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CONFIRMING THE MEASUREMENT MODEL FOR THE ROLES OF RISK PERCEPTION AND ATTITUDES TOWARD FINANCIAL INVESTMENT INTENTIONS.

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Abstract: The broader scope of this study is to examine the central roles of risk perceptions and attitudes sequentially between level of financial knowledge and financial investment intentions of individuals and to determine which factors provide strong explanatory power to risk perceptions. The current paper presents the measurement model results. In the structural equation model using Analysis of Moment Structures (AMOS), ensuring that the data fit to model is vital prior to conducting hypothesis testing. Using a structured questionnaire, 492 respondents were surveyed in major towns and cities in Malaysia. The paper advances knowledge of the literature by empirically confirming the direct-measures items for the latent variables that potentially link to behavioural intentions toward financial investment.

Key words: Risk Perception, Attitude, Risk-Taking Intention, Confirmatory Factor Analysis, AMOS

INTRODUCTION

The current paper seeks to confirm the latent variables in a study that was designed to examine the determinants of risk perception and the mediating roles of risk perception and attitude in sequence, on the effect of financial knowledge on the intention to engage in financial investment. Although studies on risk perception, attitude and risk-taking intentions is aplenty in the literature, much of the work was outside the context of financial issues or did not investigate the determinants of risk perception and the central roles of risk perception and attitude in serial, in affecting risk-taking intention with regard to financial investment. The study adds value to behavioural finance research as it can be considered as a maiden attempt that integrate the Litterer's Perception Formation Model (Litterer, 1965) and the organisational risky decision-making framework (Sitkin and Pablo, 1992; Sitkin and Weingart, 1995) with further support of the Theory of Planned Behaviour (Ajzen, 1991) and knowledge-attitude-behaviour consistency (Fabrigar, Petty, Smith and Crites, 2006).

The latent variables of the study were adapted from literature. A combination of measurement items from past studies was utilised to form the research questionnaire. Prior to conducting the measurement model assessment (MMA), all items were pretested ensure content validity. This was followed by a pilot study. An exploratory factor analysis (EFA) was carried out at the pilot stage for preliminary reliability check. The final research framework and questionnaire were in accordance to the results of the pilot study.

The fieldwork data were analyse using the covariance-based structural equation modelling (CB-SEM), i.e., Analysis of Moment Structures (AMOS) to be specific, thus, this paper presents and discusses the measurement model results. Also, commonly known as the confirmatory factor analysis (CFA), the main purpose of the MMA in AMOS is to clarify how well the direct-measured items are loaded into their respective latent variables and the degree the model fits to the data. The process is necessary in AMOS before the structural model analysis.

LITERATURE REVIEW

There are two stages of assessment in AMOS SEM, of which, the measurement model is the first stage. Like many other SEM applications, AMOS SEM relies on the normal theory methods (NTMs) of maximum likelihood (ML) for parameters estimation and model goodness of fit test (Nachtigall, Kroehne, Funke and Steyer,2003). The NTMs are developed under the assumption dataset is multivariate normal (Tomarken and Waller, 2005). The strengths of ML estimation include the capability to perform more complicated models (Brown, 2006). Due to the importance of multivariate normal assumptions, the data of the study were scrutinised to ensure that no violation could lead to other defilement of assumptions such as linearity, multicollinearity, and heteroscedasticity.

One of the requirements in MMA is the estimation of several fit-statistics to evaluate the extent of dataset match the model specifications. There are several goodness-of-fit indices. Despite the lack of consensus on the number of indices to be used, it is important to use multiple indicators (Wheaton, Muthen, Alwin and Summers, 1977) and the better practice is to use at least one fit index from each group of model fit (Hair, Black, Babin and Anderson, 2014a; Hooper, Coughlan and Muller, 2008). There are three specific groups of model fit, namely Absolute Fit, Comparative (or Incremental) Fit, and Parsimonious Fit. It is common in literature to include between four to six indicators (may be less or more) to assess how well the models fit the dataset.

Measurement reliability and validity are two important aspects in SEM. Although internal consistency reliability was checked by employing the EFA using pilot data, it was performed based on the traditional criterion, i.e., Cronbach's alpha. Hair, Hult, Ringle and Sarstedt (2014b) claims it is a conservative measure that tends to result underestimation. It is sensitive to the number of items and more importantly, it assumes all indicators are equally reliable. That does not concur well with SEM, which priorities indicators based on their individual reliability (Peterson and Kim, 2013). Composite reliability (CR), thus, is a more appropriate measure for internal consistency reliability (Bacon, Sauer and Young, 1995; Hair *et al.*, 2014) because it considers the different outer loadings of the indicator variables. Hair *et al.* (2014) suggests a CR values between 0.6 and 0.7 for latent variables to attain composite reliability when a research is exploratory in nature; and at advance stage, higher CR of 0.7 and 0.9 are considered satisfactory.

The examination of the convergent and discriminant validity is concerning construct validity, that is, to what extent in which a set of direct-measured items reflect the latent variables (Hair *et al.*, 2014a, 2014b). Convergent validity determines whether the measures of the same latent variable are correlated highly, while discriminant validity checks to what extent measures of a latent variable correlate with other latent variables. Basically, measures of discriminant validity determine if two measures that should not be correlated/related are truly not related. Convergent validity is assessed using values of factor loadings and average variance extracted (AVE). AVE is comparable to the commonality of a construct and a value of higher than 0.5 indicates on average the latent variable clarifies more than half of the variance of its indicators. Thus, convergent validity is considered to have attained when AVE of all latent variables exceed 0.5. Discriminant validity is assessible by Fornell-Larcker Criterion, where the square root of the AVE values are compared with the correlation of latent variables. Discriminant validity is established when all the correlations of latent variables are lower than the square root of AVE values. The reasoning of the method is based on the argument that a latent variable shares more variance among its group of indicators than any of the other latent variables in the measurement model.

METHODOLOGY

The endogenous variable of the research is behavioural intention toward financial investment. Six items from Lam and Hsu (2006) were adapted to capture the variable. All items used a 10-point end-defined scale ranging from 1 (highly disagree) to 10 (highly agree). There are seven exogenous variables, of which generally classified into three common themes: financial knowledge, social influence, and personal trait. The level of Objective Knowledge (OK) was directly obtained using a combination of ten multiple choice and true/false questions related to basic arithmetic and financial concepts, adapted from Lusardi and Mitchell (2008).

Except for OK, the other six exogenous variables were indirectly observed and operationalised using six-point Likert's scale items. Six items from Flynn and Goldsmith (1999) were used to capture the construct of Subjective Knowledge (SK). Items for Family Influence (Fam), Peer Influence (Peer) and Internet Influence (INT) were adapted from Jorgensen and Salva (2010), and Jorgensen (2007). Meanwhile, items from Dulebohn and Murray (2007) were employed for Risk Propensity (RP). There are two mediators. Items for the mediating variable of Risk Perception (PER) were from Hoffman, Post and Pennings (2013). The second mediating variable, i.e. Attitude (Att), were modified from the original instruments of Lee (2009) and Ramayah, Rouibah, Gopi and Rangel (2009).

The data were collected from several locations in the peninsular and the two Borneo's states of Malaysia. Purposive-sampling method was used. The study successfully garnered 492 usable samples from individuals prior the age of prime saving years. Data were rigorously screened. Following suggestions by Kumar, Abdul Talib and Ramayah (2013) and Mat Roni (2014), the research checked the data for issues related to common method variance, monotone, missing values, outliers, and normality.

Table 1
Demographic Profile of Respondents (N=492)

Demographic Variables	*Number*	*Valid Percentage*
Gender		
Male	178	36.3
Female	312	63.7
Ethnicity		
Malay	159	32.4
Chinese	133	27.1
Indian	29	5.9
Sabah and Sarawak Indigenous	156	31.8
Occupation Sector		
Government	162	35.6
Private	235	51.6
Business/Self-employed	58	12.7
Retirement Scheme		
Public Pension	138	28.9
Employee Provident Fund	250	52.4
None	89	18.7
Marital Status		
Single	248	50.6
Married	233	47.6
Divorced/Widower	9	1.8
Education Level		
Completed Primary School	5	1.0
Completed Secondary School	134	27.3
Diploma/University Degree	352	71.7

	Min	*Max*	*Mean*	*Std Dev*
Age	19	39	28.71	6.098
Monthly Income (RM)	500	10000	2909.47	1830.819

Descriptive Statistics and Measurement Model Assessment

The majority of the respondents were the Malays, followed by the indigenous ethnics of Sabah/Sarawak, Chinese and Indian. More female took part in the survey than male. More than half of respondents were working in the private sector, thus, reflected by higher number of respondents having the Employee Provident Fund (EPF) as retirement scheme. As targeted, all respondents were under 40 years old, with the mean age of 28.7. Table 1 provides the demographic profile of respondents.

A total of 40 direct-measured items were entered for measurement model assessment. At this stage, the measurement model would be adjusted if the fitness of the model is inadequate (Hox and Bechger, 1998). The study employed three common practices in model modification: (1) deleting poorly-loaded items; (2) adding on error covariance between items of the same latent variable; and (3) deleting items that may cause issues with reference to standardised residual covariance matrices (SRCM). Although attaining a good model fit is required in order to proceed with the structural model analysis, it is imperative to note that any action during this stage should only be carried out with supporting theoretical justification (Hox and Bechger, 1998; Nachtigall *et al.*, 2003; Tomarken and Walter, 2005).

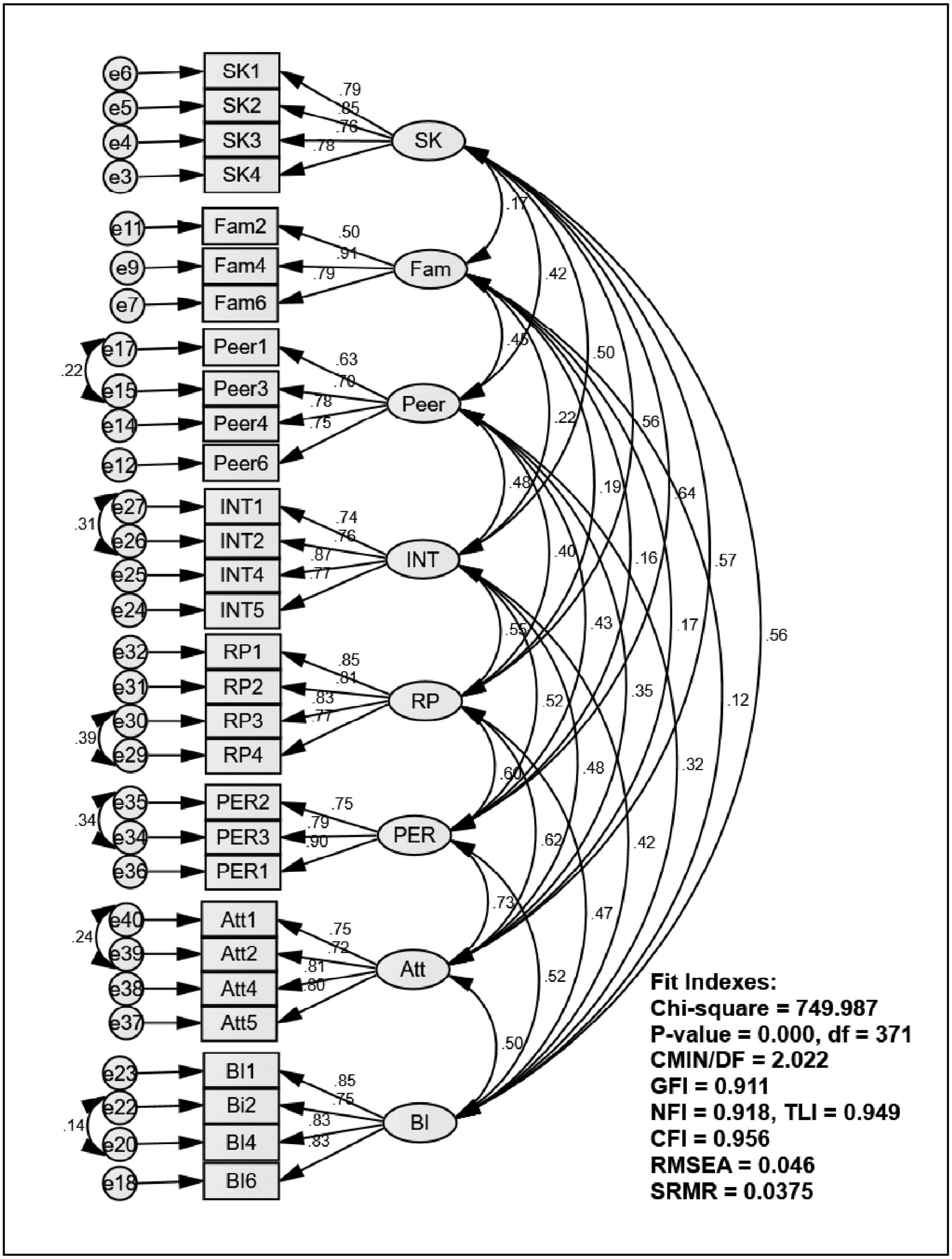

Figure 1: Path Diagram of Measurement Model

Table 2
Standard Loadings and Path Coefficients for Direct-Measured Items

Path		*Path*	*Factor Loading*	*Beta Estimate*	*S.E.*	*C.R. (t-value)*
SK4	<—	SK	0.776	1.041	0.058	18.047**
SK3	<—	SK	0.763	0.986	0.057	17.277**
SK2	<—	SK	0.849	1.095	0.056	19.399**
SK1	<—	SK	0.790	0.96	0.053	18.047**
Fam6	<—	Fam	0.790	1.378	0.129	10.672**
Fam4	<—	Fam	0.909	1.152	0.078	14.716**
Fam2	<—	Fam	0.500	0.725	0.068	10.672**
Peer6	<—	Peer	0.752	1.28	0.103	12.377**
Peer4	<—	Peer	0.777	0.986	0.065	15.149**
Peer3	<—	Peer	0.697	0.895	0.065	13.774**
Peer1	<—	Peer	0.631	0.781	0.063	12.377**
BI6	<—	BI	0.828	0.924	0.043	21.344**
BI4	<—	BI	0.826	0.954	0.047	20.181**
Bi2	<—	BI	0.747	0.805	0.046	17.544**
BI1	<—	BI	0.849	1.083	0.051	21.344**
INT5	<—	INT	0.767	1.098	0.068	16.085**
INT4	<—	INT	0.870	1.163	0.062	18.813**
INT2	<—	INT	0.761	0.922	0.056	16.596**
INT1	<—	INT	0.742	0.911	0.057	16.085**
RP4	<—	RP	0.766	0.872	0.047	18.437**
RP3	<—	RP	0.832	1.138	0.048	23.856**
RP2	<—	RP	0.815	1.164	0.065	17.848**
RP1	<—	RP	0.849	1.146	0.062	18.437**
PER3	<—	PER	0.787	0.878	0.045	19.665**
PER2	<—	PER	0.751	0.951	0.045	21.316**
PER1	<—	PER	0.904	1.139	0.058	19.665**
Att5	<—	Att	0.804	1.104	0.065	16.908**
Att4	<—	Att	0.810	0.938	0.050	18.580**
Att2	<—	Att	0.720	0.867	0.054	16.103**
Att1	<—	Att	0.752	0.906	0.054	16.908**

* $p < 0.05$ (1.645 < t-value < 2.32; **$p < 0.01$ (t-value > 2.33)

Good fit was attained after 21 iterations when evaluated based on three specific groups of model fit. Parsimonious Fit was fulfilled as evidenced by the CMIN/DF of 2.022 (lower than 3.0). The Normed-Fit Index (NFI), Tucker-Lewis Index (TLI) and Comparative Fit Index (CFI) were 0.918, 0.949, and 0.956 respectively; and as all were above 0.90, the model was said to achieve Comparative Fit. The third group of model fit indicators is the Absolute Fit. The results for Goodness-of-Fit Index (GFI) was 0.911 (above 0.90), Root-mean-square-error Approximation (RMSEA) was 0.046 (below 0.05); and Standardised-root-mean-square residual) SRMR was 0.0375 (below 0.08). Based on the three indicators, it was concluded that Absolute Fit has been attained. The χ^2 was 749.987 (df = 371) with p-value of 0.00. Even though the significance of χ^2-statistic was lower than 0.05, it was not a concern as the sample size of the study was relatively large (more than 200). Figure 1 demonstrates the path diagram of the measurement model showing the seven fit indices employed in the analysis.

Table 2 illustrates the standard-factor loadings and path coefficients for the 30 direct-measured items that were successfully retained upon the completion of the MMA. Out of 40 items, ten were dropped due to poor loadings or issues that compromised the establishment of measurement reliability and validity. The 30 items were adequately loaded as all achieved the minimum recommended standardised loading of 0.50, They were also significantly associated with their respective latent variables at 0.01 level (t-value exceeding 2.33).

Table 3
Internal Consistency Reliability, Convergent Validity, and Discriminant Validity

	CR	AVE	Att	Fam	SK	Peer	INT	RP	PER	BI
Att	0.855	0.597	**0.772**							
Fam	0.788	0.567	0.165	**0.753**						
SK	0.873	0.632	0.570	0.166	**0.795**					
Peer	0.807	0.513	0.353	0.450	0.416	**0.716**				
INT	0.866	0.619	0.479	0.221	0.498	0.483	**0.787**			
RP	0.888	0.666	0.620	0.191	0.561	0.403	0.552	**0.816**		
PER	0.856	0.667	0.733	0.159	0.639	0.431	0.517	0.605	**0.817**	
BI	0.886	0.662	0.498	0.120	0.565	0.323	0.417	0.473	0.516	**0.813**

The issues of reliability and validity were examined using figures in Table 3. Composite reliability (CR) is used to assess internal consistency reliability as it considers the different outer loadings of the indicator variables. The CR values are all more than 0.70, thus it can be concluded that internal consistency reliability of construct was achieved (Hair *et al.*, 2014a,b; Awang, 2015). The examination of convergent validity and discriminant validity are performed to what extent in which a set of measured items reflect the latent variables. Convergent validity is considered to have established when the AVE exceeds 0.50. The lowest and highest AVE values of the study are 0.581 and 0.732 respectively, thus, the model is free from convergent issues. With reference to Table 3, discriminant validity is attained. The diagonal values (square root of AVE) are higher than all other values of their respective columns and rows.

CONCLUSION

The main finding of the study is the discovery of a measurement model that has been confirmed free from issues related to unidimensionality, internal consistency reliability, convergent validity, and discriminant validity. Other than strong support for the internal consistency reliability as well as convergent and discriminant validity of the risk-taking intention toward financial investment model, the data have confirmed the direct measured items of the exogenous latent variables, namely, subjective knowledge (SK), family influence (Fam), peer influence (Peer), Internet influence (INT), risk propensity (RP), risk perception (PER), attitude (Att), and the endogenous latent variables of behavioural intention (BI). This is indeed a step forward in behavioural finance research, especially when dealing with relatively robust and complex research model. With the confirmation that the data are fitted strongly to the model, it serves as an enabler to proceed to the next stage of analysis, namely the structural model assessment. The confirmed direct-measured items for their respective latent variables may serve as future reference, especially in the behavioural finance study, which are still lacking.

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