead to fallacious parameter estimates and even induce statistical non-significance of parameter estimates (Grewal et al., 2004), consequently leading to misguided interpretation or elimination of important predictors from the model. Another basic cause of the dismissal of multicollinearity problems among marketing scholars may simply be a lack of knowledge of how to deal with these problems in the context of SEM (Grewal et al., 2004).

This paper proposes ridge estimation as one possible way of mitigating the effects of multicollinearity in SEM using the LISREL program (Jöreskog & Sörbom, 2005). Although ridge regression analysis has for long been one of the most popular approaches to addressing multicollinearity among marketing scholars (Subhash & William, 1981), to date ridge-type estimation is not commonly used in the SEM context and illustrations of its use seem virtually absent from the literature (for one rare exception see Jagpal, 1982). The main purpose of this paper is to empirically illustrate the problem of multicollinearity and the use of ridge estimation in mitigating the effects of multicollinearity in SEM. Two slightly differing ridge estimation procedures (Method A and B) are illustrated. For these illustrative purposes the Technology Acceptance Model (TAM), (Davis, 1989; Davis et al., 1992) is used.

2. An illustrative example

In the example data an extremely high correlation (0.97) between two latent exogenous variables (see Table 1), namely perceived usefulness and enjoyment, was found. This finding was somewhat unexpected and alternative explanations that are related to the particular target group, novelty of the services and nature of the services studied may be advanced. In any case, the data provides a particularly good example that may be used to illustrate the options available to mitigate effects of multicollinearity in SEM. Further, TAM provides a current example of multicollinearity because a great deal of the current effort expended on marketing modelling is likely to be directed at the issues in the field of electronic business (Mahajan & Venkatesh, 2000). The example data, used in this paper, are drawn from a study that aimed to explain acceptance of *mobile content services* among Finnish baby boomers (Niemelä-Nyrhinen, 2009). Examples of mobile content services include mobile news, mobile banking, downloading ring tones or logos, mobile shopping, mobile games and mobile ticketing.

2.1 Technology Acceptance Model, TAM

TAM is tailored to model user acceptance of information systems with the objective of both explaining and predicting user behaviour across a wide range of technologies and user populations (see Figure 1). TAM uses Fishbein and Ajzen's (1975) Theory of Reasoned Action (TRA) as a theoretical basis on which to explicate causal linkages between the variables in the model (Davis et al., 1989). Although TAM was originally created to explain user acceptance of information technology at work (Venkatesh & Davis, 2000), over the years it has been successfully applied to consumer acceptance as well (see e.g., Moon & Kim, 2001; Dabholkar & Bagozzi, 2002; van der Heijden, 2003; Pavlou, 2003; Curran & Meuter, 2005; Kim & Forsythe, 2009).

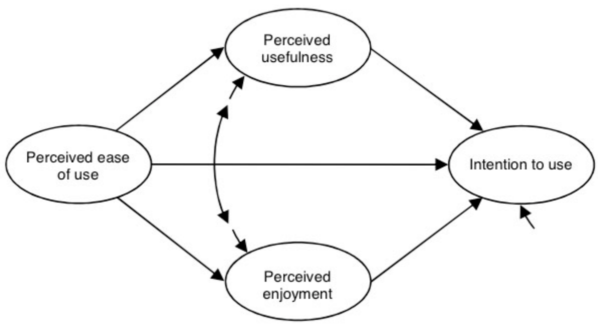

Figure 1: Technology Acceptance Model, TAM

The original TAM posited that technology acceptance can be explained by two beliefs, namely *perceived usefulness* and *perceived ease of use*. In addition to the belief-intention links, TAM states that ease of use has an effect on usefulness (Davis et al., 1989). This relation is very logical – the easier a system is, the more useful it can be (Venkatesh & Davis, 2000). Later Davis et al. (1992) made an important addition to TAM, namely a belief called *perceived enjoyment*. Taking into account the fact that many technological applications now include entertaining elements, it is important that a model explaining technology acceptance includes, in addition to utilitarian aspects, hedonic aspects too. Further, just as perceived ease of use influences usefulness, it is likely to influence perceived enjoyment, because systems that are difficult to use are less likely to be perceived as enjoyable (Teo et al., 1999).

2.2 Construct measurement

The survey instrument (see Appendix A) was developed using existing scales for the belief constructs and behavioural intention. Four of Davis's (1989) usefulness items were used. Two of the items in the original scale were left out since their wording heavily stressed work-related goals. Perceived ease of use was measured with four items adapted from Davis et al. (1989). The three items used to measure perceived enjoyment were adapted from Venkatesh (2000). For measurement of behavioural intention three items recommended by Ajzen (2002) were applied. In measuring these constructs, a seven-point Likert-scale was used with completely disagree and completely agree as anchors. For the scales used, high scale reliability was indicated by Cronbach alphas ranging from 0.82 to 0.87 (Niemelä-Nyrhinen, 2009).

2.3 Data collection and descriptive statistics

The data used in this paper were gathered through a structured postal questionnaire in 2005. It is part of a wider quantitative study of Finnish baby boomers and their usage of new innovative technological services (Niemelä-Nyrhinen, 2009). Finnish people born between 1945 and 1955 (aged between 50 and 60 at the time of the survey) were included in the sample. The sample was provided by the Population Register Centre of Finland and it was drawn from all Finnish-speaking Finns through random sampling. Gathering data on such advanced mobile content services is possible in Finland since mobile technology for communication purposes has been widely adopted. A total of 1500 surveys were mailed and 620 usable responses were gathered (response rate 41.3 per cent). A high response rate was expected as in our experience 50+ consumers respond relatively conscientiously to mail surveys. More females (58.8 per cent) than males (41.2 per cent) returned the survey questionnaire. Ages ranged from 50 to 60 years, with an average age of 55. Following the instructions given by Jöreskog (2005) missing values were imputed to the data by "matching on other variables", a procedure that is available in PRELIS. After imputation the data with no missing values, fit for use in the analyses, consist of 584 cases (Jöreskog & Sörbom, 2005).

2.4 Estimation results of TAM

The measurement models and the structural model were estimated using the LISREL program (Jöreskog & Sörbom, 2005). After a separate estimation of each measurement model, the measurement model with all four factors of TAM was estimated. Exact fit is rejected ($\chi^2(71) = 178.48$, $p = 0.000$), but rather good fit is implied by the following: RMSEA = 0.051, 90 per cent confidence interval for RMSEA = (0.042 ; 0.060), p-value for test of close fit (RMSEA<0.05) = 0.42, CFI = 0.98 and NFI = 0.97. The correlations of the latent variables are high, particularly the correlation between perceived enjoyment and perceived usefulness (see Table 1). However, these correlations support the use of TAM.

Table 1: The estimated correlation matrix of the latent variables measurement model (standard errors in parenthesis), N= 584

	η_3	η_2	η_1	ξ
intention, η_3	1.00000			
enjoyment, η_2	0.91073	1.00000		
	(.01512)			
usefulness, η_1	0.93506	0.97096	1.00000	
	(.01461)	(.01199)		
ease of use, ξ	0.72233	0.77531	0.78238	1.00000
	(.02829)	(.02428)	(.02638)	

A sequential χ^2 test was performed to assure the discriminant validity of usefulness and enjoyment. In other words, a check was performed to see that usefulness and enjoyment form not one but two separate factors. According to this test the factors should be kept separate ($\chi^2(1) = 4.73$, $p = 0.0296$). Also from a theoretical point of view this seems more reasonable. The latent variable pairs of usefulness-intention and enjoyment-intention also have correlations above 0.9 (see Table 1). To assure discriminant validity sequential χ^2 tests were performed. These tests clearly show that usefulness is a distinct construct from intentions ($\chi^2(1) = 35.13$, $p < 0.001$) and that enjoyment is a distinct construct from intentions ($\chi^2(1) = 36.37$, $p < 0.001$). Following the sequential χ^2 tests, the structural relationships of TAM were estimated (see the estimation results in Figure 2).

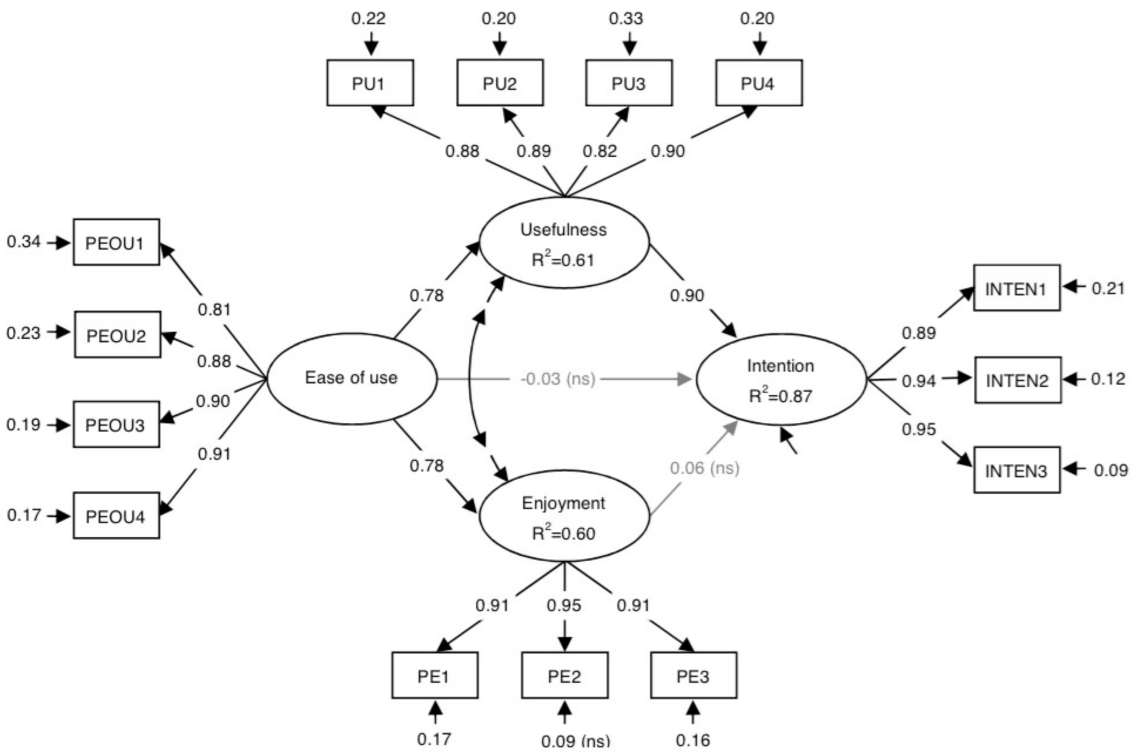

Figure 2: The estimation results for Technology Acceptance Model

The goodness-of-fit results of the estimated TAM equated with the previous four-latent-variables measurement model because of the data-equivalence of the models. Hypothesized effects are found: ease of use has a strong positive effect on both usefulness (standardized $\gamma_1 = 0.782$, $t = 21.76$) and enjoyment (standardized $\gamma_2 = 0.775$, $t = 22.29$). Usefulness in turn seems to have a strong positive effect on intention (standardized $\beta_1 = 0.897$, $t = 2.95$). Exceptional results are the effect of ease of use on intention (standardized $\gamma_3 = -0.026$, $t = -1.110$) and of enjoyment on intention (standardized $\beta_2 = 0.060$, $t = 0.985$), which are found to be non-significant. The effect of ease of use on intention is mediated by usefulness. Its standardized indirect effect on intention is positive and strong (0.749, $t = 13.02$). Ease of use explains approximately 60 per cent of the variance in both usefulness (squared multiple correlation, $R^2 = 0.61$) and enjoyment ($R^2 = 0.60$). The absence of significant effects of enjoyment on intention and ease of use on intention seems dubious since the correlation between enjoyment and intention is very high (0.91) and the correlation between ease of use and intention is high (0.72) (see Table 1 above).

3. Ridge estimation strategy

3.1 Model and data

We analyse the following recursive structural equations model (TAM) between the four factors:

$\eta_1 = \gamma_1\xi + \zeta_1,$ (1)

$\eta_2 = \gamma_2\xi + \zeta_2,$ (2)

$\eta_3 = \beta_1\eta_1 + \beta_2\eta_2 + \gamma_3\xi + \zeta_3,$ (3)

in which $\mathrm{cov}(\zeta_2, \zeta_1) = \psi_{21}$ is also estimated. The corresponding graph is presented in Figure 3.

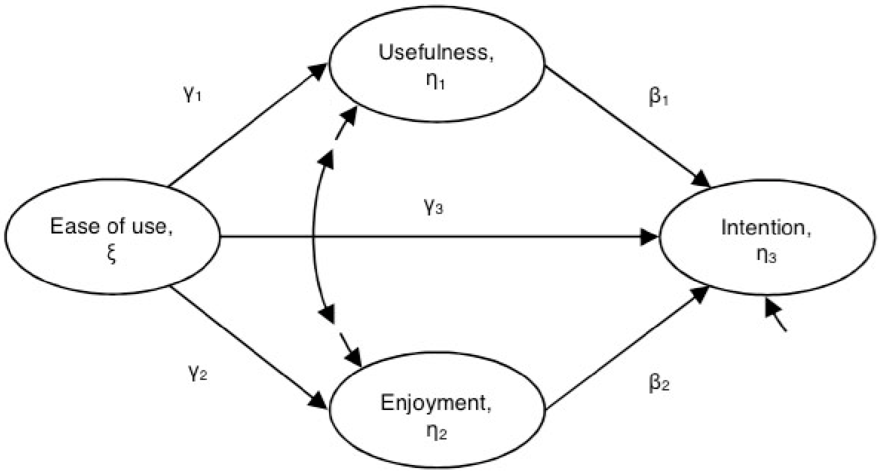

Figure 3: The parameterization of Technology Acceptance Model

Data used for ridge estimation consists of the correlation matrix given in Table 1. In order to reduce effects of multicollinearity between latent variables, we added the ridge constant to the correlation matrix given in Table 1 (see e.g., Grewal et al., 2004; Kuusinen & Leskinen, 1988).

The ridge estimation procedures are constructed in two ways, termed Method A and Method B. In *Method A* the ridge constant *k* is added to all the diagonal elements of the correlation matrix of the variables in the model (see Gunst at al., 1976) as latent root regression, and the ridge option available in the LISREL program (Jöreskog & Sörbom, 2005; Yuan & Chan, 2008). In *Method B* the ridge constant *k* is added only to the diagonal elements of the correlation matrix of the *explanatory* endogenous and exogenous variables as the ordinary ridge regression method (see Hoerl & Kennard, 1970). Table 2 below displays the collected characteristics of correlation matrices to the ridge estimation Methods A and B (see also Ofir & Khuri, 1986).

Table 2: Detecting and analysing multicollinearity between latent variables

	$\|R\|$	$\lambda_{\min}$	$\lambda_{\max}/\lambda_{\min}$	$\sum_{i=1}^{p}\frac{1}{\lambda_i}$	VIF-range
A R_{4x4}	0.00276	0.0260	136.90	52.748	2.613 - 24.536
B R_{3x3}	0.02215	0.0292	91.97	38.123	2.607 - 18.006

Note 1. $|R|$ is the determinant of R and λ's are eigenvalues of R.

Note 2. R is the 4x4-correlation matrix of η_3, η_2, η_1 and ξ for Method A, and R is 3x3-correlation matrix of η_2, η_1 and ξ for Method B, respectively.

All these values indicate strong collinearities between variables. The smallest eigenvalues are close to zero, and these values also affect other values presented in Table 2. For example, a small value of determinant of 3x3 correlation matrix R, $|R|$ = 0.02215 may be an effect of the estimation results of the model.

Further, for example, collinearity interpretations of the results of the correlation matrix by using Method B are as follows: The correlation matrix is the 3x3 correlation matrix of the variables η_2, η_1 and ξ. The value of the smallest eigenvalue λ is .0292, which is close to zero, indicating strong collinearity between explanatory variables in Equation 3.

The collinearity equation between explanatory variables can be evaluated as follows: The eigenvector corresponding to the smallest eigenvalue is

$$(.7012, -.7128, .0145)^T,$$

from which we derive the following collinearity relation between explanatory variables

$$.7012\eta_2 - .7128\,\eta_1 + .0145\xi = .0292 \approx 0.$$

Because the coefficient of the eigenvector for the variable ξ is close to zero, this variable is out of the collinearity equation, and then it can be seen that the collinearity relation is approximately

$\eta_2 - \eta_1 \approx 0$ or $\eta_2 \approx \eta_1$.

The ridge estimation procedures A and B were carried out by manually adding the ridge constant to the correlation matrices and by using the LISREL program. The SIMPLIS input files for Ridge Method A and B, Ridge constant k = .10 are provided below:

```
Testing TAM Ridge Method A
Observed variables: inten enjoy useful ease
Correlation matrix:
1.10000
0.91073    1.10000
0.93506    0.97096    1.10000
0.72233    0.77531    0.78238    1.10000
Sample size: 584
Relationships:
inten = useful enjoy ease
enjoy = ease
useful = ease
Set the Covariances of useful and enjoy free
LISREL Output: ME=GLS SC MI EF ND=5
Path Diagram
End of Problem
```

```
Testing TAM Ridge Method B
Observed variables: inten enjoy useful ease
Correlation matrix:
1.00000
0.91073    1.10000
0.93506    0.97096    1.10000
0.72233    0.77531    0.78238    1.10000
Sample size: 584
Relationships:
inten = useful enjoy ease
enjoy = ease
useful = ease
Set the Covariances of useful and enjoy free
LISREL Output: ME=GLS SC MI EF ND=5
Path Diagram
End of Problem
```

3.2 Results of ridge trace estimation

3.2.1 Results of ridge trace estimation for TAM

In Figure 4, the ridge trace (k between 0.00 – 0.50) for the TAM is presented. It should be noted that ridge point estimation results are same for both Methods A and B.

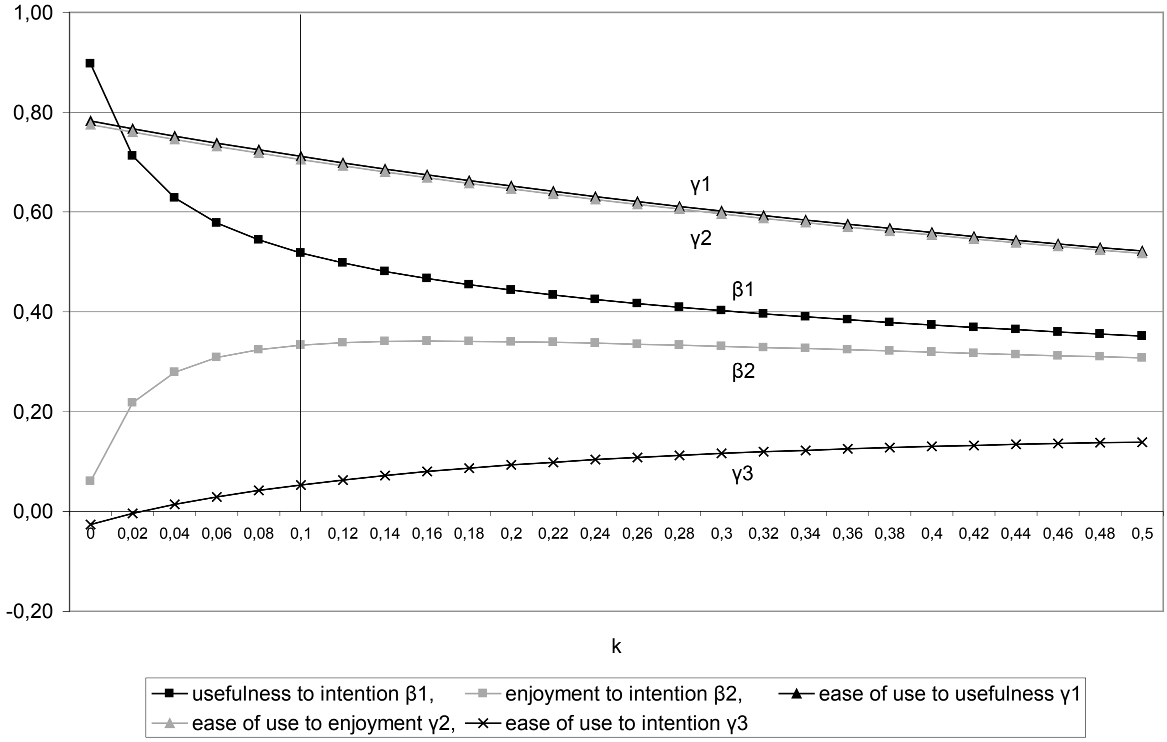

Figure 4: Equal ridge traces for Methods A and B

Furthermore, Tables 3 and 4 below present the ridge estimation results with corresponding standard errors and t-values for Methods A and B, respectively. In addition, the squared multiple correlations R^2 for the three equations are given.

Table 3: Estimation results by using Ridge Method A

Ridge constant k	β_1	β_2	γ_1	γ_2	γ_3	R^2_1	R^2_2	R^2_3
0	0.897	0.060	0.782	0.775	-0.026	0.61	0.60	0.87
(s.e.)	(.062)	(.061)	(.026)	(.026)	(.024)			
t-value	14.409	0.985	30.306	29.615	-1.110			
0.02	0.712	0.218	0.767	0.760	-0.004	0.59	0.58	0.84
(s.e.)	(.054)	(.054)	(.027)	(.027)	(.026)			
t-value	13.071	4.055	28.841	28.220	-0.148			
0.04	0.628	0.279	0.752	0.745	0.014	0.57	0.56	0.82
(s.e.)	(.051)	(.050)	(.027)	(.028)	(.027)			
t-value	12.422	5.575	27.547	26.983	0.515			
0.06	0.578	0.308	0.738	0.731	0.029	0.54	0.53	0.79
(s.e.)	(.048)	(.048)	(.028)	(.028)	(.028)			
t-value	11.987	6.457	26.392	25.876	1.023			
0.08	0.544	0.324	0.724	0.718	0.042	0.52	0.52	0.77
(s.e.)	(.047)	(.046)	(.029)	(.029)	(.029)			
t-value	11.648	7.009	25.352	24.877	1.429			
0.10	**0.518**	**0.333**	**0.711**	**0.705**	**0.053**	**0.51**	**0.50**	**0.75**
(s.e.)	**(.046)**	**(.045)**	**(.029)**	**(.029)**	**(.030)**			
t-value	**11.363**	**7.369**	**24.410**	**23.970**	**1.764**			
0.12	0.498	0.338	0.699	0.692	0.063	0.49	0.48	0.73
(s.e.)	(.045)	(.044)	(.030)	(.030)	(.031)			
t-value	11.114	7.607	23.551	23.141	2.044			
0.14	0.481	0.340	0.686	0.680	0.072	0.47	0.46	0.71
(s.e.)	(.044)	(.044)	(.030)	(.030)	(.032)			
t-value	10.890	7.766	22.764	22.380	2.281			
0.16	0.467	0.341	0.674	0.668	0.080	0.45	0.45	0.69
(s.e.)	(.044)	(.043)	(.031)	(.031)	(.032)			
t-value	10.686	7.870	22.039	21.677	2.485			
0.18	0.454	0.341	0.663	0.657	0.087	0.44	0.43	0.68
(s.e.)	(.043)	(.043)	(.031)	(.031)	(.033)			
t-value	10.497	7.935	21.367	21.027	2.661			
0.20	0.443	0.340	0.652	0.646	0.093	0.43	0.42	0.66
(s.e.)	(.043)	(.043)	(.031)	(.032)	(.033)			
t-value	10.322	7.971	20.744	20.421	2.814			
⋮								
0.50	0.352	0.308	0.522	0.517	0.139	0.27	0.27	0.47
(s.e.)	(.041)	(.041)	(.035)	(.035)	(.037)			
t-value	8.538	7.492	14.748	14.566	3.790			

Table 4: Estimation results by using Ridge Method B

Ridge constant k	β_1	β_2	γ_1	γ_2	γ_3	R^2_1	R^2_2	R^2_3
0	0.897	0.060	0.782	0.775	-0.026	0.61	0.60	0.87
(s.e.)	(.062)	(.061)	(.026)	(.026)	(.024)			
t-value	14.409	0.985	30.306	29.615	-1.110			
0.02	0.712	0.218	0.767	0.760	-0.004	0.59	0.58	0.86
(s.e.)	(.051)	(.050)	(.027)	(.027)	(.024)			
t-value	13.984	4.338	28.841	28.22	-0.159			
0.04	0.628	0.279	0.752	0.745	0.014	0.57	0.56	0.85
(s.e.)	(.045)	(.044)	(.027)	(.028)	(.024)			
t-value	13.996	6.281	27.547	26.983	0.580			
0.06	0.578	0.308	0.738	0.731	0.029	0.54	0.53	0.84
(s.e.)	(.041)	(.041)	(.028)	(.028)	(.024)			
t-value	14.087	7.588	26.392	25.876	1.202			
0.08	0.544	0.324	0.724	0.718	0.042	0.52	0.52	0.83
(s.e.)	(.038)	(.038)	(.029)	(.029)	(.024)			
t-value	14.183	8.535	25.352	24.877	1.740			
0.10	**0.518**	**0.333**	**0.711**	**0.705**	**0.053**	**0.51**	**0.50**	**0.83**
(s.e.)	**(.036)**	**(.036)**	**(.029)**	**(.029)**	**(.024)**			
t-value	**14.265**	**9.251**	**24.410**	**23.97**	**2.214**			
0.12	0.498	0.338	0.699	0.692	0.063	0.49	0.48	0.82
(s.e.)	(.035)	(.034)	(.030)	(.030)	(.024)			
t-value	14.331	9.809	23.551	23.141	2.635			
0.14	0.481	0.340	0.686	0.680	0.072	0.47	0.46	0.81
(s.e.)	(.033)	(.033)	(.030)	(.030)	(.0240)			
t-value	14.380	10.255	22.764	22.380	3.012			
0.16	0.467	0.341	0.674	0.668	0.080	0.45	0.45	0.80
(s.e.)	(.032)	(.032)	(.031)	(.031)	(.024)			
t-value	14.415	10.616	22.039	21.677	3.352			
0.18	0.454	0.341	0.663	0.657	0.087	0.44	0.43	0.80
(s.e.)	(.031)	(.031)	(.031)	(.031)	(.024)			
t-value	14.438	10.913	21.367	21.027	3.660			
0.20	0.443	0.340	0.652	0.646	0.093	0.43	0.42	0.79
(s.e.)	(.031)	(.030)	(.031)	(.032)	(.024)			
t-value	14.450	11.159	20.744	20.421	3.940			
⋮								
0.50	0.352	0.308	0.522	0.517	0.139	0.27	0.27	0.71
(s.e.)	(.025)	(.025)	(.035)	(.035)	(.022)			
t-value	14.085	12.360	14.748	14.566	6.253			

When k = 0, estimations of parameters produce statistically non-significant results for parameter β_2 = 0.060 (t = 0.985) and parameter γ_3 = -0.026 (t = -1.110), as was noted in Section 2.4 above.

In evaluating appropriate values for the ridge constant k, the value k = .10 is chosen, because the ridge trace values of estimates seem to become rather stable beyond that value. This ridge solution gives the following estimation results:

Method A, k = .10

$$\eta_1 = .711\xi\,,\ R^2 = .51 \qquad (1)$$
$$\underset{t\,=\,24.4}{(.029)}$$

$$\eta_2 = .705\xi\,,\ R^2 = .50 \qquad (2)$$
$$\underset{t\,=\,23.97}{(.029)}$$

$$\eta_3 = .518\eta_1 + .333\eta_2 + .053\xi\,,\ R^2 = .75 \qquad (3)$$
$$(.046)\quad (.045)\quad (.030)$$
$$t = 11.36 \quad 7.37 \quad 1.76$$

Method B, k = .10

$$\eta_1 = .711\xi\,,\ R^2 = .51 \qquad (1)$$
$$\underset{t\,=\,24.4}{(.029)}$$

$$\eta_2 = .705\xi\,,\ R^2 = .50 \qquad (2)$$
$$\underset{t\,=\,23.97}{(.029)}$$

$$\eta_3 = .518\eta_1 + .333\eta_2 + .053\xi\,,\ R^2 = .83 \qquad (3)$$
$$(.036)\quad (.036)\quad (.024)$$
$$t = 14.27 \quad 9.81 \quad 2.21$$

The results of point ridge estimations in Equations 1-3 are the same for both Methods A and B. However, the estimated standard errors in Equation 3 are larger for Method A than for Method B, which produce smaller t-values for Method A than Method B, respectively. Therefore, for example, the chosen ridge constant k = .10 produces estimation results for Equation 3, in which the estimate of γ_3 is non-significant using Method A (t = 1.76) but significant using Method B (t = 2.21, at a 5 per cent significance level). The differences in these results are caused by adding in Method A the ridge constant also into the diagonal element of dependent variable η_3 in the correlation matrix R. From this it also follows that the estimated squared correlation coefficients R^2_3 are smaller for Equation 3 in using Method A than when using Method B, see Tables 3 and 4.

3.2.2 Estimation results of indirect effects

Finally, indirect effects between ease of use and intention are considered, see Table 5 (see also MacKinnon, 2008). The special indirect effects are estimated using the M*plus* program, Version 6.0 (Muthén & Muthén, 1998 – 2010).

Table 5: Estimation results for direct and specific indirect effects

Ridge constant k	β_1	β_2	γ_1	γ_2	γ_3	$\gamma_1\beta_1$	$\gamma_2\beta_2$
0	0.897	0.060	0.782	0.775	-0.026	0.702	0.047
(s.e.)	(.062)	(.061)	(.026)	(.026)	(.024)	(.054)	(.048)
t-value	14.409	0.985	30.306	29.615	-1.110	13.024	0.986
Method A							
	β_1	β_2	γ_1	γ_2	γ_3	$\gamma_1\beta_1$	$\gamma_2\beta_2$
0.10	0.518	0.333	0.711	0.705	0.053	0.369	0.235
(s.e.)	(.046)	(.045)	(.029)	(.029)	(.030)	(.036)	(.033)
t-value	11.363	7.369	24.410	23.970	1.764	10.319	7.049
Method B							
	β_1	β_2	γ_1	γ_2	γ_3	$\gamma_1\beta_1$	$\gamma_2\beta_2$
0.10	0.518	0.333	0.711	0.705	0.053	0.369	0.235
(s.e.)	(.036)	(.036)	(.029)	(.029)	(.024)	(.030)	(.027)
t-value	14.265	9.251	24.410	23.97	2.214	12.327	8.638

When k = 0, the indirect effect via usefulness is statistically significant (t = 13.024) but the indirect effect via enjoyment is not statistically significant (t = 0.986). Because the direct effect γ_3 from ease of use to intention is not statistically significant (t = -1.11) usefulness can be interpreted as the perfect mediator between ease of use and intention (MacKinnon, 2008). When k = .10 both special indirect effects via usefulness and intention are statistically significant for both Methods A and B. In Method A both usefulness and enjoyment are the perfect mediators because direct effect γ_3 is not statistically significant (t = 1.764). On the other hand, using Method B, usefulness and enjoyment are now partial mediators because the direct effect γ_3 is statistically significant (t = 2.214).

4. Discussion

Multicollinearity may blur the interpretation of a structural equation model. The empirical example used in this paper demonstrated how the dismissal of multicollinearity problems may lead to fallacious parameter estimates and even erroneous non-significance of the parameter estimates. We proposed the ridge estimation method for the treatment of multicollinearity and provided a detailed illustration of it in SEM using LISREL.

The ridge estimation procedure was applied by using two different methods: Method A, in which the ridge constant was added manually to all diagonal elements of the correlation matrix of the variables in the model, and Method B, in which the ridge constant was added manually only to the diagonal elements of the correlation matrix of the *explanatory* exogenous and endogenous variables in the model. When evaluating suitable values of the ridge constant, the ridge trace method was used. For both Methods A and B, ridge point estimates were equal for the same ridge constant. Method B produced smaller standard errors of parameter estimates and larger squared multiple correlations, R^2, than Method A. Estimating the special indirect effects between variables produced results of the same kind.

Although no assessment of superiority of one method over another can be made based on this study, we may conclude that Method A, which corresponds to the ridge option installed in the LISREL program, is not necessarily preferable to Method B. Overall, it should be noted that ridge option procedure in LISREL is not recommended to be used automatically, because it may produce arbitrary ridge constant values. Since it is beyond our illustrative purpose to untangle which of the two methods is actually superior to another, this endeavour is left for future studies. However, both methods illustrated in this paper would be easy to apply also to path models that are more versatile than the models considered herein.

In our example when multicollinearity was not taken into consideration, the effect of a theoretically important variable – perceived enjoyment – on intention was estimated to be non-significant. The real non-significance of the enjoyment-intention link would most likely lead to the elimination of this independent variable from the model. However, closer scrutiny revealed that the non-significance of the effect found was caused by multicollinearity, that is, the extremely high correlation between usefulness and enjoyment.

As a short-cut solution to multicollinearity, the highly correlated variables of usefulness and enjoyment could have been combined into one aggregate variable. However, this procedure would have had some negative implications compared to the handling of multicollinearity with ridge estimation, as it would have led to the formation of a theoretically difficult variable that combines behavioural beliefs regarding both usefulness and enjoyment of the services in question. Forming this aggregated variable would have caused the loss of interesting information, as in interpreting the results it certainly makes a difference if intention to use mobile content services among mature consumers is affected by their beliefs about the usefulness of the service alone or by both usefulness and enjoyment of the service. Further, since intention to use was affected by both usefulness and enjoyment the extent of those effects adds to our understanding of technology acceptance among mature consumers. Finally, if usefulness and enjoyment were combined, comparing research results with previous research would be difficult, if not impossible.

In addition to the erroneous non-significance of the enjoyment-intention link, the direct effect of perceived ease of use on intention was estimated as non-significant when multicollinearity was not taken into consideration. The non-significance of the effect of ease of use on intention would imply that the effect of ease of use on intention is wholly mediated by usefulness and enjoyment. However when multicollinearity was addressed with ridge estimation (Method B) a small but significant direct effect of ease of use on intention was found, and usefulness and enjoyment were partial mediators of ease of use. This suggests that although ease of use also directly affects intention, alone it is not likely to induce intention to use mobile content services. However, it is an important variable in acceptance research since it has an effect on intention mediated by usefulness and enjoyment. Further, the effect of ease of use on usefulness and enjoyment is very logical as has been noted in previous research (see Venkatesh & Davis, 2000; Teo et al., 1999). Ease of use alone is not enough to make a service useful or enjoyable but services that are difficult to use are less likely to be perceived as useful or enjoyable.

Unfortunately, multicollinearity is a common problem in marketing research that often deals with models including such latent variables as quality, satisfaction, beliefs, attitudes and values. Latent constructs may be seen as the building blocks of marketing theory (Gilliam & Voss, 2013). Dismissing multicollinearity simply means unreliable results when testing marketing models and jeopardises the development of marketing theory. It is hoped that the illustration presented in this paper adds to the understanding of multicollinearity problems in SEM and provides marketing scholars with guidance on handling such problems.

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Appendix A

Perceived usefulness

PU1 Using mobile content services makes it easier for me to use certain services.
PU2 I find mobile content services useful.
PU3 Using mobile content services enables me to accomplish tasks more quickly.
PU4 Using mobile content services improves my performance in certain tasks.

Perceived ease of use

PEOU1 Learning to use mobile content services is easy for me.
PEOU2 It is easy for me to become skilled at using mobile content services.
PEOU3 I find mobile content services easy to use.
PEOU4 I find it easy to get a mobile content service to do what I want it to do.

Perceived enjoyment

PE1 I have fun using mobile content services.
PE2 I find using mobile content services enjoyable.
PE3 Using mobile content services is pleasant.

Intention to use

INTEN1 I intend to use mobile content services during the forthcoming year.
INTEN2 I plan to use mobile content services during the forthcoming year.
INTEN3 I will try to use mobile content services during the forthcoming year.