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 processes 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 an 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-factorizing and/or under-factorizing 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); benefit 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.

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

| Determinant     | 1.15E-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.

![Scree Plot](image)

**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

| Root | Raw Data Eigenvalue | Random Data Eigenvalue |
|------|---------------------|-----------------------|
| 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    | 1.899048            | 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 test the
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 tried to measure the respondents’ opinions on bequest. The statements indicated that the factor can conveniently be labelled “Selfish-Lifecycle 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 |
|-------|--------------------------------------------|---------|---------------|
| INT3  | Pay-off existing mortgage loan             | .898    | .904          |
| INT4  | Pay-off other debts                        | .705    | .829          |
| INT5  | Pay medical bills                          | .659    | .745          |
| INT8  | Pay unforeseen financial needs             | .610    | .830          |
| INT1  | House upgrading/repairs                    | .559    | .690          |
| INT6  | Supplement existing source of income       | .525    | .714          |
| RM1   | Children                                   | .837    | .700          |
| RM4   | Pay for long term goal such as a car        | .823    | .759          |
| RM2   | House upgrading/repairs                    | .816    | .861          |
| RM3   | Save money from every monthly income       | .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          |
| ATT5  | Useful                                     | -       | .751          |
| ATT1  | A good deal                                | -       | .638          |
| 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 |
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.

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 χ² (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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