

Measuring Interaction: An Empirical Comparison of Three OLS Regression Models

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Abstract

The capacity to correctly assess the existence of interaction is a high-value modeling capability among researchers of information systems (IS), especially those focusing on behavioural paradigm studies. Interaction is a notable aspect for the major theoretical frameworks of the IS field, particularly the adoption theories. Allowing for crossover effects in the Theory of Planned Behaviour resulted in improvements in model prediction (Taylor & Todd, 1995b). This study presents the trimmed model, which does not permit crossover effect relations among variables. In complex models, as mentioned by Pedhazur (1997), one variable may affect another variable indirectly through multiple paths. According to him, it stands to reason that indirect effects, through certain paths, may be more meaningful and/or stronger than others. The findings of this quantitative study lead one to conclude that crossover effect models are more capable of showing the interaction among models' variables, as well as explaining the highest percentage of variation for a single dependent variable, in comparison to the full and trimmed models.

Keywords: Information Systems, Interaction Effect, Behavioural Intention, OLS

1. Introduction

Studies that attempt to examine the interaction and compare several models of single theory are rare. In this study, the theory of planned behaviour is employed as the foundation base as well as for the comparison of the three derived models. The researchers observe adoption by combining the three models that examine Internet banking adoption.

A summary of findings and conclusions, derived from each model, is provided in a comparative assessment of the capabilities of three regression models to predict the acceptance of Internet banking (IB).

2. Literature Review

2.1 Theory of Planned Behaviour (TPB)

In the TPB there are three constructs that determine the user's intention. These are attitude, subjective norms (SN) and Perceived Behavioural control (PBC). The TPB has been used to study the adoption of different information systems such as

spreadsheets (Mathieson, 1991), computer resource centres (Taylor and Todd, 1995a), electronic brokerages by Battacherjee (2000), and negotiation support systems by Lim et al., (2002). Figure (1) presents the Theory of Planned Behaviour as follows;

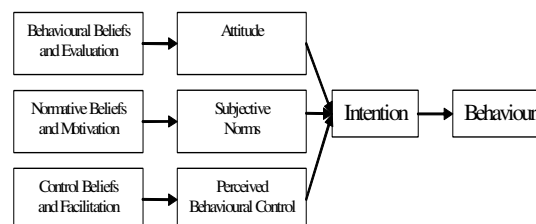


Figure (1) Theory of Planned Behaviour
(Source: Ajzen, 1991)

Although studies of adopting IB among individuals using the TPB are rare, three studies use the theory of planned behaviour (TPB) to study intention toward adopting IB. Liao et al. (1999) provide an example from the context of Hong Kong and Shih and Fang (2004) in the Taiwanese context. Based on these two studies, the findings demonstrate that the TPB is only partially applicable in predicting the adoption intention of virtual banking (Liao et al., 1999 and Shih & Fang, 2004). They prove that behavioural intention is a significant function of attitude and PBC (PBC) while the SN is not a significant determiner in either study. In addition, Brown et al. (2004), in a comparative study of IB adoption in Singapore and South Africa, demonstrate that SN shows no influence on the adoption of IB in either Singapore or South Africa as hypothesised in their model. Shih and Fang (2004) compare the TRA to two versions of the TPB model. They demonstrate that intention to adopt IB can be explained by attitude in both models and only relative advantage and complexity are related to attitude.

In the study of consumer adoption intentions, Taylor and Todd (1995b) suggest a new format for the TPB theory, which is considered as helpful for a better understanding of the relationships between the belief structures and the antecedents of intention. Several researchers have examined approaches to decomposing beliefs into multidimensional constructs. The decomposed TPB model is inspired by Taylor and Todd (1995a; 1995b). This model provides three sets of belief structures in a multi-dimensional belief construct. These beliefs, according to Taylor and Todd

(1995b), can be referred to as attitudinal beliefs, normative beliefs, and control beliefs, which are related to attitude, SN and PBC respectively. The decomposed TPB model has many valuable advantages as it represents the TRA's core constructs. Also, it provides more attitudinal belief dimensions, derived from Rogers (1995)'s five attributes of innovation, rather than the two factors of ease of use and usefulness, which are proposed in the technology acceptance model (TAM) model.

3. Methodology

The aim of this study is to assess the existence of interaction effects in modelling behaviour of innovation adopters. The study utilizes the comparison techniques of variables resulted from three different models of OLS to help researchers identify the determinants of IB services adoption. **Research Methodology**, This study is considered as a quantitative research in which the researcher employs the deductive method and the survey instrument is the tool for collecting the primary data. To achieve the study's aims the researcher employs the authoritative method, with the creation of the theoretical research framework together with a survey instrument designed to collect the study's data. Items with a 7-point Likert scale have been adopted from previous IS studies to ensure constructs face validity (see Appendix A)

All the variables of interest are subjected to several possible safeguards such as pre-testing, a pilot study, scales validation and statistical and methodological assumption assessment as recommended by Hair et al., (2006) and Malhotra (2004). These included tests for normality, independence of residual, representativeness of the sample and outliers. of the 1,000 self-administrated questionnaires distributed to bank account holders, of the 17 banks operating in Yemen, the overall response rate was roughly 62 %. Eventually, the achievable sample size of 623 responses was obtained with 254 incomplete forms, resulting in a gross response rate of 59 %. The reliability and validity of the constructs are ascertained by measuring the internal reliability and convergent and discriminant validity (Hair et al., 2006; Malhotra, 2004). Collectively, the results suggest that the constructs demonstrate adequate measurement properties

4. Analysis and Results

The aim of using path analysis is to provide quantitative estimates of the causal connections between sets of variables. According to Bryman & Cramer (2001), a direct effect occurs when a variable has an effect on another variable without a third variable intervening between them; an indirect effect occurs when there is a third intervening variable through which two variables are connected. Along these lines, Pedhazur (1997, p.765) points out that multiple regression analysis can be viewed as a special case of path analysis.

Following Pedhazur's (1997) guidelines, this study's construct can be interpreted as loadings in factor analysis while the paths can be interpreted as standardized beta weights in regression analysis. In order to illustrate further the study utilizes path diagrams and path coefficients. The path diagram, according to Pedhazur (1997, p.770), is very useful for displaying graphically the hypothesised pattern of causal relations among a set of variables. In line with Bryman & Cramer (2000), the arrows indicate expected causal connections between variables. Thus, in the diagram presented in Figure (2), the study uses upper case letters and numerical figures to represent variables in the model. The letter – "I" refers to the variable Intention, "R" User Informational Based Readiness, "A" Attitude, "N" Subjective Norm, and "C" Perceived Behavioural Control. The number – "1" refers to the variable Relative Advantage/Compatibility, "2" Ease of use, "3" Observability, "4" Trialability, "5" Personal Norm, "6" Mass Media Norm, "7" Technology Facilitating Condition, "8" Resource Facilitating Condition, "9" Government Support, and "10" Self-Efficacy.

In studying causal connections, the researcher must distinguish between exogenous and endogenous variables (Kerlinger & Pedhazur, 1973). Therefore, all the variables represented by numerical figures are examples of exogenous variables while those represented by letters with the exception of "R" are endogenous variables. In Pedhazur's (1997) words:

"An exogenous variable is one whose variation is assumed to be determined by causes outside the hypothesized model. Therefore, no attempt is made to explain the variability of an exogenous variable or its relations with other exogenous variables. An endogenous variable... ..is one whose variation is explained by exogenous or other endogenous variables in the model." (Page 770)

Based on this distinction of variables in path analysis, it is implied that variables could be dependent and independent in the same model. Kerlinger & Pedhazur, (1973, p.309) highlighted some assumptions underlying the application of path analysis as follows;

1. The relations among the variables in the model are linear, additive, and causal.
2. Residuals are not correlated with variables preceding them in the model.
3. There is a one-way causal flow in the system.

4. Variables are measured on an interval scale.

The diagram in Figure (2) below represents the a priori model' as follows;

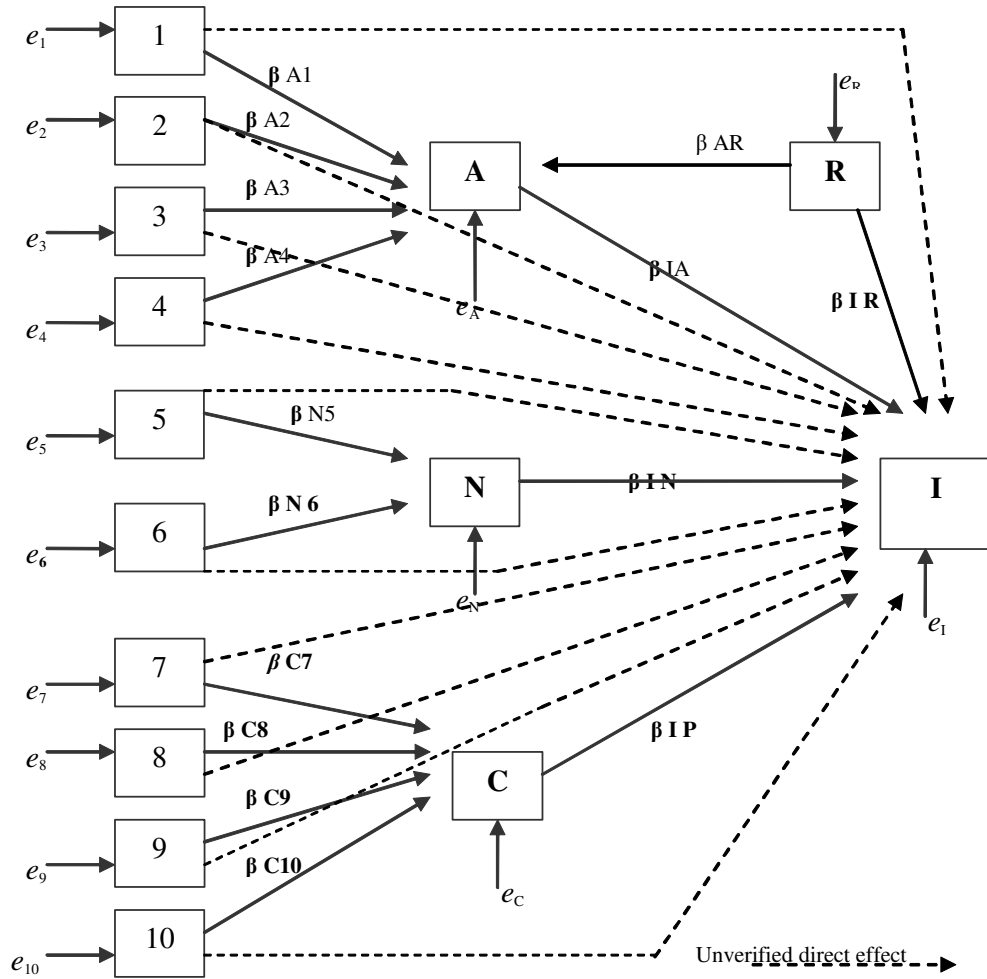


Figure (2) A priori Model

This study checks for the aforementioned assumption required for using the application of path analysis and there is no violation. In addition, both the simple and multiple linear regressions employed in previous sections are helpful in explaining the predictive power of independent variables in direct relation. The arrows in the above diagram are drawn from the independent variable (*exogenous*) to the dependent variable (*endogenous*). For instance, variable A is perceived to be dependent on variables 1, 2, 3, 4 and variable R. Similarly, variable N is perceived to be dependent on variables 5 and 6, and variable C is perceived to be dependent on variables 7, 8, 9 and variable 10. Consequently, variable I is perceived to be dependent on A, N, C, and variable R. As shown in the a priori model, variables with a numerical symbol from 1 to 10, including the

variable R, are exogenous variables, while the variables in uppercase letters (I, A, N, and C) are said to be endogenous variables. Furthermore, an endogenous variable treated as a dependent variable in one set of variables may also be conceived as an independent variable in relation to other variables (Kerlinger & Pedhazur 1973). Along these lines, the path coefficient indicates the direct effect of variable taken as a cause of a variable taken as an effect. Variable 1 is exogenous and is therefore, represented by a residual (e_1).

4.1 Findings of the Full Effects Model

According to Kerlinger and Pedhazur (1973, p.310), a set of equations, referred to as a recursive model, are required to assess the full effects model and for identifying significance paths. In Cohen and Cohen's (1983) words;

“Recursive models are those in which there is no reciprocal causation, feedback loops, or unmeasured common causes...involving one or

more endogenous are present...Non-recursive models are more complex models”, page 376.

Recursive models, according to Cohen and Cohen (1983, p. 355), can be estimated by ordinary regression equations. In the testing hypotheses part, this study performs a series of multiple regressions to derive the various path coefficients for the full effects model and to identify significance paths. A

path analytic approach using the Ordinary Least Squares (OLS) technique is utilized to test the proposed model as recommended by Cohen and Cohen (1983), shown in Figure (3). The relationships among the variables in the recursive model, depicted in series equations, are as follows;

$$\begin{aligned}
 X1 &= e_1 \\
 X2 &= e_2 \\
 X3 &= e_3 \\
 X4 &= e_4 \\
 X5 &= e_5 \\
 X6 &= e_6 \\
 X7 &= e_7 \\
 X8 &= e_8 \\
 X9 &= e_9 \\
 X10 &= e_{10} \\
 XR &= e_R \\
 XA &= PA1X1 + PA2X2 + PA3X3 + PA4X4 + PARXR + e_A \\
 XN &= PN5X5 + PN6X6 + e_N \\
 XC &= PC7X7 + PC8X8 + PC9X9 + PC10X10 + e_C \\
 XI &= PI1X1 + PIRXR + PIAXA + PA2X2 + PI3X3 + PN5X5 + PINXN + PI6X6 + PI7X7 + PI8X8 \\
 &\quad + PI9X9 + PICXC + PCI10X10 + e_I
 \end{aligned}$$

The notion PA1X1, PN5X5, PC7X7, PIAXA, etc denotes a specific path coefficient. Thus, PA1X1 would indicate the path coefficient relating the exogenous variable X1 to the endogenous variable

A1. The full effects model is displayed in Figure (3) below and the results of the series of regressions are shown in Table (1).

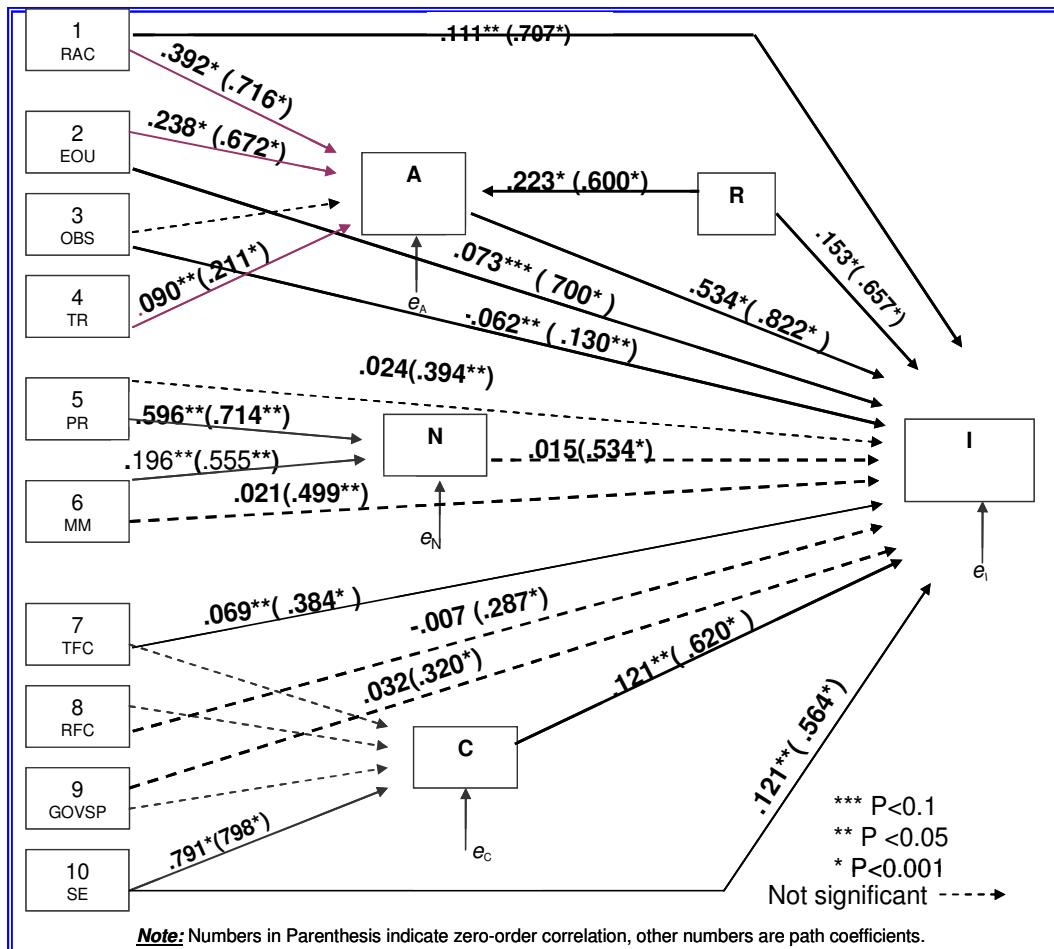


Figure (3) Full Effect Model

In Pedhazur’s (1997) words;

“In path analysis, more than one regression analysis may be called for. At each stage, an endogenous variable is regressed on the variables that are hypothesized to affect it. The β’s thus calculated are the path coefficients for the path leading from the particular set of independent variables to the dependent variable under consideration.” Page 776

The model in Figure (4) requires five regression analyses for the calculation of all the path coefficients. The path coefficient from R to I (P_{IR}) is calculated by regression I on R, from A to I (P_{IA}) is calculated by regression I on A, from N to I (P_{IN}) is calculated by regression I on N and from C to I (P_{IC}) is calculated by regression I on C. For the purpose of this research, a path is deemed significant if it passes the 90 % confidence level.

Table (1) Results of Path Analysis on the Full Effects Model

DV	Regression	R ²	ΔR ²	Beta value	t-value	Sig
Intention	PI1X1	.756	.747	.110	2.353	.021
	PIRXR			.153	4.043	.000
	PIAXA			.533	12.839	.000
	PI2X2			.072	1.550	.124
	PI3X3			-.064	-2.064	.057
	PI4X4			.004	.135	.893
	PI5X5			.024	.581	.564
	PINXN			.015	.355	.729
	PI6X6			.021	.555	.578
	PI7X7			.069	2.170	.031
	PI8X8			-.007	-.238	.812
	PI9X9			.032	1.041	.299
	PICXC			.121	2.408	.017
PI10X10	-.094	-1.950	.052			
Attitude	PA1X1	.593	.587	.392	7.309	.000
	PA2X2			.238	4.444	.000
	PA3X3			-.011	-.285	.776
	PA4X4			.090	2.238	.026
	PARXR			.223	4.961	.000
Subjective Norms	PN5X5	.535	.532	.596	13.334	.000
	PN6X6			.196	4.396	.000
Perceived Behavioural Control	PC7X7	.638	.634	.020	.554	.580
	PC8X8			.023	.685	.494
	PC9X9			-.028	-.788	.431
	PC10X10			.791	21.181	.000

4.2 Findings of the Trimmed Model

In the model revision analysis, all insignificant paths (identified through the multiple regression carried out in the first part of the analysis) were eliminated from the full effects model. This step is necessary to derive a more parsimonious model via benefits from the approach of *theory trimming*. Many researchers like Pedhazur (1997)

prefer to use a criterion of meaningfulness for the deletion of the paths, even when their coefficients are statistically significant. The study performed another round of regression analysis to drive new regression statistics. The regressions were carried out based on the following equations, which represent the significant relationship identified in the full effect model.

$$\begin{aligned}
 XA &= PA1X1 + PA2X2 + PA4X4 + PARXR + e_A \\
 XN &= PN5X5 + PN6X6 + e_N \\
 XC &= PC10X10 + e_C \\
 XI &= PI1X1 + PIRXR + PIAXA + PI3X3 + PI7X7+ PICXC + PI10X10 + e_I
 \end{aligned}$$

Consequently, Table (2) presents the results of path analysis of the trimmed model of this study, which is enhanced by the diagram in Figure (4). The trimmed model result shows a lack of support for the Subjective Norms (SN) affect on BI. This is not

consistent with Ajzen's (1991) theory that potential adopters intend to act based on others' perceptions or with the results reported by Taylor & Todd (1995a), who found subjective norms to be important in affecting adoption. In contrast, this study's results are consistent with findings of previous IB studies conducted by Liao et al. (1999), Tan & Teo (2000) and Shih & Fang (2004). The findings support the importance of observability in directly affecting a person's intention to use IB in a negative way.

Table (2) Result of Path Analysis on the Trimmed Model

DV	Regression	R ²	ΔR ²	Beta value	t-value	Sig	VIF	Durbin-Watson
Intention	PIIX1			.132	2.926	.004	2.570	1.972
	PIRXR			.151	4.012	.000	2.022	
	PIAXA			.541	13.207	.000	2.343	
	PI2X2	.753	.746	.078	1.705	.089	3.024	
	PI3X3			-.052	-1.857	.064	1.118	
	PI7X7			.082	2.732	.007	1.298	
	PICXC			.124	2.570	.011	3.229	
	PI10X10			-.088	-1.870	.062	3.222	
Attitude	PA1X1			.389	7.389	.000	2.481	2.042
	PA2X2	.593	.588	.240	4.583	.000	2.459	
	PA4X4			.085	2.387	.017	1.127	
	PARXR			.224	5.002	.000	1.790	
SN	PN5X5	.535	.532	.596	13.334	.000	1.570	1.794
	PN6X6			.196	4.396	.000	1.570	
PBC	PC10X10	.637	.636	.791	21.181	.000	-	1.863

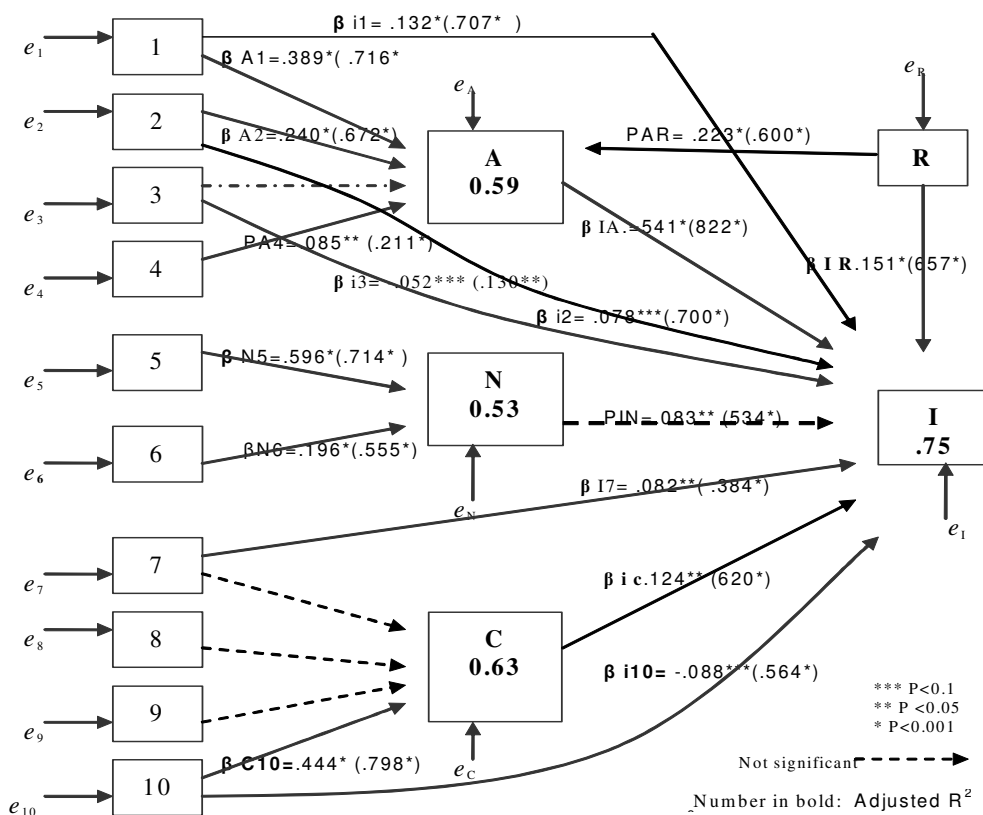


Figure (4) The Trimmed Model

4.3 Findings of the Crossover Effects Model

According to Taylor and Todd (1995b) allowing for crossover interaction effects in the Theory of Planned Behaviour results in an improvement in model prediction. Figure (5) presents the trimmed model, which permits crossover

effect relations among variables. In complex models, as mentioned by Pedhazur (1997), one variable may affect another variable indirectly through multiple paths. According to him, it stands to reason that indirect effects through certain paths may be more meaningful and/or stronger than others.

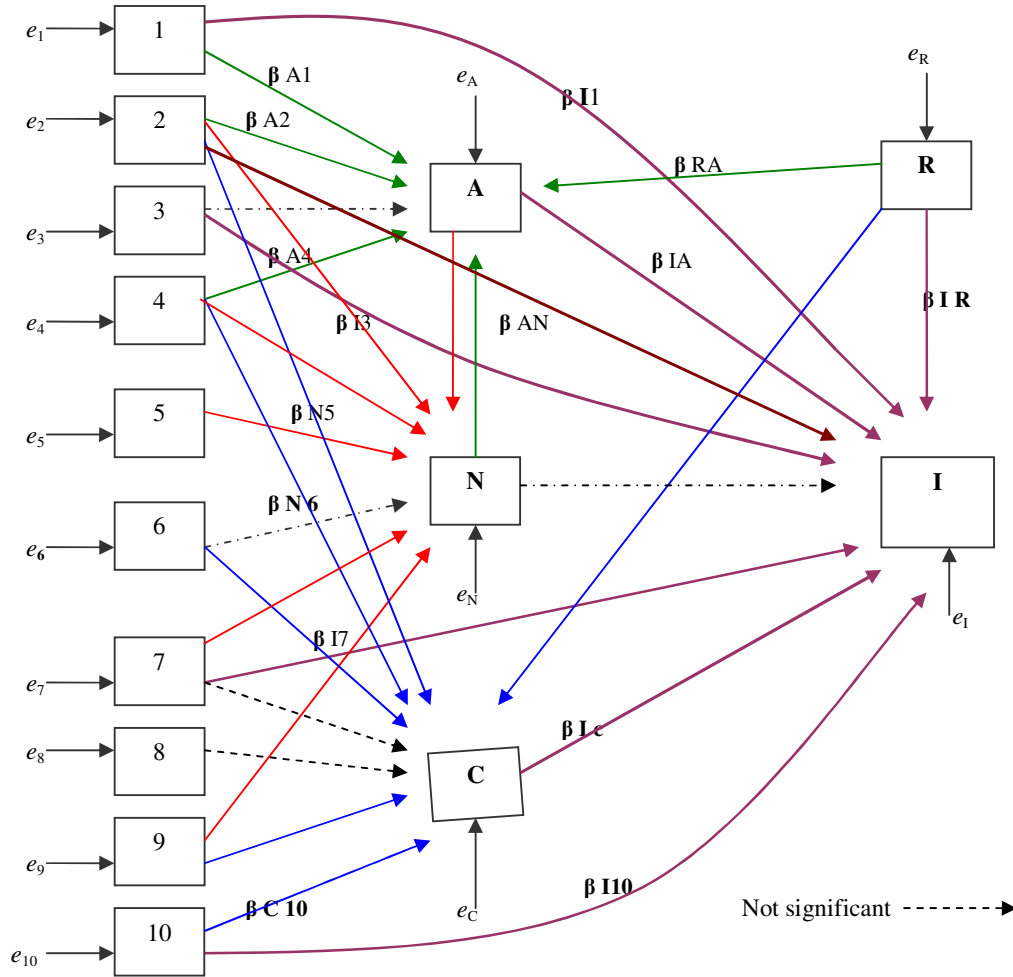


Figure (5) Crossover Effects Model

Table (3) Results of Path Analysis on the Crossover Effects Model

DV	Regression	R ²	ΔR ²	Beta value	t-value	Sig
Intention	READINESS	.756	.746	.153	4.035	.000
	ATT			.533	12.724	.000
	SN			.015	.346	.729
	PBC			.121	2.406	.017
	PR			.024	.577	.564
	MM			.021	.544	.587
	RAC			.110	2.317	.021
	OBS			-.064	-1.910	.057
	EOU			.072	1.540	.124
	TR			.004	.135	.893
	SE			-.094	-1.950	.052
	TFC			.069	2.169	.031
	RFC			-.007	-.239	.811
GOVSP	.032	1.041	.299			
Attitude	READINESS	.607	.593	.186	3.939	.000
	SN			.143	2.645	.009
	PBC			-.017	-.266	.791
	PR			-.074	-1.406	.161
	MM			.046	.934	.351
	RAC			.336	5.839	.000
	OBS			-.022	-.511	.610
	EOU			.203	3.470	.001
	TR			.088	2.147	.032
	SE			.100	1.634	.103
	TFC			-.027	-.677	.499
	RFC			-.019	-.488	.626
	GOVSP			-.007	-.186	.852
SN	READINESS	.627	.613	.067	1.435	.152
	ATT			.136	2.645	.009
	PBC			-.008	-.125	.901
	PR			.542	12.658	.000
	MM			.038	.792	.429
	RAC			.041	.695	.488
	OBS			-.077	-1.866	.063
	EOU			.089	1.540	.124
	TR			.043	1.063	.289
	SE			-.014	-.232	.817
	TFC			.062	1.575	.116
	RFC			.018	.489	.625
	GOVSP			.076	2.035	.043
PBC	READINESS	.729	.719	.113	2.849	.005
	ATT			-.012	-.266	.791
	PR			-.033	-.749	.455
	MM			.171	4.259	.000
	RAC			.032	.629	.530
	OBS			-.047	-1.337	.182
	EOU			.244	5.099	.000
	TR			-.065	-1.898	.058
	SE			.566	13.740	.000
	TFC			-.055	-1.635	.103
	RFC			-.043	-1.347	.179
	GOVSP			-.062	-1.937	.053
	SN			-.006	-.125	.901

5. Determining the Indirect Effects

Following Pedhazur's (1997, p.795) suggestion, the indirect effect of the exogenous variables on the research main endogenous variable

“I”, Behavioural Intention, could be calculated based on path multiplication. Table (4) shows the indirect effects of behavioural belief, normative belief, and

control belief on the behavioural intention to adopt IB as well as their relevant path coefficients.

Table (4) Path Analysis Indirect Effects

Model	Cause /effects	Indirect Paths	Path Coefficient	Total	
Full effects	Behavioural belief → Intention	X1 → XA → XI X2 → XA → XI X4 → XA → XI XR → XA → XI	0.392 × 0.534 = 0.209 0.238 × 0.534 = 0.127 0.090 × 0.534 = 0.048 0.223 × 0.534 = 0.119	0.503	
	Normative belief → Intention	X5 → XN* → XI X6 → XN* → XI	0.596 × 0.015 = 0.009 0.196 × 0.015 = 0.024	0.033	
	Control Belief → Intention	X10 → XC → XI	0.791 × 0.121 = 0.096	0.096	
Trimmed	Behavioural belief → Intention	X1 → XA → XI X2 → XA → XI X4 → XA → XI XR → XA → XI	(.389 × .541) = 0.211 (.240 × .541) = 0.130 (.085 × .541) = 0.046 (.223 × .541) = 0.121	0.508	
	Normative belief → Intention	X5 → XN* → XI X6 → XN* → XI	(.596 × .083) = 0.049 (.196 × .083) = 0.016	0.065	
	Control belief → Intention	X10 → XC → XI	(.791 × .124) = 0.098	0.098	
Crossover Effects	Behavioural belief → Intention	X1 → XA → XI X2 → XA → XI X4 → XA → XI XN → XA → XI XR → XA → XI X2 → XC → XI X4 → XC → XI X6 → XC → XI X9 → XC → XI X10 → XC → XI XR → XC → XI	(0.336 × 0.533) = 0.179 (0.203 × 0.533) = 0.108 (0.088 × 0.533) = 0.047 (0.143 × 0.533) = 0.076 (0.186 × 0.533) = 0.099 (0.244 × 0.121) = 0.030 (-0.065 × 0.121) = -0.008 (0.171 × 0.121) = 0.021 (-0.062 × 0.121) = -0.008 (0.566 × 0.121) = 0.069 (0.113 × 0.121) = 0.014	0.627	
	Normative belief → Intention	X5 → XN* → XI X9 → XN* → XI XA → XN* → XI X2 → XN* → XI X7 → XN* → XI	(0.542 × 0.015) = 0.008 (0.076 × 0.015) = 0.001 (0.136 × 0.015) = 0.002 (0.089 × 0.015) = 0.001 (0.062 × 0.015) = 0.001	0.013	
	Control belief → Intention	X2 → XC → XI X4 → XC → XI X6 → XC → XI X9 → XC → XI X10 → XC → XI XR → XC → XI	(0.244 × 0.121) = 0.030 (-0.065 × 0.121) = -0.008 (0.171 × 0.121) = 0.021 (-0.062 × 0.121) = -0.008 (0.566 × 0.121) = 0.069 (0.113 × 0.121) = 0.014	0.118	

* Insignificant path

6. Determining the Total Effects

The calculation of the total interaction effect in this study can be obtained mathematically through the submission of both direct and indirect effect as shown by the following equation;

$$\sum_{i=1}^n TE = IE + DE$$

The results presented in Table (5) are obtained by calculations reported in Figure (4). In both the full and the trimmed Model, the total indirect effect of a customer’s behavioural beliefs on their Intention is equal to the sum of four components (0.50), which are the composed products of standardized regression

coefficients. Obviously, the result differs for the crossover effects model where the total indirect effect of a customer’s behavioural beliefs is increased to the sum of eight components (0.63). It is clear that normative belief is virtually zero – a potentially important finding that is obscured when only the total indirect effect is reported. The total indirect effect of a customer’s behavioural beliefs on their Intention is almost 0.00, while the total indirect effect of a customer’s normative beliefs on their subjective norm is equal to the sum of two components (almost 0.03). The total indirect effect of a customer’s control beliefs on their perceived behavioural control is equal to the sum of one component of Self-efficacy (0.10).

Table (5) Total Effects Model: Behavioural Intention

	Cause /effects	Indirect Effect (IE)	Direct Effect (DE)	Total Effect (TE)	Sig Factors
Full Effects	<i>Behavioural belief</i> → <i>Intention</i>	0.503	.110+.153+.533+.072+ (-.064)+.069+.121+ (-.094) = .900	1.403	RAC,R,ATT, EOU,OBS, TFC,C and SE
	<i>Normative belief</i> → <i>SN</i>	0.033	00	0.033	
	<i>Control belief</i> → <i>PBC</i>	0.096	.791	.887	SE
Trimmed	<i>Behavioural belief</i> → <i>Intention</i>	0.508	.132+.151+.541+.078+ (-.052)+.082+.124+ (-.088) = 0.968	1.476	RAC, R,ATT, EOU,OBS, TFC,C, and SE
	<i>Normative belief</i> → <i>SN</i>	0.065	00	0.065	
	<i>Control belief</i> → <i>PBC</i>	0.098	.791	.0889	SE
Crossover Effects	<i>Behavioural belief</i> → <i>Intention</i>	0.627	.153+.533+.121+.110+ (-.064)+.072 (-.094)+.069 = -0.9	1.527	R, ATT, PBC,RAC, OBS,EOU, SE, and TFC
	<i>Normative belief</i> → <i>SN</i>	0.013	00	0.013	ATT, PR and GOVSP
	<i>Control belief</i> → <i>PBC</i>	0.118	.113+.171+.244+ (-.065)+.566+ (-.062) = 0.967	1.085	R, MM, EOU,TR, SE and GOVSP

7. Discussion

Empirically, this study compares the results of three OLS regression models utilized to test for interaction. The findings of the study show that there are some notable differences between these models. The first is that the crossover model is able to capture additional interaction between three new normative belief components (ATT, PR and GOVSP) and Subjective Norm, as well as interaction between six new control belief components (R, MM, EOU, TR, SE and GOVSP) and PBC, whereas the Trimmed regression model does not. Also the level of significance of the interaction as captured by the crossover model is slightly more significant than for the Trimmed model. This indicates that the OLS may be somewhat more conservative, with the crossover interaction model, than the trimmed model.

The second major notable difference is that the correlation coefficient (R^2) of the dependent variable, customer service process (CSP), indicates that in both full ($R^2_{BI} = .76$, $R^2_{ATT} = .59$, $R^2_{SN} = .54$, $R^2_{PBC} = .64$) and trimmed ($R^2_{BI} = .75$, $R^2_{ATT} = .59$, $R^2_{SN} = .54$, $R^2_{PBC} = .64$) instances the overall explanatory power of the model is slightly higher when the crossover interaction terms are included in the analysis ($R^2_{BI} = .76$, $R^2_{ATT} = .61$, $R^2_{SN} = .63$, $R^2_{PBC} = .73$). As expected the F-statistic showed this outcome to be highly significant in both instances (Cohen, 1988; Chin et al, 2003).

Implications of this paper's findings that deserve to be mentioned include that it clearly shows that past research, which sought to measure the contributions of the different salient beliefs effect to 'intend' and 'expected behaviour', related to the adoption of innovation, may have severely understated the true impact by neglecting to consider the crossover interaction effect. Another interesting point is the fact that the analysis reveals the existence of both positive and negative interactions. Basically, the results show that the three models share same salient behavioural beliefs such as RAC, R, ATT, EOU, OBS, TFC, C and SE, which statistically could be considered as prominent determinants of the intention for this research in modelling behaviour. However, the complexity and diversity in understanding the nature of the interaction effects, in modelling the behaviour for the Internet banking adopters from different contexts, needs to give consideration to the sources of possible interaction effects. However, overall, our results indicate that with the right level of austerity and statistical diagnosis, the

crossover interaction regression analysis model can yield statistical results comparable to trimmed and full effect models based on OLS. With respect to *Nomological Validity*, Lee & Baskerville (2003) pointed out that generalizability of an IS theory to different settings is important not only for the purpose of basic research, but also for the purpose of managing and solving problems that corporations and other organizations experience in society. In order for a Multiple Linear Regression equation to have utility for prediction it must be generalized beyond the sample that was used to derive it. Generalizability in Information Systems, according to Lee & Baskerville (2003), refers to the validity of a theory in a different setting from the one where it was empirically tested and confirmed. A theory that lacks such generalizability also lacks usefulness. Statistical sampling-based generalizability is a valid concept within its bounds, but its uncritical application as the norm for all generalizability can lead to an improper assessment of the generalizability of many research studies (Lee & Baskerville, 2003).

A variety of methods are available for assessing such generalizability. Since this study does not have the resources available to replicate and validate the results, it employs statistical procedures to ensure that the solution that fits our data sample can be generalized. In this connection, Hair et al. (2006, p. 259) suggest one of two approaches by which the researcher can assess the validity of the results. The first method includes an assessment of adjusted R^2 and the second is split sample. This study's first indicator of generalizability is the adjusted R^2 value, which is adjusted for the number of variables included in the regression equation. The adjusted R^2 is used to estimate the expected shrinkage that would not generalize to the population because our solution is over-fitted to the data set by including too many independent variables. Hair et al. (2006, p.234) reported that the adjusted R^2 is useful in comparing models between different data sets because it will compensate for the different sample. If the adjusted R^2 value is much lower than the R^2 value, it is an indication that the regression equations may be over-fitted to the sample, and of limited generalizability. $R^2 = .751$ and the Adjusted R Square = .746 are very close values, anticipating minimal shrinkage based on this indicator (Tabachnick & Fidell, 2007). Nomological validity according to Hair et al. (2006) refers to the degree to which the

summated scale makes accurate predictions of other concepts in a theoretical based model. This type of validity here assesses the relationship between theoretical constructs and seeks to confirm significant correlations between the constructs as predicted by theory (Malhotra 2004, p.269). Moore & Benbasat (1996) found support for the predictive validity of innovation characteristics (see also Agarwal & Prasad 1997, 1998; Karahanna et al., 1999; Plouffe et al., 2001).

8. Conclusion

Unfortunately, the test of generalizability could lead one to conclude that Subjective Norm (SN) is the weakest psychological determinant of intention in this study with respect to Internet banking adoption. The findings on observability could lead one to conclude that this innovation's attribute is an undesired attribute for Internet banking, which negatively affects the customers' intention to adopt Internet banking. It was noted that customers' intention to adopt IB will be influenced by both personal and media norms. This study has fulfilled both objectives of the research and supported the theory of planned behaviour. This study could be a valuable contribution to the body of knowledge where the crossover effect has not been carried out before and results show new and different findings to the existing body of knowledge.

8. References

[1] Agarwal, R. and Prasad, J. "The Role of Innovation Characteristics and Perceived Voluntariness in the Acceptance of Information Technologies," *Decision Sciences*; (28:3); Summer97, pp. 26-557.

[2] Ajzen, I. "The Theory of Planned Behaviour", *Organizational Behavior and Human Decision Processes*, (50:2), 1991, pp. 179-211.

[3] Battacherjee, A. "Acceptance of E-Commerce Services: the Case of Electronic Brokerages," *IEEE Transactions on Systems, Man and Cybernetics —Part A: Systems and Humans*, (30:4), 2000, pp. 411-420.

[4] Brown, I., Hoppe, R., Mugera, P., Newman, P. & Stander, A. "The Impact of National Environment on the Adoption of Internet Banking: Comparing Singapore and South Africa," *Journal of Global Information Management*, (12:2), 2004, pp. 1-26.

[5] Bryman, A. & Cramer, D. *Quantitative data analysis with SPSS release 10 for windows: a guide for social Scientists*, Philadelphia, ROUTLEDGE Taylor & Francis Group, 2001.

[6] Cohen, J. & Cohen, P. *Applied Multiple Regression/Correlation Analysis for the Behavioural Sciences*, 2nd edn, New Jersey, Lawrence Erlbaum Associates, 1983.

[7] Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E. and Tatham, R.L. *Multivariate Data Analysis*, 6th edn, Prentice Hall international, Upper Saddle River, New Jersey, USA, 2006.

[8] Karahanna, E., Straub, D.W. & Chervany, N.L. "Information Technology Adoption across Time: A Cross-Sectional Comparison of Pre-Adoption and Post-Adoption Beliefs", *MIS Quarterly*, (23:2), 1999, pp. 183-213.

[9] Kerlinger, F.N. & Pedhazur, E.J. *Multiple Regression in Behavioural Research*, Holt, Rinehart and Winston Inc, New York, 1973.

[10] Lee, A.S. & Baskerville, R.L. "Generalizing Generalizability in Information Systems Research," *Information Systems Research*, (14:3), 2003, pp. 221-243.

[11] Liao, S., Yuan, P.S., Huaiqing, W. & Ada, C. "The Adoption of Virtual Banking: An Empirical Study," *International Journal of Information Management*, (19:1), 1999, pp. 63-74

[12] Lim, J., Gan, B. & Chang, T-T "A Survey on NSS Adoption Intention," Proceedings of the 35th Hawaii International Conference on System Sciences, on 7-10 January 2002 (2002), pp. 399-408.

[13] Malhotra, N.K. *Marketing Research: an applied orientation*, 4th edn, Pearson Prentice Hall. Upper Saddle River, New Jersey, USA, 2004.

[14] Mathieson, K. "Predicting User Intention: Comparing the Technology Acceptance Model with the Theory of Planned Behaviour", *Information Systems Research*, (2:3), 1991, pp. 173-191.

[15] Moore, G.C. and Benbasat, I. "Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation," *Information Systems Research*, (2:3), 1991, pp. 192-222.

[16] Pedhazur, E.J., *Multiple Regression in Behavioural Research: Explanation and Prediction*, 3rd edn, Thomson Learning, Florida, USA, 1997.

[17] Plouffe, C.R., Hulland, J.S. & Vandenbosch, M. "Richness versus Parsimony in Modelling Technology Adoption Decisions: Understanding Merchant Adoption of a Smart Card-Based Payment System," *Information Systems Research*, (12:2), 2001, pp. 208-222.

[18] Rogers, E.M., *Diffusion of Innovations*, the Free Press, 4th edn, London: Collier Macmillan, New York, NY, 1995.

- [19] Shih, Y. and Fang, K. "The Use of a Decomposed Theory of Planned Behavior to Study Internet Banking in Taiwan," *Internet Research*, (14:3), 2004, pp. 213-223.
- [20] Tabachnick, B.G., & Fidell, L.S. *Using Multivariate Statistics*, 5th edn, Pearson education Inc, Boston, 2007.
- [21] Tan, M. and Teo, T. S. H. "Factors Influencing the Adoption of Internet Banking," *Journal for association of information system*, (1:5), 2000, (accessed on 18 March from WWW.isworld.org).
- [22] Taylor, S. and Todd, P. "Decomposition and Crossover Effects in the Theory of Planned Behaviour: A Study of Consumer Adoption Intentions," *International Journal of Research in Marketing*, (12:2), 1995b, pp. 137-155.
- [23] Taylor, S. and Todd, P.A. "Understanding Information Technology Usage: A Test of Competing Model," *Information Systems Research*, (6:2), 1995a, pp. 144-176 (accessed from EBSCOhost on 18-Mar-04)
- [24] Taylor, S. and Todd, P.A. "Assessing IT Usage: The Role of Prior Experience," *MIS Quarterly*, (19:4), 1995c, pp. 561-570.

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