DELIVERING SERVICE VALUE NETWORKS: SMART BUSINESS

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ABSTRACT

Service Value Networks (SVNs) postulated, theorized, empirically developed, and discussed extensively by the author from 2002 onwards [8] [9] [10] [11] [12], have, for the first time been empirically confirmed at an industry-wide level. A matched-multiple-survey, exploratory factor analysis (EFA), regression and structural equation modelling (SEM).approach was utilized. The Australian pharmacy industry and its customer base, was used throughout this study.

Key Words: Service Value Networks, Pharmacy, Services, Competitive, Smart, Business, Networks

INTRODUCTION

Service Value Networks (SVNs) deliver a new high-level approach to investigating the business and its relations with its customer base. This empirically based process engages multiple business and customer survey techniques, exploratory factor analysis (EFA), regression and structural equation modelling (SEM).

Researchers [4] [5] [6] [14] [15], demonstrate that programs like regression, show limitations when dealing such complex relationships, and constructs may or may not display equal errors. Such difficulties are largely overcome using EFA. Here, the latent variables or factors, and the measurement errors associated with the measurement of each of the independent (manifest) variables, and the factor loadings yield a set of factor score regression coefficients which may be used to compute composites for the latent variables, but this also is problematic. In EFA, all factors are loaded on all observed measured variables. Thus, each composite or construct is created by using factor score regression coefficients as functions of all observed variables, not just as a function of the indicator variables specifically collected to measure a single latent variable. EFA also assumes error terms are uncorrelated – an assumption that is untenable when one considers that for this research, 165 SVN variables were measured, (with 20 eliminated due to poor customer recognition of available web options), and the remainder subsequently drawn down to 43 valid items, with each valid item overall contributing to one of the eleven latent factors. These observed (measurement) items emanated from either a SVN pharmacy customer or a pharmacy business representative; hence clearly some overlap of measurement error is likely.

In the SEM approach, such problems may be overcome [4] [5] [6] [16]. Specifically, SEM may be used to: (1) estimate the relationships amongst dependent (exogenous) variables, including feedback or reciprocal relationships, (2) estimate relationships among latent constructs underlying observed variables, (3) allow unequal weightings for multiple indicators of latent observed variables, (4) estimate the nature of measurement error associated with the observed variables, (5) allow for correlations amongst the measurement errors. SEM also allows for the estimation of the construct reliability and construct validity, provides new tests of fit for systems of equations, and allows for the estimation of higher order factor analysis where no observed indicator of these higher-order factor is available.

SEM encapsulates multiple regression goals, but also accounts for the modelling of interactions, nonlinearities, correlated independents, measurement error, correlated error terms, multiple latent independents (each measured by multiple indicators), and one or more latent dependents, also with multiple indicators.

THE SVN SEM MODEL

The SVN SEM model for the Australian pharmacy industry was developed using business-customer matched data sets. The final SEM analysis solution is portrayed in Figure 1. The SVN SEM model has a full compliment of fifteen significant (p<0.05) business covariances.

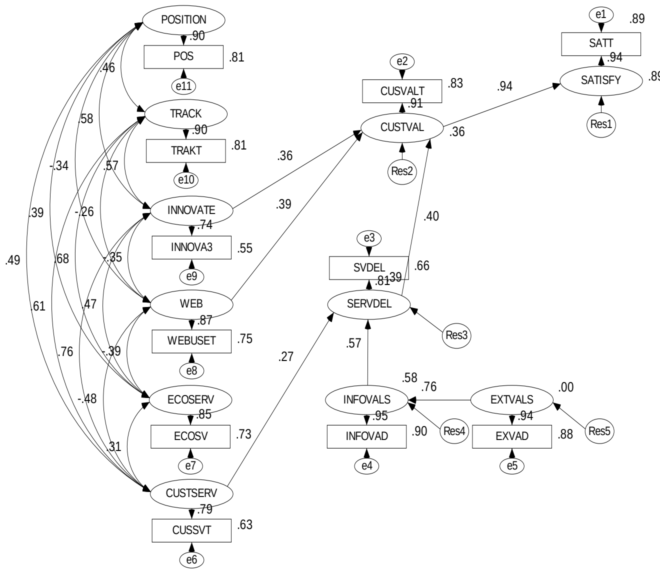

Figure 1: SVN SEM Model © Hamilton, 2007

The net multivariate kurtosis (Mardia's coefficient) for the eleven variables totalled 5.36 (C.R. 1.68). This being greater than 3.202 [4], indicates a small degree of model non-normality existed, but was still acceptable, and was thus treated as per 'normal' data. The skew for each observed latent variable was also between zero and one, again indicating little deviation from normal for each observed variable. Variable transformations (denoted with a concluding 'T') helped maximise normality, (and hence maximise SEM accuracy).

The 'Covariances Matrix' indicated no variable pairs were identical, plus all values were low, and under 0.45. Hence, no significant multicolinearity existed, and no large variance in path parameters was displayed, indicating sound discriminant validity, and suitable constructs built from measured variables. The eigen values indicated eleven discrete observed variables.

The 'Correlations Matrix' indicated all SEM paths were under 0.75, and hence displayed uniqueness as model latent variables (factors). The customer value-satisfaction path (CUSTVALT-SATT) was borderline and on retesting retained construct uniqueness. The eigen values also supported the eleven factors. Hence eleven latent variables (factors) were retained in the full SVN SEM model.

A minimal (optimal) SEM solution was achieved, with the model was over-identified as desired, The low chi-square to degrees of freedom ratio ($\chi 2$ / df < 2) shown in Table 1, indicated a high goodness-of-fit, while the probability level above p > 0 0.05 indicates an excellent final model fit.

Table 1: SVN SEM Model Fit Summary

MODEL	NPAR	CMIN	DF	P	CMIN/DF
Default model	33	18.369	33	0.981	0.557
Saturated model	66	0.000	0		
Independence model	11	398.915	55	0.000	7.253

The scalar regression weights, shown in Table 2, indicated all pathways were significant ($p < 0.05$), and these pathways offered the greatest chance of reproducing the observed data.

Table 2: SVN SEM Regression Weights Summary

			ESTIMATES	S.E.	C.R.	P
INFOVALS	<---	EXTVALS	.869	.091	9.569	***
SERVDEL	<---	INFOVALS	.554	.105	5.294	***
SERVDEL	<---	CUSTSERV	.210	.094	2.241	.025
CUSTVAL	<---	WEB	.508	.162	3.243	.002
CUSTVAL	<---	INNOVATE	.925	.339	2.731	.006
CUSTVAL	<---	SERVDEL	.649	.183	3.548	***
SATISFY	<---	CUSTVAL	1.008	.073	13.737	***

The covariances table, displayed as Table 3, shows all p values under 0.05. Hence, all pathways listed are significant, and all were required. As such, all fifteen covariance paths displayed had an indirect influence on the final SEM business-customer encounter paths generated in the model.

Table 3: SVN SEM Covariances Summary

			ESTIMATES	S.E.	C.R.	P
INNOVATE	<-->	WEB	-.090	.039	-2.335	.020
INNOVATE	<-->	ECOSERV	.085	.028	3.081	.002
INNOVATE	<-->	TRACK	.158	.041	3.831	***
INNOVATE	<-->	POSITION	.108	.028	3.883	***
INNOVATE	<-->	CUSTSERV	.203	.047	4.368	***
WEB	<-->	ECOSERV	-.137	.046	-2.946	.003
WEB	<-->	TRACK	-.139	.066	-2.090	.037
WEB	<-->	POSITION	-.122	.045	-2.701	.007
WEB	<-->	CUSTSERV	-.249	.075	-3.426	***
ECOSERV	<-->	TRACK	.258	.053	4.896	***
ECOSERV	<-->	POSITION	.099	.033	3.016	.003
ECOSERV	<-->	CUSTSERV	.115	.052	2.218	.027
TRACK	<-->	POSITION	.180	.049	3.702	***
TRACK	<-->	CUSTSERV	.342	.081	4.229	***
POSITION	<-->	CUSTSERV	.185	.053	3.504	***

The generated implied covariances' were generally small (< 0.423). The information and value adding dependant variables (INFOAD and EXTVAD) were not directly related to business exogenous variables. The customer value and satisfaction (CUSTVALT and SATT) exogenous latent variables displayed insignificant covariances with all business exogenous variables, and other dependants.

Table 4 showed each indicator's standardised loading (R), the percent of variance explained (or R^2), and key bootstrapping data for each endogenous variable. The R^2 measures of reliability (or consistency of measurement), and the error variance ($1– R^2$), showed each latent variable remained a significant contributor to the model. Implied correlations matrix, residual covariances and standardised residual covariances correlations also supported this solid SVN model validity. The standardised total effects (direct and indirect) for the customer dependant latent variable SATT showed excellent fit with all its prime effectors: (1) the three business pathways, (2) the external information pathways, (3) the services experienced, and (4) the customer perceived value. The SVN SEM approach delivered convergent validity, with standardized factor loadings significantly different to zero - actually above 0.7 in all but two cases (which were still above 0.6). In addition, all estimated SE-bias values were smaller in magnitude than their latent variable standard error (SE), thereby indicating acceptable and minimal bias. Thus direct structural relationship between observed variables and associated latent variables was successfully indicated. Construct validity was readily shown with all goodness of fit measures being excellent. In all cases discriminant validity measures also displayed high acceptability.

Table 4: SVN SEM Validity

	Standardized Loading	**Bootstrapped Squared Multiple Correlations:**				**Bootstrapped Squared Multiple Correlations:**				
	R	Estimate R^2	Lower	Upper	P	SE	SE-SE	Mean	Bias	SE-Bias
Customer										
EXTVALS	0.00	**0.00**	0.00	0.00	**...**	0.00	0.00	0.00	0.00	**0**
INFOVALS	0.76	**0.58**	0.42	0.71	**0.005**	0.07	0.00	0.59	0.01	**0.002**
SERVDEL	0.63	**0.39**	0.15	0.58	**0.011**	0.11	0.00	0.42	0.03	**0.003**
CUSTVAL	0.60	**0.36**	0.08	0.57	**0.014**	0.12	0.00	0.40	0.04	**0.004**
SATISFY	0.94	**0.89**	0.74	1.00	**0.005**	0.06	0.00	0.90	0.01	**0.002**
INFOVAD	0.95	**0.90**	0.87	0.92	**0.001**	0.01	0.00	0.89	0.00	**0**
SVDEL	0.81	**0.66**	0.56	0.72	**0.002**	0.04	0.00	0.65	-0.01	**0.001**
EXVAD	0.94	**0.88**	0.85	0.90	**0.001**	0.01	0.00	0.88	0.00	**0**
CUSVALT	0.91	**0.83**	0.79	0.87	**0.001**	0.02	0.00	0.83	-0.01	**0.001**
SATT	0.94	**0.89**	0.85	0.91	**0.001**	0.02	0.00	0.88	0.00	**0**
Business										
CUSSVT	0.79	**0.63**	0.54	0.70	**0.001**	0.04	0.00	0.62	-0.01	**0.001**
POS	0.90	**0.82**	0.76	0.87	**0.001**	0.03	0.00	0.81	-0.01	**0.001**
TRAKT	0.90	**0.81**	0.76	0.85	**0.001**	0.02	0.00	0.81	-0.01	**0.001**
ECOSV	0.85	**0.73**	0.64	0.81	**0.001**	0.05	0.00	0.72	-0.01	**0.001**
WEBUSET	0.87	**0.75**	0.68	0.80	**0.001**	0.03	0.00	0.74	-0.01	**0.001**
INNOVA3	0.74	**0.55**	0.44	0.64	**0.001**	0.06	0.00	0.54	-0.01	**0.002**

Bootstrapping the SVN SEM data 1000 times, under maximum likelihood (ML) and 95% confidence, helped verify the sample was representative of the underlying population, and that the observations were independent, while supporting bootstrapped (1) ML charts and (2) optimized data (KL) charts indicated clear approximation to normality existed, and significant calculation misspecifications were thus avoided.

The key ‘goodness-of-fit’ indices – RMR (0.230), GFI (0.972) AGFI (0.944), RMSEA (0.000) also all indicated excellent goodness-of-fit, while the CFI (1.000) and TLI (1.071) indicate excellent incremental fit. Further, considering parsimony PRATIO (0.600) for this small sample size is satisfactory, as is the 84.4 value for the AIC default model – when compared to the saturated model value of 132.0 [1]. Thus, an excellent SVN SEM model fit existed.

SVN MODEL SAMPLE INVARIANCE

When testing sample invariance, ML bootstrapping as a validation procedure, is not as strong as a unique calibration data set supported by a second unique validation data set. A reduced SVN SEM calibration and validation path approach, using the available smallish calibration and validation sample sizes, facilitated as an indicator of model pathway validity [6] [13] [15] [17]. The subsequent validation analysis for the reduced SVN SEM model whilst acceptable, in a minimalist sense, should be treated with due precaution, and it should be noted that this aspect of the research whilst exploratory, warrants further investigation with a larger sample size.

The procedure adopted utilized (1) a reduced number of latent variables drawn into in a reduced, validated, bootstrapped, potentially more parsimonious, SEM model - focusing on the business-customer encounter pathways [3] [7], (2) smaller data sets split randomly by SPSS into a calibration and a validation data set [4] [16], and finally (3).an iterative sample invariance procedure [2] [4] [17] [18].

The reduced SVN SEM model, shown in Figures 2 and 3, incorporated one additional significant covariance pathway, deemed logical and acceptable. For example, a new business offered innovation may be detected by the customer from a host of sources, including those external to the system.

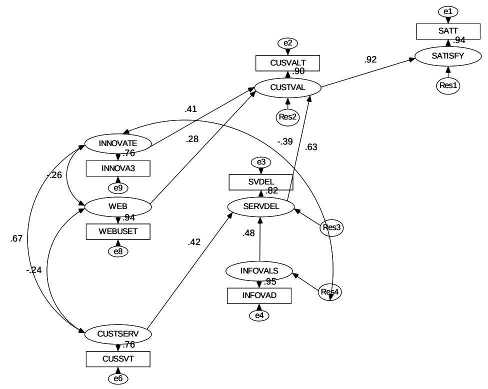

Figure 2: Reduced SVN SEM Calibration Model

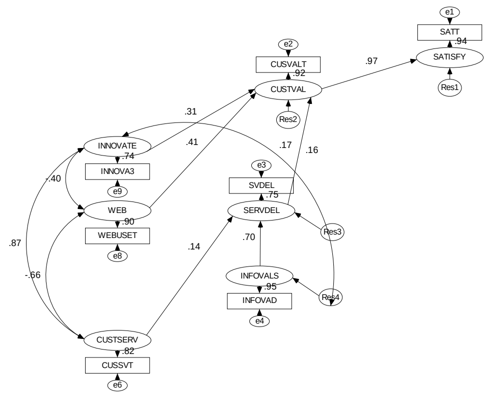

Figure 3: Reduced SVN SEM Validation Model

The two baseline calibration and validation models, show in Figures 2 and 3, were first tested for partial invariance, and these results are tabulated in the first two rows of Table 5. Both calibration and validations data sets indicate excellent model fit compared to the full SVN SEM. Under successive iterative constraining across the reduced SVN SEM model component loadings [4], only small variations in indicative measurements emerged. Typically, non-significant chi-square value ($\chi2 < \chi2_{crit}$) have been used as indicator of invariance between the two nested models, but it is now commonly accepted that this index is sample size dependant [17]. Hence, differences in absolute and incremental indices of fit are also generated as further indicators of invariance [2] [18]. All parameters in the iterative constraining of reduced SVN SEM calibration and validation models were iteratively set to identical parameter values of '1', as they were selectively, constrained under this multi-sample restriction invariance analysis approach [4]. Hence, despite a small drop in the overall degree of fit, as additional constraints were added, the model at all stages of constraint remained strong, and continued to show an excellent fit.
Although this procedure strictly cannot be embedded into the full model because of model reduction and sample size restrictions, it is possible that the full SVN SEM model would likely also be a 'valid' measurement model.

Table 5: Calibration and Validation Analysis – Tightened Reduced SVN SEM Model

Validation of Data Set	df	Δdf	χ2	Δχ2	$\chi2_{Crit}$ (0.05)	Accept χ2	RMR	GFI	AGFI	NNFI	IFI	TLI	PRATIO	RMSEA	AIC vs Sat	EVCI vs Sat	HOELTER (.05)
Calibration Sample N=Data Set 1	11		6.20	12.24	21.03	N/A	0.013	0.971	0.925	0.954	1.039	1.081	0.524	0.000	0.718	0.718	178
Validation Sample N=Data Set 2	11		6.03				0.010	0.968	0.919	0.944	1.052	1.111	0.524	0.000	0.715	0.715	160
Base Model Sample N=Full data Set	22	0	12.24	0.01	33.92	Yes	0.011	0.969	0.922	0.949	1.045	1.094	0.524	0.000	0.716	0.725	309
Constraint of Factor Loadings	22	0	12.24	0.00	33.92	Yes	0.011	0.969	0.922	0.949	1.045	1.094	0.524	0.000	0.716	0.725	310
Constraint of Covariances	25	3	15.86	3.62	37.65	Yes	0.016	0.961	0.913	0.934	1.042	1.077	0.595	0.000	0.695	0.695	265
Constraint of Regression Paths	31	6	23.09	7.23	44.99	Yes	0.021	0.945	0.901	0.904	1.038	1.054	0.738	0.000	0.653	0.652	218
Constraint of Residual Covariance	32	1	27.60	4.51	46.19	Yes	0.028	0.938	0.891	0.885	1.021	1.029	0.762	0.031	0.675	0.675	187

CONCLUSION

This exploratory research targeted competitive services strategies employed within existing Australian pharmacy business models. It was developed from both theory, and researched measures [8] [9] [10] [11] 12], and showed that using a SVN SEM approach, the business-customer encounter, could be investigated, and that significant SVN SEM model pathways between the business and its customers existed.

The author's concept of SVNs, developed, and theoretically modelled from the literature, showed that the pharmacy industry businesses (as an example of a service industry), when combined, and viewed from a front-end perspective, engaged the environmental, the business, the customer blocks, and the funnelled these blocks into a contact point - termed the business-customer encounter. This front-end engagement point (or business-customer encounter), behaved in, around, and across the business-customer encounter as a SVN (this theorized concept was first published in 2004 [8]). Further, using a SEM approach engagement pathways between the business and its customer were indicated.

Understanding such business-customer pathways, may, in the future, enable the pharmacy industry to improve its business-customer alignment. For example, pharmacy businesses may concentrate on improving a selection of these significant business-customer encounter pathways, or may focus on improving their internal SVN business cell blocks, and/or front-end business cell interactors (or their effects) that indirectly or directly influence these significant business-customer encounter pathways.

The cross validation procedure presented herein, reduces the SEM model to an acceptable sample size model. Under tight analysis criteria, the business-customer encounter may be tested iteratively for sample invariance. This cross validation procedure creates potential flaws like working with a more parsimonious model, and sample size issues, but if carefully approached, and used in conjunction with bootstrapping and other SEM validation tools, it may be considered as another indicative validation tool.

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