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Analysing the electricity consumers' attitude with Structural Equation Modeling

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Abstract. Demand Side Management (DSM) is a set of measures, policies and strategies sensitive to the electricity consumers' attitude that is a sum of perceptions and expectations influenced by relevant information, related to the benefits that can change the consumers' behaviour towards sustainable electricity consumption. Internet access, Pro-environmental measures, Expectations and Relation with supplier are several unobserved factors that impact the Attitude of consumers. The Structural Equation Model (SEM) allows us to identify the latent factors and indicate the directional relationships among these factors that are behind the measured items of questionnaire data. Thus, in this paper we propose to analyse a complex data set from a pre-trial questionnaire with SEM and reveal interesting insights related to latent factors that have the potential to enhance the DSM strategies. For simulations, a complex data set with 4,232 observations and 143 items is considered and several smaller data subsets verify whether the model capitalize on change characteristics of a certain data set or not.

1. Introduction

The current context marked by high price fluctuations and renewables volatility [1], [2] make us reconsider the support that the residential electricity consumers and prosumers can provide to securely operate the power systems [3]. The purpose of this paper is to identify several latent factors and relationships among them that influence the electricity consumers' attitude towards pro-environmental measures and behavioural changes [4]. Thus, we analyse a questionnaire data set with the Structural Equation Model (SEM) that has not been analysed yet from this point of view. The Irish pre-trial questionnaire created by the Commission for Energy Regulation containing numerous respondents (about 4,232) and 143 questions [5], [6] is analysed grouping the questions that are relevant for a certain concept such as demographics, house characteristics, heating systems, Internet access, expectations, perceived relation with supplier, attitude, etc. They are considered as unobserved factors (or latent) that are behind the items and that are usually not easy to measure but can be further analysed using SEM [7], [8].

However, from the set of unobserved factors, five are selected to test the relationships and the hypothesis that consumers' attitude is influenced by Internet access, expectations, measures and perceived relation with supplier. The context of our research reveals its importance as the electricity consumers and prosumers prove to sustain the load control and the security of power systems.

SEM are usually applied in analysing questionnaire data [9], for various themes such as learning [10], psychology [11], medicine [12], electricity consumption [13], [14], [15], etc.

It is significant to understand the factors that influence the electricity consumers attitude and create demand response programs that embed relevant aspects to determine a behaviours change towards load control and pro-environmental and sustainable measures [16], [17].

2. Structural Equation Model

In this model, we analyze the relationship among the five factors as in Figure 1 and check whether there is a tenable model that can confirm the proposed hypothesis. The Internet access (F1) and Relation with supplier (F5) directly impact the Measurements (F3) that consumers take, whereas Measurements and Expectations (F4) directly impact the Attitude (F2). These relations are described in Figure 1 with straight single-arrow lines. The three factors that are not impacted by other factors (Relation with supplier, Internet access and Expectations) may covary and that is marked with curved double-arrow lines. Disturbance terms (d1, d2) are similar to measurement errors assuming that such errors are normal.

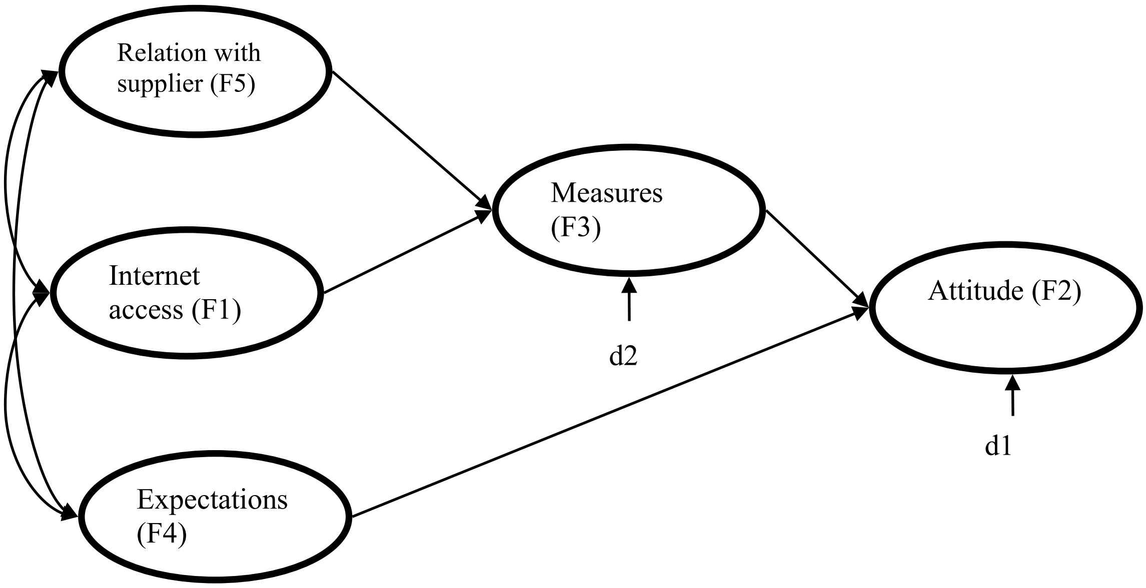

Figure 1. Structural Equation Model

The SEM model is written in SAS using PROC CALIS, a SAS procedure that can be adapted to create several models such as path and Confirmatory Factor Analyses (CFA). PROC CALIS is almost identical for SEM as for CFA, but additionally it contains the equations that reveal the relationships among latent factors [17]. The model is designed in Appendix 1. As the data set has numerous observations (4,232), we split the set into four subsets (each with 1,058 observations) with statistical power in order to check whether the model is able to generalize on various data sets.

3. Results

The model is consisting of linear equations created with the model type **lineq**. q1-q25 are the relevant items that were grouped by the five latent factors (F1-F5). These equations admit the influence of a latent factor on groups of items. At the same time, the items are influenced by a measurement error or residual (e). p1-p25 are the loading factors, whereas the two equations below represent the relationships between the two categories of latent factors: endogenous F2, F3 and exogenous F1, F4, F5. Items q1-q4 load on Internet access (F1), q5-q9 load on Attitude (F2), q10-q15 load on Measures (F3), q16-q20 load on Expectations (F4), and q21-q25 load on Relation with supplier (F5).

$$F2 = p26\ F4 + p29\ F3 + d1 \quad (1)$$

$$F3 = p27\ F5 + p28\ F1 + d2 \quad (2)$$

The modeling information is presented in Table 1. The simulations are performed for a subset of 1,058 observations that has statistical power. Eleven iterations are necessary to find a solution as in Table 2.

Table 1. Modeling information

Robust Maximum Likelihood Estimation	
Data Set	WORK.PREQSEL5_25Q_MEAN_12K
N Records Read	1058
N Records Used	1058
N Obs	1058
Model Type	LINEQS
Analysis	Means and Covariances

Table 2. Optimization results

Iterations	**11**	**Function Calls**	**27**
Jacobian Calls	13	**Active Constraints**	0
Objective Function	0.5201724283	**Max Abs Gradient Element**	0.000103984
Lambda	4.440892E-14	**Actual Over Pred Change**	1.4421858347
Radius	1141702.0212		

Table 3. Standardized effects in linear equations

Variable	Predictor	Parameter	Estimate	Standard Error	t Value	Pr > |t|
q1	**F1**	**p1**	0.93107	0.03363	27.6898	<.0001
q2	**F1**	**p2**	-0.17368	0.03217	-5.3991	<.0001
q3	**F1**	**p3**	0.35977	0.03051	11.7934	<.0001
q4	**F1**	**p4**	0.64770	0.02941	22.0219	<.0001
q5	**F2**	**p5**	0.71897	0.02743	26.2084	<.0001
q6	**F2**	**p6**	0.66313	0.02776	23.8919	<.0001
q7	**F2**	**p7**	0.45761	0.03098	14.7693	<.0001
q8	**F2**	**p8**	0.47383	0.03064	15.4664	<.0001
q9	**F2**	**p9**	0.14945	0.03577	4.1779	<.0001
q10	**F3**	**p10**	-0.05189	0.04681	-1.1086	0.2676
q11	**F3**	**p11**	-0.27436	0.04688	-5.8519	<.0001
q12	**F3**	**p12**	-0.36794	0.04786	-7.6882	<.0001
q13	**F3**	**p13**	0.19861	0.04673	4.2503	<.0001
q14	**F3**	**p14**	0.32994	0.04730	6.9751	<.0001
q15	**F3**	**p15**	0.36252	0.04776	7.5902	<.0001
q16	**F4**	**p16**	0.84446	0.02717	31.0844	<.0001
q17	**F4**	**p17**	0.63829	0.02699	23.6526	<.0001
q18	**F4**	**p18**	0.53074	0.02810	18.8877	<.0001
q19	**F4**	**p19**	-0.22776	0.03331	-6.8382	<.0001
q20	**F4**	**p20**	0.14442	0.03412	4.2323	<.0001
q21	**F5**	**p21**	0.51224	0.03493	14.6669	<.0001
q22	**F5**	**p22**	0.49300	0.03500	14.0846	<.0001
q23	**F5**	**p23**	0.62870	0.03531	17.8067	<.0001
q24	**F5**	**p24**	0.39819	0.03597	11.0715	<.0001
q25	**F5**	**p25**	0.15852	0.03860	4.1066	<.0001
F2	**F4**	**p26**	-0.23456	0.03951	-5.9359	<.0001
F2	**F3**	**p29**	0.22771	0.05462	4.1691	<.0001
F3	**F5**	**p27**	-0.12044	0.06583	-1.8295	0.0673
F3	**F1**	**p28**	0.35727	0.05511	6.4823	<.0001

Most of the loading factors (p1-p28) are significant except p10 and p27 for which the *t* value is in the interval -1.96 ÷ 1.96 (as in Table 3). If the q10 item is eliminated, the results did not improve.

Figure 2 represent the path diagram of our model. It shows the relationships among latent factors, the loading factors, and covariances among exogenous factors (Expectations, Internet access and

Relation with supplier). Furthermore, the main metrics of the model are displayed (chi-square, RMSEA, SRMR, CFI, etc.)

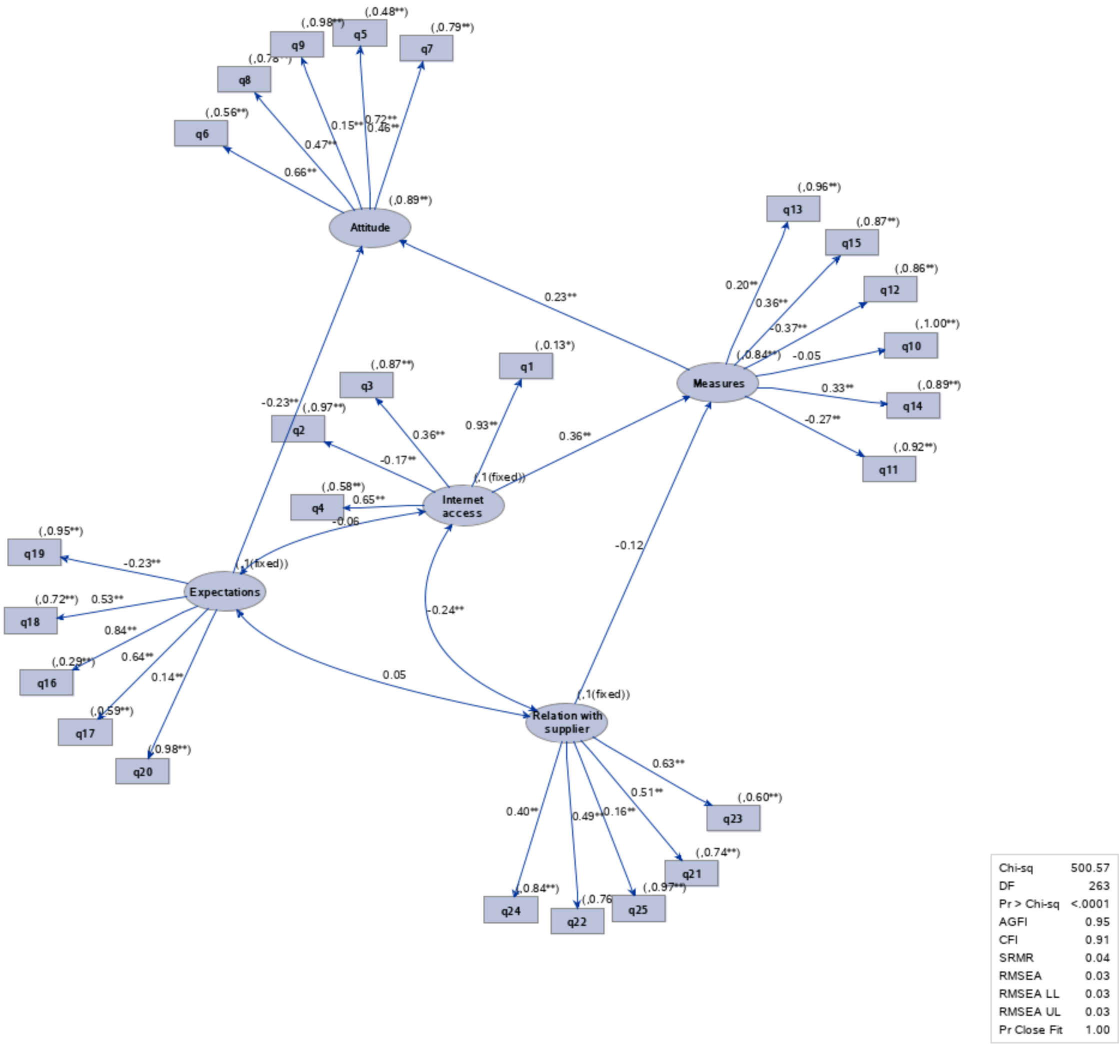

Figure 2. Path diagram for SEM

The results of the SEM consist in metrics and are displayed in Table 4 by category (absolute index, parsimony index, incremental index).

Table 4. Results of the model by category

Absolute Index	Fit Function	0.4736
	Chi-Square	500.5747
	Chi-Square DF	263
	Pr > Chi-Square	<.0001
	Z-Test of Wilson & Hilferty	8.2609
	Hoelter Critical N	638
	Root Mean Square Residual (RMR)	0.0278
	Standardized RMR (SRMR)	0.0405
	Goodness of Fit Index (GFI)	0.9620
Parsimony Index	Adjusted GFI (AGFI)	0.9530
	Parsimonious GFI	0.8433
	RMSEA Estimate	0.0292
	RMSEA Lower 90% Confidence Limit	0.0253
	RMSEA Upper 90% Confidence Limit	0.0331
	Probability of Close Fit	1.0000

	ECVI Estimate	0.5939
	ECVI Lower 90% Confidence Limit	0.5373
	ECVI Upper 90% Confidence Limit	0.6580
	Akaike Information Criterion	624.5747
	Bozdogan CAIC	994.3512
	Schwarz Bayesian Criterion	932.3512
	McDonald Centrality	0.8938
Incremental Index	Bentler Comparative Fit Index	0.9129
	Bentler-Bonett NFI	0.8347
	Bentler-Bonett Non-normed Index	0.9007
	Bollen Normed Index Rho1	0.8114
	Bollen Non-normed Index Delta2	0.9141
	James et al. Parsimonious NFI	0.7317

We analyse at least one index from each category. From the first category, chi-square is around 500 with a probability <0.0001, but this index is not relevant especially with numerous data sets. SRMR is 0.0405 that is ideal. Additionally, RMSEA and RMSEA UL, LL are ideal. CFI is 0.9129, higher than 0.9 indicating an adequate fit to data.

4. Conclusion

The pre-trial questionnaire data was analysed using SEM dividing the questions into groups that reflect unobserved variables that can have a influence on each other. Thus, we investigated this influence and found out that the pro-environmental measures that consumers take to improve their energy consumption are impacted by the two latent factors: relation with supplier and Internet influence. Furthermore, the other two latent factors: measures and expectations significantly influence the consumers' attitude towards a sustainable development and clean environment.

Very good results in terms of performance indicators from each category (absolute, parsimony and incremental index) are obtained with SEM. They confirm that there is a clear relationship between measures, expectations and attitude. The measures and expectations influence the electricity consumers' attitude, whereas the measures are influenced by the Internet access and relation with supplier. Thus, the pro-environmental measures taken by consumers are impacted by relevant information that can be transmitted via Internet and by the relation with supplier and indirectly by the demand response programs implementation. The electricity consumers' expectations or perceptions related to the demand response are also important and impact the electricity consumers' attitude.

A similar analysis can be performed on the post-trial questionnaire. The results could be compared to investigate and understand the impact of the DR programs that were implemented after the pre-trial questionnaire had been collected.

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Appendix 1. SEM

```
data preqsel5_25q_mean_12k;
infile '/home/so/preqsel5_25q_mean_12k.csv' dsd;
input id $ q1-q25;
run;
proc calis data=preqsel5_25q_mean_12k
modification residual robust plots=caseresid;
lineqs
q1 = p1 F1 + e1,
q2 = p2 F1 + e2,
q3 = p3 F1 + e3,
q4 = p4 F1 + e4,
q18 = p18 F4 + e18,
q19 = p19 F4 + e19,
q20 = p20 F4 + e20,
q21 = p21 F5 + e21,
q22 = p22 F5 + e22,
q23 = p23 F5 + e23,
q24 = p24 F5 + e24,
q25 = p25 F5 + e25,
F2 = p26 F4 + p29 F3 + d1,
F3 = p27 F5 + p28 F1 + d2;
variance
```

```
q5 = p5 F2 + e5,
q6 = p6 F2 + e6,
q7 = p7 F2 + e7,
q8 = p8 F2 + e8,
q9 = p9 F2 + e9,
q10 = p10 F3 + e10,
q11 = p11 F3 + e11,
q12 = p12 F3 + e12,
q13 = p13 F3 + e13,
q14 = p14 F3 + e14,
q15 = p15 F3 + e15,
q16 = p16 F4 + e16,
q17 = p17 F4 + e17,
```

```
e1-e25 = vare1-vare25,
F1 = vare26, F4 = vare27, F5 = vare28,
d1-d2=vard1-vard2;
cov F1 F4 = covF1F4, F1 F5 = covF1F5, F4 F5 =
covF4F5;
var q1- q25;
pathdiagram diagram = standard arrange = grip scale =
0.75 EXOGCOVARIANCE
label=[F1="Internet access" F2="Attitude"
F3="Measures" F4="Expectations"
F5="Relation with supplier"]
dh = 1000 dw = 1000 textsizemin = 10;
run;
```

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