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Barriers to Energy Efficiency: Low-Income Households in Australia

Samaneh Azimi [1], Carol K. H. Hon [1,*], Tanja Tyvimaa [2] and Martin Skitmore [3]

[1] School of Architecture and Built Environment, Queensland University of Technology (QUT), Brisbane, QLD 4001, Australia; samaneh.azimi@connect.qut.edu.au
[2] City of Tampere, Real Estate and Housing, Sustainable Housing and Construction, PL 487, 33101 Tampere, Finland; tanja.tyvimaa@tampere.fi
[3] Faculty of Society and Design, Bond University, Robina, QLD 4226, Australia; mskitmor@bond.edu.au
* Correspondence: carol.hon@qut.edu.au

Abstract: Low-income housing plays an important, but frequently overlooked, role in energy use reduction. Barriers persist for low-income households to participate in energy efficiency programs and adopt efficient lifestyles. However, there has been only limited research into energy efficiency barriers faced by low-income households. Existing energy research studies primarily focus on homeowners whose demographic and socio-economic profiles are likely to be very different from low-income households or renters—limiting the applicability of previous findings to low-income households. This study aims to identify and evaluate the importance of the energy efficiency barriers faced by low-income households. A questionnaire survey was conducted with 212 low-income households in Australia. After randomly dividing the data into calibration and validation samples, an exploratory factor analysis (EFA) of the calibration sample identifies four energy efficiency barrier factors of financial, decision-making, information, and split incentives. These four factors are then validated by confirmatory factor analysis (CFA) of the validation sample in terms of goodness-of-fit, reliability, and validity to confirm financial as the most highly rated energy efficiency barrier. This research contributes to bridging the knowledge gap of the energy efficiency barriers of low-income households and providing a validated CFA model as a tool for assessment. The results provide a better understanding of the barriers involved and research evidence to facilitate the formulation of policies to overcome them.

Keywords: Australia; energy efficiency; barriers; low-income households

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1. Introduction

Climate change is starting to have a dramatic effect on all our lives, with particular ramifications on cities and their residents, especially the poor [1]. One of the most important initiatives to address this situation is to reduce greenhouse gas emissions from the consumption of fossil fuels [2], of which buildings contribute a large share both nationally and globally—their operation accounting for around a quarter of the country's total. Despite the huge impact of buildings on greenhouse gas emissions, the majority of buildings are constructed without regard to sustainability [3].

In recent years, dramatic increases in energy prices have compelled Australian households to cut their energy use by investing in more energy-efficient appliances, home improvements, and rooftop solar panels. Otherwise, while most citizens of developed countries are concerned about climate change, they will only undertake actions that require little financial effort because they believe that governments, companies, and industries should take the necessary action [4]—an attitude more obvious among low-income households.

Low-income households are often overlooked for energy use improvements [5] for obvious reasons of financial hardship together with other monetary and non-monetary barriers [6]. Nevertheless, significant opportunities remain [7]. In fact, it is estimated that a 20% reduction in energy consumption by such households would save at least AUD 1 billion annually.

Previous studies have not gone into great depth about energy efficiency initiatives. Moreover, rather than considering low-income households or renters, most have been confined to local surveys and primarily focused on homeowners whose levels of income and education were usually above the national average [8,9]. There is limited research identifying the challenges that prevent energy efficiency in low-income households in terms of unique demographic and socio-economic profiles. Moreover, the importance of an assessment tool in identifying energy efficiency barriers has gone unnoticed.

In response, the present study provides a theoretical contribution to the existing body of knowledge regarding the energy efficiency barriers of the low-income households and a tool to assess them. The findings contribute to developing policies and programs for mitigating energy efficiency barriers of low-income households. Hence, this study further contributes to improving their standard of living, making a positive impact on their health, and reducing the negative impact of climate change on them.

The paper is organized as follows. The literature review in Section 2 offers an overview of the current literature relating to the major barriers to the household adoption of energy efficiency measures. The third section explains the methodology used to achieve the research's aims and objectives, followed by a justification for the choice of variables in the models, the questionnaire design, and details of the data collection and data analysis process. The results of the survey questionnaire are presented in the fourth section, followed by their discussion in the fifth section. The final section concludes the paper with a brief summary of the research, its limitations, and prospects for future work.

2. Energy Efficiency Barriers

Using a taxonomy devised by Sorrell et al. [10], this section delves into the nature of the four major barriers to energy efficiency. Sorrell et al. [10] describe the energy efficiency gap as the difference between the actual level of energy efficiency obtained in practice and what seems to be a possible cost-effective level of energy efficiency. The barriers involved were initially classified into four broad groups: (1) financial, (2) informational, (3) decision-making, and (4) split incentives [11,12].

2.1. Financial Barriers

One key barrier to energy efficiency emphasized by Sorrell et al. [12] is limited access to capital. In general, this applies to the restricted access to capital and limited access to capital for energy efficiency [11]. One other crucial argument against the "efficiency gap" hypothesis is hidden costs, identified along with access to capital as the most significant barriers to increased energy efficiency [12]. Energy efficiency is marred by the high up-front cost of energy upgrades, especially for low-income households [4]. Over the years, improvements in energy performance in households have been obstructed by financial barriers, either through dissatisfaction with the payback period or lack of finances. As Wilson et al. [13] state, the most important financial barriers are capital availability and extreme dislike of delayed gains. Similarly, according to Murphy [14], failure to adopt energy efficiency measures can be ascribed to a lengthy payback period and lack of finances.

2.2. Information Barriers

A considerable amount of the literature states that the main obstacle to domestic energy savings is the lack of energy awareness among energy consumers [15]. Another is the skepticism or lack of awareness about existing resources. Erroneous perceptions that households have towards energy saving or consumption are revealed by Ameli and Brandt [16], who suggest that residents possessed little or no knowledge of the efficiency of various energy-saving techniques. Investment decisions regarding energy conservation and renewal energy may be affected by this lack of knowledge. In a survey by Murphy [14], the failure of energy efficiency adoption measures is attributed to homes being assumed to have adequate energy-saving measures; however, the information barriers identified by Wilson et al. [13] include: (1) misperceptions about energy costs, as well as doubts about contractor's reliability and cost-saving outcomes, and (2) unavailability of relevant information on efficiency measures, a perceived lack of credibility.

2.3. Decision-Making Barriers

Bukarica and Tomšić [17] have studied the ratio and impact of psychology on people's decisions pertaining to energy conservation, observing that people's psychology affects their decision-making; in most cases, they are unable to make optimal energy-saving decisions even when they have all the relevant information at their disposal. This phenomenon is described by the term "bounded rationality". Generally, achieving satisfaction is the reason people make decisions, which may not be optimal. Thus, people cannot rationalize their behavior if they cannot make such a connection, especially when the enormity of the problems involved makes their individual effect seem insignificant [17]. Wilson et al. [13] highlight the following decision-making barriers: (1) the anticipated stress and disruption that comes along with conducting renovations in the home, and (2) the cognitive challenge (or transaction costs) of making irreversible and complicated decisions.

Sorrell et al. [12] identify technical risk as another essential factor that affects decision-making to enhance energy efficiency. Technical risk is concerned with the technical performance and unreliability of individual technologies [11].

2.4. Split Incentives Barrier

Split incentives are an obstacle to investment in the energy efficiency of such fixed appliances as hot-water heaters and air conditioners, and in improving the thermal performance of rental buildings [6]. The tenant–landlord split incentive is a persistent and powerful market failure that has been recognized as a major barrier to tenants' decision to install energy efficiency products and insulation [18]. In Sorrell et al. [12], the problem lies in the inability to realize the benefits of an investment, which is a product of the combination of high transaction costs and asymmetric information. The absence of information asymmetry would enable landlords and tenants to have a share in the net gains of energy efficiency investments by entering into a contract [12].

This barrier should also be considered from the Australian perspective. Tax laws in Australia do not allow landlords to claim a tax depreciation or deduction for energy efficiency upgrades or embedded generation or installation of solar hot water on their rental properties. Such upgrades are regarded as capital improvements that are included in the cost of the property to calculate capital gains during the sale of the property [19]. Conversely, there is a tax deduction for "maintenance" expenses involving "like for like" replacement of inefficient equipment. Many landlords possibly consider deductions from capital gains to be less attractive than tax offsets on rental returns. As tenants have no means or right to upgrade permanent fixtures or the building, they are left to bear the high cost of running inefficient hot-water systems or cooling and heating leaky homes. Not installing free energy efficiency upgrades is even evidence of the absence of landlord involvement in energy efficiency [6]. As seen in the aggregated data from the NSW Home Power Savings Program, only 10.2% of private homeowners were granted permission to install free efficient draught strips and showerheads for the low-income tenants taking part in the program. The Central Victorian Solar City program also had a significantly low representation for renters, who accounted for just 2% of the beneficiaries of the program's energy savings assistance [6].

3. Research Methodology

3.1. Questionnaire Design

A structured questionnaire is used to identify the energy efficiency barriers of low-income households in Australia. The questionnaire is divided into three sections. The first section comprises 13 questions designed to extract dwelling characteristics, home tenure, and household characteristics. The second section comprises 11 questions concerning the adoption of energy efficiency measures (EEMs) and knowledge of energy efficiency. The third section comprises 26 questions about financial barriers, information barriers, decision-making barriers, and split incentives barriers (Appendix A). The data collected through this section aims to validate the factors and barriers discovered in the literature. The last section of the survey is designed to collect data concerning household energy efficiency plans towards energy saving.

Content validity is a subjective examination of the characteristics of the contained variables. Statisticians disagree about the appropriateness of the size of Cronbach's alpha [20,21]. An alpha of 0.65 to 0.8 is usually regarded to be "adequate" for a scale employed in human dimension studies [22–24]. Some academic scholars were also assigned to oversee the questionnaire's content validity. Convergent and discriminant validities, which measure the patterns of relations or comparative strengths among several variables, were often studied jointly.

3.2. Participants and Procedures

The survey was randomly conducted across cities in Australia to ensure that the findings are generalizable and accurate to the greatest possible degree. To obtain valid results, any common estimation procedure requires a sampling size of at least 200, as recommended for structural equation modelling (SEM) and standard statistical analysis [25].

The factors affecting EEMs were first assessed by conducting a pilot survey before the large-scale survey was carried out to determine if the survey questions would be clear to the participants and relevant to the study, or if there was a need for further action to address any vague question. A number of 15 respondents, consisting of colleagues and academics, participated in the pilot study, which was conducted after completing an initial literature review in September 2020. Suggestions on how to improve the readability, language, and other aspects of the questionnaire were requested from the pilot study respondents.

The survey was administered by a research panel firm with vast networks of low-income families. Based on information from the Australian Bureau of Statistics [26], low-income households in this study are defined as those with a taxable income of less than AUD 69,999. Hence, the questionnaire was sent to a network of low-income families in Australia with a taxable income of less than AUD 69,999 with eligible participants invited respondents who should be a household resident, at least 18 years old, and the household's financial decision-maker paying the rent and utilities. A total of 212 participants completed the questionnaire. The respondents were asked to identify and rank a number of barriers that impeded the adoption of energy efficiency programs by these households. Table 1 summarizes the demographic characteristics of the respondents.

Table 1. Demographic characteristics of the survey sample.

Variable	Description	*n*	%
Age	18–24	6	1.9
	25–34	12	5.7
	35–44	21	10
	45–54	18	8.6
	55–64	46	21.9
	65–74	68	32.4
	75–84	39	18.6
	85 or older	2	1
Gender	Male	102	48.1
	Female	109	51.4
	Non-binary	1	0.5

Table 1. *Cont.*

Variable	Description	*n*	%
Annual personal income	Less than AUD 10,000	21	9.9
	AUD 10,000–AUD 19,999	36	17.0
	AUD 20,000–AUD 29,999	79	37.3
	AUD 30,000–AUD 39,999	36	17.0
	AUD 40,000–AUD 49,999	24	11.3
	AUD 50,000–AUD 59,999	13	6.1
	AUD 60,000–AUD 69,999	3	1.4
Annual household income	Less than AUD 10,000	7	3.3
	AUD 10,000–AUD 19,999	11	5.2
	AUD 20,000–AUD 29,999	51	24.1
	AUD 30,000–AUD 39,999	37	17.5
	AUD 40,000–AUD 49,999	45	21.2
	AUD 50,000–AUD 59,999	31	14.6
	AUD 60,000–AUD 69,999	10	4.7
	AUD 70,000–AUD 79,999	4	1.9
	AUD 80,000–AUD 89,999	3	1.4
	AUD 90,000–AUD 99,999	5	2.4
	AUD 100,000–AUD 149,999	7	3.3
	More than AUD 150,000	1	0.5

3.3. Data Analysis

The data are arbitrarily divided into samples of calibration and validation in order to analyze the results. An exploratory factor analysis (EFA) is first conducted on the calibration sample data. EFA is used to decrease the number of variables into factors that are smaller in size. In order to perform a factor analysis, data must be normally distributed on the univariate and multivariate levels, and with no outliers [27]. In general, a factor that has two different variables can be seen as reliable only in cases wherein the variables have a high correlation among themselves ($r > 0.70$) but are less correlated with other variables [27]. Guadagnoli and Velicer [28] propose that a small dataset ($n > 150$) would be appropriate if it had several high factor loading scores (>0.80) [27]. In this study, at least three variables are selected to qualify as factors [27]. A factor loading score is used to determine whether a variable contributes substantially to a factor; therefore, high scores indicate that variables and dimensions are more closely aligned [27]. If the correlation r is lower than 0.30, then the relationship between the variables is quite weak [27]. Cross loading is defined as a factor scoring 0.32 or more on two or more factors [29]. Cross-loaded variables may be retained if they are considered latent qualities, but they may also be dropped if their interpretation is challenging. To make the interpretation easier, it is feasible to choose a significant loading cut-off. Bartlett's test (or regression approach) is one way to produce factor scores. These unbiased scores are only related to their respective factors. Bartlett's test is used here because it is generally the easiest to understand. According to Field [30], 0.5 is considered a good measure of sampling adequacy. As a rule of thumb, factor loadings of 0.3–0.4 are minimally acceptable for determining factor significance [25]. Variables that have factor loadings of less than 0.4 should be removed from the analysis [25]. In this study, all factor loadings were above 0.4, and therefore no item was removed. The communalities of all variables were all above 0.33.

Principal component analysis is the first step in data reduction, followed by a "true" factor analysis. It is important to remember that factor loadings are fairly similar no matter what extraction technique is selected [31]. It is essential that the extraction method is appropriate for the research question of this study and easy to interpret [27]. Principal component analysis (PCA) extraction is used to examine EFA, with 26 items affecting adoption of energy efficiency measures. Kaiser's criterion, a scree test, and Horn's parallel analysis are then used to identify the number of factors to be extracted. Horn's parallel analysis is widely acknowledged as the most precise way for determining the number of elements to keep [32]. The number of components to keep tends to be overestimated by both Kaiser's criterion and the scree test [32]. Based on this criterion, factors above eigenvalue 1 should be retained. The use of criteria may overestimate the number of factors to be extracted [29,30]; therefore, a scree test coupled with eigenvalues is used to define how many factors to retain. Eigenvalues and factors are used in the scree test [33].

The "component correlation matrix", which can help choose the best rotation method by identifying the correlation between the components, was considered. Tabachnick and Fidell [31] advocated utilizing oblique rotation if factor correlations are greater than 0.32. Cronbach's alpha is used to determine each factor's internal consistency and reliability. The size of Cronbach's alpha has been debated for years [20,21]. Cronbach's alpha is an indicator of whether a set of items is capable of measuring a single latent construct. A scale's alpha should be within the range of 0.65–0.80 to be considered adequate by convention [22–24].

Using the validation sample, confirmatory factor analysis (CFA) is employed to confirm the four-factor structure derived from the EFA [25,34]. CMIN relates to the chi-square values, which are traditionally used to test a model for goodness-of-fit. This is frequently used to assess whether a model differs significantly from a model that fits the data exactly [35]. The p value indicates the significance. A null of a model fitted exactly is rejected if $p \leq 0.05$. If the χ^2 is not statistically significant, the data are not substantially distinct from the hypothesized model. Despite this, several models are assessed as inaccurate with the rise of sample size, since χ^2 is a function of sample size. In light of this, χ^2/df has often been used as an alternative fit index [36]. A good fit is evident, where χ^2/df is less than 2 (df denotes degrees of freedom). A root mean square error of approximation (RMSEA) is considered an "absolute fit index", in which a value of zero denotes the "best fit", and a value > 0 suggests a poorer fit [35]. Close-fitting models are generally considered to have RMSEA values of 0.05 or lower. Acceptable values are those up to 0.08 [37] or 0.10 [38]. Browne and Cudeck [37] propose RMSEA $\geq$ 0.10 as a model that may have more serious problems in its specification according to Kline [35]. The RMSEA in the output for this study is 0.051, which is between 0.05 (close fit) and 0.10 (poor fit). Thus, the RMSEA shows a very good fit for this model. RMSEA, comparative fit index (CFI), non-normal fit index (NNFI), and χ^2 to the degrees of freedom (χ^2/df) are used in to assess the goodness-of-fit of the SEM model. CFI and NNFI of 0.95 or more indicate a good fit as determined by the RMSEA value of less than -0.05 (lower value of the 90% confidence interval is less than 0.05 and upper value is less than 0.08) [39,40].

It is crucial to examine the model's assumptions for validity before conducting theory testing. This validity is described as the measuring tool's capacity to measure the attributes accurately and consistently. Convergent and discriminant validities are used in this test. Discriminant validity is investigated to find the unique indicators that measure the latent construct without being influenced by other constructs in the model [41]. The indicators that have positive correlations with other indicators measuring the same latent components are then used to verify convergent validity [41]. Testing the average variance extracted (AVE) and composite reliability (CR) values accomplishes this and recommends a composite reliability of 0.70, although Fornell and Larcker [42] advocated a CR value of 0.60 or higher [25]. An AVE larger than 0.5 is advocated by Fornell and Larcker [42]. All AVE values in this study are greater than correlation squared, which indicates that they met the discriminant validity requirements.

4. Analysis Results

4.1. EFA Results

The factorability of 26 items is examined to assess the factorability of correlation being assessed using a number of well-known criteria. To begin, it is found that all 26 items are at least correlated, with four having at least one additional item, indicating that factorability is feasible. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy is 0.921, above the commonly recommended value of 0.6, and Bartlett's test of sphericity is significant (χ^2_{325} = 4000.4, $p < 0.001$), indicating that the correlation matrix does not suffer from multicollinearity and suggesting the correlation between variables to be sufficient for PCA [30]. The communalities are all above 0.4, further confirming that each item shares some common variance with other items. Given these overall indicators, factor analysis is deemed to be suitable with all 26 items. The eigenvalues and factors are used in the scree test. As Figure 1 shows, the number of components to keep is equal to the number of data points above the break (i.e., point of inflexion).

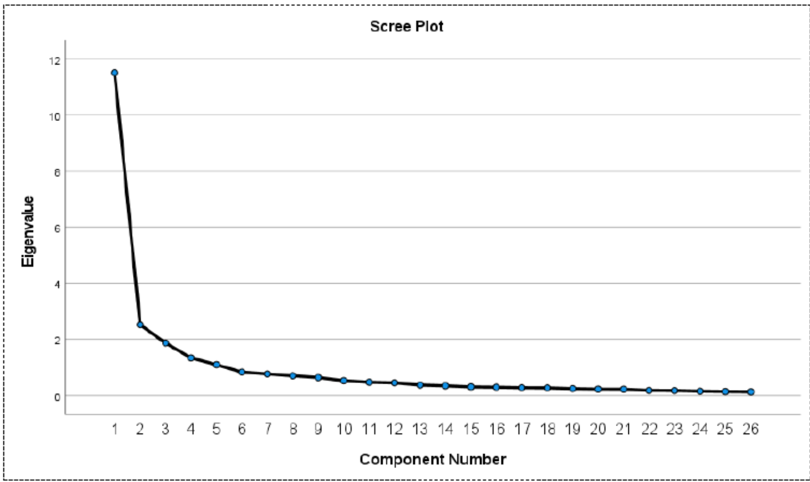

Figure 1. EFA scree plot.

Testing begins by drawing a horizontal and vertical line from each end of the curve to establish the "break". Only a sample size of at least 200 people is required for the scree test to be valid, which is applicable here. The initial eigenvalues indicate that the first five factors have eigenvalues just over unity. Parallel analysis is then applied to validate the number of factors, which results in four factors in total (Table 2).

Table 2. Comparison of eigenvalues from PCA and Horn's parallel analysis.

Component	Actual Eigenvalue from PCA	Criterion Value from Parallel Analysis	Decision
1	11.498	1.725673	Accept
2	2.518	1.592229	Accept
3	1.866	1.510609	Accept
4	1.437	1.435158	Accept
5	1.093	1.373765	Reject

The "component correlation matrix", which can help choose the best rotation method by identifying the correlation between the components, is considered. Because the components are not correlated, varimax rotation is chosen as the method of rotation [31]. Table 3 signifies the rotated component matrix that shows the number of each of the factors retained. High upfront cost, with a mean score 4.01, is perceived to be the greatest energy efficiency barrier.

Three items are excluded because they do not contribute to a simple factor structure and fail to meet the minimum criteria of having a primary factor loading of minimum 0.4 or they are cross loaded. For example, doubts about the costs of transaction has factor loadings between 0.5 and 0.6 on both financial and decision-making. Lack of information about energy efficiency programs has factor loadings between 0.4 and 0.7 on both financial and information, while physical distance from resources has similar factor loadings between 0.4 and 0.5 on both information and decision-making. The remainder of the 23 items have primary loadings over 0.5. Cronbach's alphas are moderate: 0.68 for energy efficiency adoption (three items), 0.9 for information (six items), 0.8 for financial (seven items), 0.9 for decision-making (seven items), and 0.8 for split incentives (two items). Eliminating more items will not result in a significant boost in alpha for any of the scales.

Table 3. Factor loadings based on PCA with varimax rotation.

Item	Factor Loading				M	SD
	F1	F2	F3	F4		
Factor 1, Decision-making (eigenvalue = 11.498; percentage of variance = 44.529; cumulative percentage = 44.529)						
172. Measure implementation comes with too much stress	0.820				2.88	1.16
177. Periods of transition in the household lifecycle	0.783				2.96	1.12
171. Disruption that comes along with conducting renovations in the home to adopt energy efficiency	0.763				2.89	1.21
176. The stress that comes along with making irreversible and complicated decisions	0.749				3.17	1.21
174. Technical risk	0.733				2.96	1.09
173. Doubts about the contractor's reliability	0.682				3.17	1.14
178. Households' social communication behavior as a particular type of personal influence	0.674				2.57	1.08
Factor 2, Financial (eigenvalue = 2.518; percentage of variance = 9.402; cumulative percentage = 53.931)						
156. Financial risks		0.786			3.67	1.11
152. Immediate loss for delayed gains		0.771			3.4	1.02
154. Lack of saving		0.761			3.67	1.11
151. High upfront costs		0.752			4.01	0.96
155. Hidden costs		0.746			3.75	1.07
153. Lack of incentives, subsidies from government		0.649			3.4	1.02
167. Lack of support for low-income or vulnerable households		0.600			3.73	1.2
Factor 3, Information (eigenvalue = 1.866; percentage of variance = 7.205; cumulative percentage = 61.136)						
164. Unavailability of relevant information on efficiency measures			0.769		3.16	1.05
165. Lack of trust in available information			0.745		3.18	1.14
161. Lack of awareness or skepticism of existing resources			0.731		3.02	1.12
168. Lack of marketing campaigns			0.681		2.87	1.07
162. Misperceptions about energy costs			0.681		3.02	1.05
163. Doubts about cost-saving outcomes			0.607		3.27	1.06
Factor 4, Split incentives (eigenvalue = 1.437; percentage of variance = 5.141; cumulative percentage = 66.276)						
183. Landlord's unwillingness to adopt efficiency measures				0.853	2.56	1.55
169. Uncertainty about the period of residence at a particular dwelling				0.711	2.9	1.31

Notes: Factor loadings <0.4 are suppressed. Extraction method: principal component analysis. Rotation method: varimax with Kaiser normalization (N = 204).

4.2. Empirically Tested CFA Model

Figure 2 shows the empirically tested CFA model of the energy efficiency barriers using the validation sample. The 22 items represented by the item numbers shown in Table 3 are the observed variables. They are shown within the boxes. The ellipses indicate the latent factors. As a result of the model, four factors are hypothesized to be related to energy efficiency barriers: (1) information barriers, (2) financial barriers, (3) decision-making barriers, and (4) split incentives.

There are significant correlations between the observed variables and latent factors. Ideally, the standardized factor loading must exceed 0.5 [25]. The standardized factor loadings surpassed 0.5 for all paths except the one from the split incentive barrier to 169 (standardized path coefficient = 0.49). Of all the six observed variables in the information barrier factor, observed variable 163 (doubts about cost-saving outcomes) has the strongest standardized path coefficient of 0.80. The strongest standardized path coefficient in financial barrier factor are the following: 154 (lack of saving), with a standardized path coefficient of 0.80; and 156 (financial risks), with the same standardized path coefficient of 0.80. Further, in the decision-making barrier factor, they are 176 (the stress that comes along with making irreversible and complicated decisions) and 177 (periods of transition in the household lifecycle), each with a standardized path coefficient of 0.87. Finally, the split incentives factor has the strongest standardized path coefficient of 0.91, which belongs to the observed variable of 183 (landlord's unwillingness to adopt efficiency measures). Table 4 provides an overview of the items chosen to assess goodness-of-fit (χ^2 = 311.092, p < 0.001). The current model is a good fit to the data based on both factors presented.

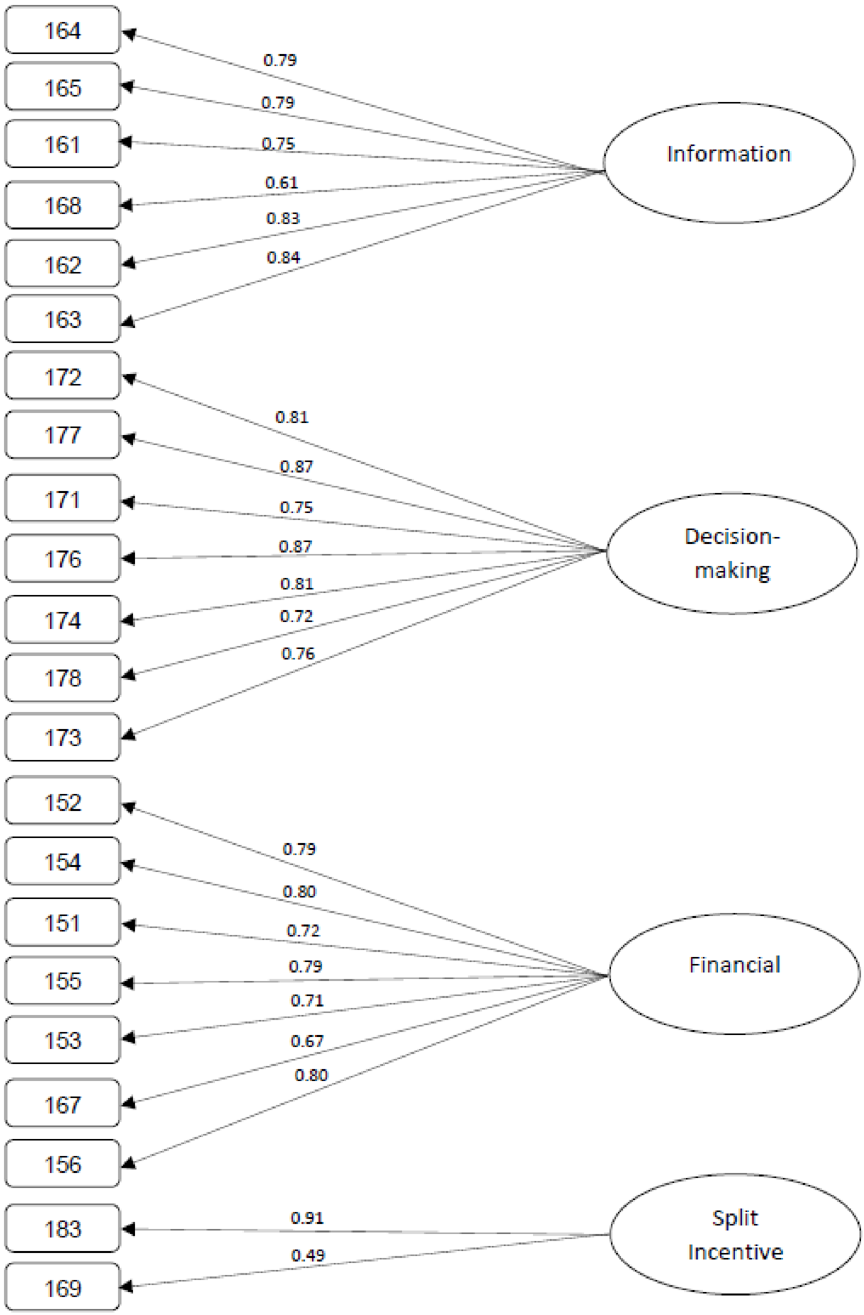

Figure 2. Empirically tested CFA model. Note: The squares denote the observed variables with item numbers listed in Table 3 whereas the ellipses denote the latent factors.

Table 4. Fit indices for the proposed measurement model and their acceptable threshold.

Goodness-Of-Fit Measure	Value	Acceptable Threshold	Results Supporting Model Fit
χ^2/df	1.288	<2	√
RMSEA	0.053	<0.06	√
CFI	0.957	>0.90	√
IFI	0.959	>0.90	√
TLI	0.948	>0.90	√

All AVE values are greater than correlation squared, which indicates that they meet the discriminant validity requirements. The data also meet the converge validity condition, as all the values meet the requirements. By calculating the factor loadings, composite scale indicators are used to analyze the structural model. AMOS is used to calculate the composite scale model by hand-loading factors and error variances. Construct reliability is assessed using composite reliability (CR) values. The CR ranges from 0.711 to 0.919, which is higher than the 0.60 threshold suggested by Bagozzi and Yi [43]. Table 5 presents the specifics of the measuring model. Convergent validity is measured by calculating the AVE. The AVE values range from 0.461 to 0.653, showing that all constructs have convergent validity. Discriminant validity is confirmed when the square of the AVE values is greater than the highest inter-construct correlation value [42]. Finally, all constructs contained in the conceptual model have convergent and discriminant validity. As Table 5 shows, all AVE values are greater than correlation squared, which indicates that they meet the discriminant validity requirements. As Table 6 shows, the data met the convergent validity condition, as all the values meet the requirements.

Table 5. Discriminant validity table.

Discriminant Validity	Estimate	Correlation Squared	AVE 1; AVE 2 (AVEs Should Be > r^2)	Discriminant Validity
Financial <–> Information	−0.055	−0.003	0.593; 0.461	Established
Financial <–>Split incentives	0.347	0.120	0.593; 0.490	Established
Financial <–> Decision-making	0.672	0.451	0.593; 0.653	Established
Split incentives <–> Information	0.158	0.024	0.490; 0.461	Established
Decision-making <–> Information	0.109	0.0118	0.653; 0.461	Established
Decision-making <–> Split incentives	0.641	0.4108	0.653; 0.490	Established

Table 6. Convergent validity table.

Convergent Validity	Information	Financial	Decision-Making	Split Incentives
AVE value > 0.5	0.461	0.593	0.653	0.490
CR value > 0.7	0.771	0.897	0.919	0.711
Factor loading $\sqrt{\mathrm{CR}}$	0.878	0.947	0.958	0.843
Error variance $1-\mathrm{CR}$	0.229	0.103	0.081	0.289
Convergent validity	Established	Established	Established	Established

5. Discussion

This study identifies the barriers that prevent low-income Australian households from adopting energy efficiency measures. There is confusion and disagreement regarding the concept of energy efficiency barriers in the literature. In spite of the wide usage of the terms, there seems to be no unanimous agreement regarding the importance of barriers in different contexts, how they should be understood, and ways to address them in low-income families. The classifications and interpretations of energy efficiency barriers are therefore numerous, and it is particularly difficult to interpret the empirical literature due to the lack of both consistency and rigor [44]. In accordance with the literature, this study primarily focuses on energy efficiency misconception as a factor that discourages low-income families from utilizing energy efficiency. As participants need to understand the terms used in any particular research study before they can partake in it, research focusing on households becomes complicated due to the misconception and confusion over the term "energy efficiency" among households, particularly those with low income.

The identified barriers are divided into four categories: information, financial, decision-making, and split incentives. The questionnaire requires the participants to rate their willingness to employ EEMs. In the last part of the survey, data were collected in relation to households' energy efficiency plans to save energy.

The next section discusses the significance of the four categories of barriers.

5.1. Financial

Financial is a major barrier mitigating against the implementation of technical EEMs such as retrofitting, purchasing energy-efficient appliances, and investing in renewables. Approximately 70% of participants state that their adoption of EEMs is highly impacted by high upfront costs. This shows upfront costs to be a major problem and is consistent with the findings of several previous studies carried out in the field of energy efficiency [4,12]. "Hidden costs" is another commonly reported financial barrier, with more than half the participants (61%) reporting that their use of EEMs was highly affected by this. These results correspond with Sorrell et al. [45], who identified access to capital and hidden costs as the most relevant barriers to the application of energy efficiency measures. Another financial barrier found here is the difficulty in obtaining extra capital for investment in energy-efficient measures. In addition, there is limited access to capital as a result of limitations on money lending, which corresponds with the results of most previous research [12,13].

5.2. Decision-Making

Decision-making is one of the barriers that could prevent low-income households in Australia from adopting energy efficiency measures. In reference to the present survey results, previous studies also traced one of the reasons for not undertaking cost-effective energy efficiency measures to this barrier [13,44]. Although the findings of this study are similar to previous studies, only 26% of the respondents agreed that their adoption of energy-saving measures was impacted in this way.

The finding of Sorrell et al. [12] that technical risk is a crucial element that impacts decision-making to improve energy efficiency was not consistent with the results found in this study (which indicates that technical risk had a moderate impact on the application of energy efficiency measures). It is possible that many dimensions of risk may have contributed to these results. It is not easy to conduct an objective risk evaluation, and risk perceptions may thwart investment decisions, even though they may not be reasonable. Technical risks only exist for some technologies, and the risks associated with many of the technologies considered in this study are seemingly low. However, this does not make technical risk a strong basis for rejection, despite the possible existence of site-oriented reasons [11].

Additionally, social communication behavior is the personal factor that had the least influence on the decision-making of low-income households, though people were fond of seeking advice from those on whom they relied and already trusted. In their study, Lusambili et al. [46] arrived at a different result, in which most older people are likely to seek advice and assistance from family and friends, indicating that low-income households may behave differently in this aspect of decision-making. It may be possible to explain this through the impact of bounded rationality on decision-making, which is equally recognized in past studies that examine the relationship between EEMs adoption and the decision-making barrier [11,14,17]. Complex decision-making procedures in the present study are affected by low-income households' personal management agendas.

5.3. Split Incentives

The split incentive barrier is a key factor that hinders low-income households' adoption of energy efficiency measures. This finding aligns with the results of past research that focuses on energy efficiency barriers among renters [6,47]. In Australia, 39% of households in the lowest 20% of incomes are renters who make up a similar but bigger part (65%) of households where allowances are their main source of income. Because managers or owners of rental properties bear the costs of adopting energy efficiency measures, they have little incentive to invest in them, whereas tenants enjoy the benefits of reduced energy bills and improved living environment [6,13]. These findings offer the disturbing conclusion that a split incentive hinders the adoption of energy efficiency interventions despite raising energy efficiency among the most vulnerable and lowest-income renters, which is a critical factor. This is most likely explained on the grounds that the party that adopts an investment is often not the one that pays the energy bill. Another way to explain this is that the potential adopter does not have enough information about existing cost-effective energy efficiency measures and, as such, they only adopt these measures if they can recoup their investment from the party that benefits from the energy savings [47].

5.4. Information

Information is identified as another barrier to the application of energy efficiency measures in households. Only 15% of the low-income households surveyed in this study agree that the information barrier significantly affects their decision to adopt energy efficiency measures. It is possible to explain this from the viewpoint that information becomes effective when it aligns with people's key priorities and values, making it unrealistic to disregard this aspect of the study [48]. The result could be linked to the contextual difference between low-income households and other households. It is arguable that different households have distinct values and priorities, and that the research findings can often be significantly predicted by demographic characteristics [48]. Thus, the information barrier may not be effective for people who do not have the same priorities. As a result, in cases where the financial priorities of low-income households allow them to apply energy efficiency measures, the information barrier may seem irrelevant. The importance of information accessibility is another interesting aspect of this study's primary findings. Apart from the content of the information program, how the information is presented is also important. As long as the problem-solving processes match the problem representation, decision-making becomes less stressful, which can be attributed to the impact of bounded rationality on decision-making [17].

6. Conclusions, Limitations, and Recommendations

In summary, the energy efficiency barriers that prevent low-income households from adopting energy efficiency are identified with EFA on the calibration sample, and then validated with CFA on the validation sample. Four primary categories of barriers are identified as financial, information, decision-making, and split incentives. The CFA model has goodness-of-fit, reliability, and validity, thus indicating that these four represent the main barriers to energy efficiency adoption by low-income households.

This study is limited in relation to location and cultural context. It is conducted in Australia and, as such, data were obtained from low-income households in Australia only. Thus, the extent to which findings are applicable to other countries with less similar cultural contexts remains to be established by further research across different countries. This study is also limited to the energy efficiency barriers of low-income households to the exclusion of such other factors as the drivers or critical success factors leading to the better energy efficiency adoption of this group. A wider scope of factors affecting low-income households' energy efficiency adoption should also be further investigated to determine whether the positive effect of drivers could offset the negative effect of these barriers. The number of survey responses and the number of interviews conducted could be construed as restrictive because, although the 212 survey responses met the data analysis requirement and nine interviews reached data saturation, it would be beneficial to obtain a larger dataset to produce more representative and generalizable findings.

Despite these reservations, this study has contributed to bridging the gap of very limited research into the energy efficiency of low-income households and providing a model to assess the level of energy efficiency barriers involved. This model provides research-based evidence to design mitigation strategies to overcome energy efficiency barriers of such households by energy efficiency professionals and policy-makers.

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Appendix A

Table A1. An Extract of the Questionnaire Survey.

How much do the following points influence your decision to adopt energy efficiency? (Such as energy-saving renovations, purchasing energy-efficient appliances, and adoption of renewable energy.) Please choose the appropriate box.					
	Very High Impact	**High Impact**	**Moderate Impact**	**Low Impact**	**Very Low Impact**
High upfront cost					
Immediate loss for delayed gains					
Lack of incentives, subsidies from government					
Lack of saving					
Hidden cost					
Financial risks					
Lack of awareness or skepticism of existing resources					
Misperceptions about energy costs					
Doubts about cost-saving outcomes					
Unavailability of relevant information on efficiency measures					
Lack of trust in available information					
Lack of information about energy efficiency programs					
Lack of support for low-income or vulnerable households					
Lack of marketing campaigns					
Uncertainty about the period of residence at a particular dwelling					
Disruption that comes along with conducting renovations in the home to adopt energy efficiency					
Measure implementation comes with too much stress					
Doubts about the contractor's reliability					
Technical risk					
Doubts about the costs of transaction					
The stress that comes along with making irreversible and complicated decisions					

Table A1. *Cont.*

Periods of transition in the household life cycle
Households' social communication behavior as a particular type of personal influence
Physical distance from resources
Difficulty to access professional services
Landlord's unwillingness to adopt efficiency measures

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