Dimensionality and Reliability of the Determinants of Reverse Mortgage Use Intention

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Abstract. The decision to use reverse mortgage is influenced by a myriad of factors among which some are behaviourally related. Identification and validation of these behavioural factors are necessary to be able to objectively explain their interrelationships and effect on individual's decision to use the product in the future. This paper reports a pilot survey result that aimed at validating a questionnaire designed specifically to collect data on the behavioural factors that might likely influence individual's intention to use reverse mortgage in the future. Using a convenient sampling strategy, a total number of 102 sampled respondents were used in the study. The data were analyzed with the aid of the Statistical Package for the Social Sciences (SPSS) version 23 where a factor analysis and reliability analyses were conducted. The result revealed that out of the 53 items that originally formed the questionnaire items, only 41 were retained. A total of 10 components emerged from the data which were named in accordance with their underlying constructs. All the factor loadings in reported satisfied the acceptable threshold of .50. The reliabilities of the items and the respective scales were also within the acceptable range of .70. It was therefore concluded that the questionnaire was reliable and can be used for the purpose to which is was designed for.

Keywords: factor analysis; pilot study, principal axis factoring, reliability, validity.

INTRODUCTION

Reverse mortgage is a financial product that allows elderly homeowners aged 62 years and above to liquidate the accumulated housing equity in their primary residential homes to enable them address various financial needs that might arise during their remaining life. The product is considered an innovative means to tackle the risk of financial insecurity in old-age. Previous studies mostly conducted in United States have shown that the product have market potential to provide millions of older people additional income to fulfil their financial needs [18, 23, 24, 30, 31, 32, 34, 39]. Despite these promising potentials, the mismatch between projected demand and actual market demand for the product persist. Researchers and experts have severally commented on the possible reasons behind the identified wide gap between the actual demand and the hypothesized reverse mortgage product demand [5, 7, 9, 13, 17, 22, 41, 26, 33]. Review of these studies indicated that demand for reverse mortgage is affected by a combination of institutional/political, economic, socio-cultural and behavioural factors [2, 3, 4, 7, 19]. Emphasizing on the behavioural factors, Authors [26] proposed a theoretical model that included six underlying constructs as the determinants of behavioural intention to use reverse mortgage. Therefore, in an attempt to validate the constructs in the model, this paper reports the result of a pilot survey with the view of determining the dimensionality and reliability of the underlying behavioural factors that could potentially affect individual's intention to use reverse mortgage in the future.

Overview on Exploratory Factor Analysis (EFA)

The purpose of conducting factor analysis is to discover the underlying constructs or dimensions in the dataset [16] while reliability analysis measures the performance of the construct. The EFA was conducted following the five methodological steps explained by [10]. These steps involve a series of iterative process that are interrelated to one another and involved evaluation of data suitability for EFA (measure of sampling adequacy), factor extraction method, factor retention method, selection of rotational method and interpretation and labelling [36]. Ensuring sampling adequacy is one of the important steps in EFA. There are arguments on what constitute adequate sample when EFA is considered as analytical tool. Some researchers use the minimum number of cases criterion while others are inclined towards cases-to-variable ratio criterion [1]. In the case of the minimum number of cases criterion, many rules of thumbs had been advanced. Authors [6] considered 50 cases as very poor, 100 cases as poor, 200 as fair, 300 as good, 500 as very good and 1000 and above as excellent sample sizes in EFA. Authors [22] argued that in conducting an EFA the number of observations must be greater than the number of variables and that a sample size of 100 is considered adequate. In respect of the cases-to-items criterion, authors had suggested the ratios of 20:1; 10:1; 5:1 rule of thumbs as the appropriate ratio for EFA [28]. However, the ratio criterion had severally been criticized [1]. Instead, [14] suggested that determining the required sample size in EFA should be based on the strength of the relationship between the factors and the items. Based on this argument, they operationalized the relationship as follows:

- if factors have four or more items with loadings of 0.60 or higher; then the size of the sample is not relevant;
- if factors have 10 to 12 items that loads moderately (.40 or higher), then a sample size of 150 or more is required;
- if factors are defined with few variables and have moderate to low loadings, a sample size of at least 300 is needed [1].

Supporting this argument, [10] indicated that with a sample as low as 100 cases, a stable solution can be obtained when three or four items have higher loadings of .70 and above. Therefore, being a pilot survey, a total number of 102 samples were used for this analysis. This number meets the recommended minimum sample size advanced by [22].

Having established the factorability of the dataset, the next step in the factor analytical process is to determine the factor extraction method. Factor extraction involves the task of choosing the most suitable factor analysis method from series of alternative methods in order to ensure the selection of an optimum method that explains the dataset substantially. There are various factor extraction methods from which a researcher can choose when conducting factor analysis: principal component analysis (PCA); principal axis factoring (PAF); maximum likelihood (ML); alpha factoring etc. with each having its own peculiarity and requirements. The PCA and the PAF were identified as the most widely used methods among all the methods [40]. However, there are arguments whether PCA is a factor analysis technique or not. For instance, [28] argued that PCA is a mere data reduction technique and it is not suitable when the goal of the analysis is to detect structure or pattern within a given dataset. On the other hand, PAF is considered the appropriate factor analysis technique when the goal is to detect the underlying latent constructs from many variables. Notwithstanding, others believed that the results of the two converges [37, 38]. In this respect it was advocated that the researcher should apply both methods so that the best result that most accurately depicts the research goal is chosen [1].

The initial extraction of factors in factor analysis displays results with as many factors as the number of variables in the dataset. However, only a few factors would be considered for retention for further analysis and interpretation. Different criteria have been devised to guide the researcher in making the decision about the number of factors to be retained from factor analysis [10]. Researchers often resort to the use of Kaiser Criterion, scree plot test, variance extracted, or parallel analysis criterion when making decision on the number of factors to be retained [1, 10].

The Kaiser Criterion has been identified as the most widely used method among researchers [1, 28]. It involves computing the eigenvalues for the correlation matrix of the dataset to determine how many of these eigenvalues are greater than 1 which is then used as the cut-off point for the number of factors to be retained [10]. However, the method has been criticized as being too arbitrary and it is prone to over-factoring and/or under-factoring as the case may be [10, 28].

The scree plot test involves plotting a graph of the eigenvalues and then examining it to identify the point at which the bend breaks or flattens out. The number of factors retained is usually determined by the number of data points that occurred above the break-point [28]. However, identification of the cut-off point that determines the number of extracted factors has been criticized as being subjective [1, 28]. Notwithstanding, with the presence of strong common factor the scree plot test is considered to functions well [10]. Another method of determining number of factors to retain is variance extracted method. The criterion involves retaining factors that explains certain percent of extracted variance [1]. The decision rule for acceptable percentage benchmark is, however, a subject of debate among researchers. Whereas some suggested as low as 50 percent explained variance as acceptable, other argued that the variance explained should be 75 percent and above [1]. The parallel analysis method is considered the most appropriate method to decide the number of factors to retain in factor analysis [36]. The procedure involves comparing the actual eigenvalues obtained from the working data with the eigenvalues expected from a completely random sample. The decision rule is to retain the factors whose eigenvalue is greater than the eigenvalues expected from the random data [10, 40]. However, the method was also criticized as being arbitrary in the choice of the factors as any factor with eigenvalue that falls marginally below the expected eigenvalue is not considered [10]. In order to avoid bias in the factor retention decision, the use of multiple criteria was advocated [11].

The next step in the factor analytic process is the choice of rotation method. The main goal of rotation in factor analysis is to simplify and clarify the structure of the data [28]. There are different types of rotation that can be performed in factor analysis which broadly categorized into two: orthogonal rotation and oblique rotation. The orthogonal rotation (varimax, equamax, quartimax) is used when no correlation among factors is assumed while the oblique rotation (direct oblimin, quartimin and promax) is used when the researcher assumes correlation among the factors [10, 11, 28].

The final step in the factor analysis process is the interpretation and labelling the retained factors. The process involves assigning name for a given factor in order to reflect its theoretical or conceptual meaning it is intended to convey [36].

METHODOLOGY

The indicators that measured the seven (7) constructs were generated through literature review and by modifying the original statements in the TPB questionnaires to reflect the peculiarity and suit the context of the present study. The questionnaire was designed in a Likert-scale type rating scale. This scale type is chosen because of it provides ordinal level measures of multiple-indicator measurements of behavioural, attitudinal and psychological concepts which provide greater flexibility for data analysis [20]. Moreover, many studies have used Likert-scale to assess beliefs, attitude and behaviour [12]. The questionnaire contained a total of 53 items measuring the seven constructs. The questionnaire assessed the intensity and direction of respondents' agreement or disagreement with series of statements that measure Attitude (ATT), social influence (SI)' perceived ability (PA); bequest motive (BM), and sense of place attachment (SPA) on a five-point "strongly disagree" (1) to "strongly agree" (5) scale. Reverse mortgage use intention (RMUI) was assessed using a five-point rating scale of "extremely not willing" (1) to "extremely willing" (5) while financial behaviour (FB) was assessed using a five-point rating scale of "never" (1) to "always" (5). The questionnaire was self-administered to 102 households in Parit Raja District of Batu Pahat, Johor using the convenience sampling strategy. All questionnaires were retrieved and used for the analysis. The collected data was analysed using the Statistical Package for Social Science (SPSS) version 23.

RESULT AND DISCUSSION

Data suitability for EFA

The suitability of the dataset for EFA was evaluated by examining suitability of the dataset for EFA was evaluated by examining the correlation matrix of the variables, the Kaiser-Mayer-Olkin (KMO) Measures of Sampling Adequacy and the Bartlett's Test of Sphericity as recommended by [40]. The decision rule applied in assessing the correlation matrix is to examine the determinant. A non-zero determinant indicates that, at least, a factor can be extracted from the dataset [1]. On the other hand, best practice among researchers recommends the KMO value to be greater than .50 while the Bartlette's Test statistic should be less than .05 [21, 29, 40]. Table 1 shows the determinant, KMO and the Bartlett's statistics from the analysis.

Table 1 – Determinant, Kaiser-Mayer-Olkin measures of sampling adequacy

Determinant		1.15 E-020
The Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.750
Bartlett's Test of Sphericity	Approx. Chi-Square	3650.095
	df	820
	Sig.	.000

As revealed by the result, the determinant of the correlation matrix is 1.15E-020 which is a non-zero, thus indicating that, at least, one factor can be extracted from the dataset. To test whether this value is statistically different from zero at p=.05, the Bartlette's Test of Sphericity is required. The result confirmed that the determinant is statistically different from zero (p=.000). The KMO returned a value of .750 which also falls within the recommended threshold. Based on these criteria, it can be concluded that the dataset is suitable for EFA.

Factor extraction and rotation method

The extraction follows an iterative procedure where the analysis was conducted 13-times before arriving at a simple solution. The process was conducted using the PAF method with Direct-Oblimin rotation option. The choice of this method was informed by the fact that the main goal of conducting the factor analysis is to identify the underlying constructs that best represent the original variables in the dataset. Identifying the latent constructs will provide a manageable representative data without substantially losing the inherent characteristics of the original data. PAF is considered the appropriate factor analysis technique when the goal is to detect the underlying latent constructs from given number of variables [37, 38]. Other specifications involve the suppression of factor loadings to .50 such that only variables that load .50 or higher would appear in the output. This was based on the recommendation of [21] who suggested that factor loadings can be suppressed to as high as .50. A total number of 14 variables that either substantially cross-loaded or were freestanding (not loading on any factor) were removed from the analysis. Table 2 shows the 10 extracted factors that resulted from the analysis.

Factor retention criteria

Multiple criteria were used to decide the number of factors retained in the present analysis. This is to ensure the retention of "optimal" number of factors. By using multiple criteria, the risk of substantial data loss because of under-factoring was hopefully avoided. In the same vein, the risk of including extraneous factors as a result of over-factoring was likely avoided too. Factor retention decision was based on scree-plot test, the Kaiser Criterion and parallel analysis.

Figure 1 shows the scree-plot generated from the data.

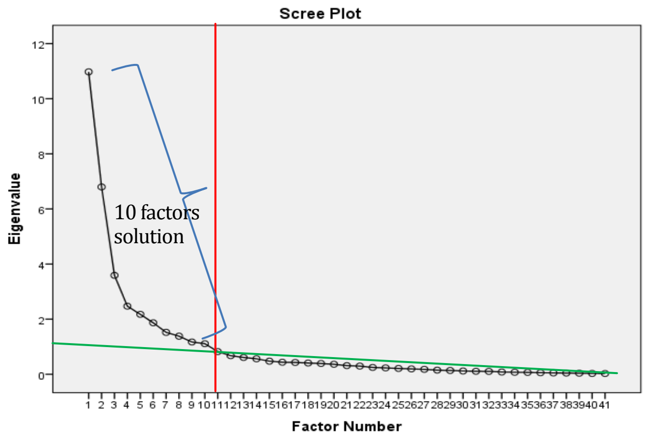

Figure 1 – Scree-plot Test

By visual observation the point where apparent break occurs in the graph is at the point where the horizontally inclined line crosses the vertical line. This point coincided with the number 11, which represents the 11th factor in the series. Authors [40] and [11], explained that factors that occurred above the elbow or point of inflexion should be retained in the scree-plot test. Therefore it is considered that 10 factors can appropriately be extracted for further analysis.

To compliment the scree-test method, the Kaiser Criterion was also used to determine the number of factors to retain. Table 2 shows the eigenvalues of the first 10 factors extracted from the analysis.

The total eigenvalue for 8 out of the 10 factors were all above 1 which is the Kaiser's benchmark for factor retention. The 9th and the 10th factors both yielded values that were less than 1. Strictly following the Kaiser Criterion, only 8 factors should be retained. However, [15] cited in [11] criticized the Kaiser Criterion as being too strict and suggested that factors with eigenvalue as low as .70 should also be retained. Following this argument, 10 factors were retained based on the Kaiser criterion.

Table 2 – Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadingsa
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	10.976	26.772	26.772	10.740	26.196	26.196	7.236
2	6.798	16.579	43.351	6.542	15.955	42.151	4.907
3	3.591	8.758	52.109	3.386	8.260	50.410	2.668
4	2.470	6.025	58.134	2.204	5.377	55.787	5.450
5	2.177	5.309	63.443	1.902	4.638	60.425	3.280
6	1.869	4.558	68.002	1.607	3.919	64.344	7.606
7	1.521	3.710	71.712	1.250	3.049	67.393	3.915
8	1.383	3.372	75.084	1.103	2.689	70.082	3.632
9	1.172	2.858	77.941	.923	2.251	72.333	4.516
10	1.109	2.704	80.646	.849	2.070	74.403	3.079

Notes: Truncated to show only the 10 extracted factors

In addition, parallel analysis was conducted to compare the result from the previously mentioned methods. Lamentably, there is no in-built provision for conducting parallel analysis in the popular software use for factor analysis such as the SPSS; however, the analysis can be conducted using a sort of Monte Carlo simulation. Using a specialized syntax written by O'Connor, (2000) the parallel analysis was executed. Table 3 shows the truncated output obtained from the analysis.

Table 3 – Parallel Analysis [1]

Root	Raw Data Eigenvalue	Random Data Eigenvalue [2]
1	10.837471	2.187853
2	6.630496	1.943753
3	3.454269	1.763427
4	2.306854	1.619544
5	1.994559	1.490361
6	1.699048	1.382154
7	1.353997	1.285071
8	1.187431	1.190211
9	.999713	1.107307
10	.948271	1.022674

Notes: 1) Truncated to show only 10 extracted factors; 2) Based on 95% Confidence interval

The result indicated that from factor 1 to factor 6, the eigenvalues of the original data exceed that of the generated random data while the remaining eigenvalues of the original data were all below the generated eigenvalues of the random data. This indicates that only 6 factors should be retained. However, considering that this is an exploratory study that aimed at detecting the structure of the data and refining a questionnaire that would be used in the full-scale study, 10 factors were retained as indicated by the previous methods. This is to avoid the issue of losing important information which might be required in the research.

Interpretation and labelling of factors

The final step in the factor analysis process is the interpretation and labelling the retained factors. The process involves assigning name for the given factor to reflect its theoretical or conceptual meaning it is intended to convey [35]. Table 4 shows the questionnaire items and their loadings on the extracted factors. As shown in the Table the items that load highly on factor 1 were statements that express respondents' willingness to use reverse mortgage in the future, hence the factor can conveniently be labelled "Reverse Mortgage Use Intention (RMUI)". Four items loaded highly on factor 2. The questions associated with these items asked the respondents to indicate who could likely influence them when they are contemplating entering into reverse mortgage contract. As shown in the table all the four items relate to family, therefore factor one was labelled as "Family Influence (FI)". Factor 3 has three items that loaded highly on it. The items related to a question that asked the respondents to indicate the frequency at which they performed some listed financial activities. As indicated in the table, all the three activities coincided with savings, thus the factor was named "Savings Motive (SM)". The fourth factor constitutes of items from a question that test the respondents' reactions about bequeathing their properties to their families. The four items that loaded highly on this factor inclined towards dynastic behaviour, hence the factor was named "Dynastic Bequest Motive (DB)". With regards to the factor 5, the three items that loaded highly on it, formed part of a question that measured the respondents' perception about the idea of reverse mortgage. All the three items tend to portray reverse mortgage product as useful, therefore the factor was labelled "Perceived Usefulness (PU)". Factor number 6 contains eight items that dealt with a question that measured the respondents' sense of place. This factor was tagged "Sense of Place Attachment (SPA)". Factor 7 contains items related to a question that measured the respondents' opinion about their capability to engage in reverse mortgage transaction. A look at the statements from these items, it can be concluded that they can conveniently be labelled as "Perceived Ability (PA)". The items that load on factor 8 relates to the same question asked about factor 2. Examining the statements shows that the items reflect the influence of other people external to the respondent on decision to enter into reverse mortgage transaction in future, hence the factor is labelled "Community Influence (CI)". Other three items that relate to the question that measured the respondents' financial behaviour load highly on factor 9. Examination of the statements reflects respondents' behaviour with respect to insurance. Therefore, the factor was named "Financial Planning (FP)". The items that load on factor 10 also belong to the question that tried to measure the respondents' opinions on bequest. The statements indicated that the factor can conveniently be labelled "Selfish-Lifecyle Bequest Motive (SB)". Table 4 shows the factors and the respective items that loaded on them.

Table 4 – Pattern Matrix of Factors

Codes	Items	Factors										Communalities
		1 RMUI	2 FI	3 SM	4 DB	5 PU	6 SPA	7 PA	8 CI	9 FP	10 SB	
INT3	Pay-off existing mortgage loan	.898										.904
INT4	Pay-off other debts	.705										.829
INT5	Pay medical bills	.659										.745
INT8	Settle unforeseen financial needs	.610										.830
INT2	House upgrading/repairs	.559										.690
INT1	Supplement existing source of income	.525										.714
RM1	Children		.837									.700
RM4	Parents		.823									.759
RM2	Spouse		.816									.861
RM3	Siblings		.772									.813
FB4	Maintained an emergency savings fund			.824								.778
FB3	Save for long term goal such as a car, education or home			.805								.742
FB5	Save money from every monthly income			.747								.752
BM2	I will leave my house to my children				.745							.752
BM4	I will be ashamed not to leave my house to my children to inherit				.737							.651
BM1	I plan to leave my house as bequest to my children				.728							.702
BM3	My children expect that I leave my house for them to inherit				.698							.726
ATT4	Beneficial					-.754						.806
ATT5	Useful					-.751						.749
ATT1	A good deal					-.638						.611
SPA3	I identify strongly with my neighbourhood						.957					.875
SPA2	I am very attached to my neighbourhood						.938					.855
SPA4	I have special bonding to my neighbourhood and the people living around						.904					.833

Continuation Table 4

Codes	Items	Factors										Communalities
		1 RMUI	2 FI	3 SM	4 DB	5 PU	6 SPA	7 PA	8 CI	9 FP	10 SB	
SPA7	Living in my neighbourhood is more important than any other place						.696					.814
SPA1	My house meant a lot to me						.676					.623
SPA8	I will not relocate from this neighbour-hood						.570					.748
SPA5	I drive more pleasure living in my house than any other house						.553					.697
SPA6	I am completely satis-fied with my accom-modation						.527					.660
PBC1	I own my house free of any housing loan debt							.757				.814
PBC3	I am free to enter into reverse mortgage transaction							.704				.580
PBC2	I almost paid off my housing loan							.693				.770
PBC4	I have absolute con-trol over my house							.603				.624
RM7	Community lead-ers/religious leaders								.864			.765
RM6	Peers								.716			.678
RM5	Financial advisor								.611			.587
FB9	Obtained or main-tained adequate life insurance									.896		.911
FB7	Obtained or main-tained adequate health insurance									.806		.873
FB8	Obtained or main-tained adequate property insurance									.803		.814
BM6	My children can only inherit my house if they help me while I am alive										-.647	.611
BM5	I have no children to leave my house for										-.639	.543
BM7	My children will/are already self-sufficient and do not care if I sell my house										-.619	.718
Sum of Square Loadings (Eigenvalues)		10.740	6.542	3.386	2.204	1.902	1.607	1.250	1.103	.923	.849	Total 30.506
Percentage Variance Explained		26.196	15.955	8.260	5.377	4.638	3.919	3.049	2.689	2.251	2.070	74.403

The factor loadings range from a minimum value of .525 associated to RMUI factor to a maximum of .957 associated with SPA factor. Similarly, all the reported communalities are high (.580-.911) which is an indication that the factors are sufficiently explained by the loaded items [11].

Reliability analysis

Having established the number of factors to be retained it is recommended that the reliability of the items and their respective constructs be examined.in order to establish the validity of the questionnaire scales. In this section the reliability of the constructs was tested using the Cronbach's Alpha method. The acceptable threshold for scale reliability is .70 and above although .60 is also regarded as acceptable when the study is at its exploratory stage. Similarly, another important statistic usually examined is the corrected item-total correlation. This measures the internal consistency of the scale and value of .30 and above is recommended [11].

Table 5 show the result of the reliability analysis. The reported Scale's Cronbach's Alphas indicated that all the scales are reliable.

Table 5 – Reliability analysis of the questionnaire scales

Codes	Corrected Item-Total Correlation	Cronbach's Alpha if item Deleted	Scale's Cronbach's Alpha
INT3	.831	.929	.941
INT4	.862	.925	
INT5	.814	.931	
INT8	.842	.928	
INT2	.783	.936	
INT1	.816	.931	
RM1	.811	.905	.924
RM4	.773	.917	
RM2	.875	.883	
RM3	.837	.896	
FB4	.778	.739	.852
FB3	.658	.860	
FB5	.741	.780	
BM2	.736	.819	.864
BM4	.651	.851	
BM1	.764	.805	
BM3	.717	.829	
ATT4	.744	.730	.831
ATT5	.720	.735	
ATT1	.633	.840	
SPA3	.852	.933	.944
SPA2	.858	.933	
SPA4	.850	.934	
SPA7	.839	.934	
SPA1	.742	.941	
SPA8	.777	.939	
SPA5	.739	.941	
SPA6	.738	.941	
PBC1	.751	.742	.830
PBC3	.663	.788	
PBC2	.701	.766	
PBC4	.539	.837	
RM7	.736	.761	.844
RM6	.735	.760	
RM5	.668	.824	
FB9	.899	.907	.945
FB7	.904	.905	
FB8	.851	.945	
BM6	.610	.712	.790
BM5	.615	.705	
BM7	.628	.691	

The Financial Planning sub-scale reported the highest alpha value (α= .945) with corrected item-total correlations ranging from .851 to .904. The next highest alpha values are associated with the Sense of Place Attachment (α= .944), Reverse Mortgage Use Intention (α= .941), and Family Influence (α= .924). The corrected item-total correlations in respect of these scales range from .738 to .904, related to SPA and IB respectively. The reported alpha values and the corrected item-total correlations of the remaining six scales also satisfy the recommended threshold of .70 and .30 respectively with the lowest reported alpha value and item-total correlation associated with the Selfish-lifecycle Bequest and the Perceived Ability constructs respectively. In general, therefore, it could be concluded that the scales are reliable and could be use in measuring what they were intended to measure.

CONCLUSION

A principal Axis Factoring (PAF) was conducted on 53 items with orthogonal rotation (varimax). The Kaiser–Meyer–Olkin measure verified the sampling adequacy for the analysis, KMO = .750, which is well above the acceptable limit of .5. Bartlett's test of sphericity χ^2 (820) = 3650.095, $p < .000$, indicated that correlations between items were sufficiently large for factor analysis. An initial analysis was run to obtain eigenvalues for each component in the data. Ten components had eigenvalues over Kaiser's criterion of 1. The scree plot showed inflexions point at the 11th component. The analyses resulted in retaining 41 items out of the 53 items that were originally included in the first draft questionnaire. The factor analysis result indicated that the 41 items can appropriately be clustered into 10 factors which were labelled Reverse Mortgage Use Intention, Family Influence, Saving Motive, Dynastic Bequest, Perceived Usefulness, Sense of Place Attachment, Perceived Ability, Community Influence, Financial Planning, and Selfish-Lifecycle Bequest. The result of reliability analysis showed that all the scales were reliable which therefore lead to the conclusion that the questionnaire can be used to gather information from the larger sample in the main survey.

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