Applied Energy 362 (2024) 123007

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Navigating the community renewable energy landscape: An analytics-driven policy formulation

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ARTICLE INFO

Keywords:
Energy cooperation
Data science
Regional energy equity
Decentralised energy
Citizen-led finance
Interdisciplinary analytics
Community renewable energy

ABSTRACT

In an era where climate change and energy security have become paramount concerns, community renewable energy (CRE) projects have emerged as an essential tool for engaging citizens in the transition to sustainable energy sources. Despite growing interest in CRE, limited research has been conducted to statistically understand the non-economic social factors that along with the economic and technical factors influence adoption and investment in such initiatives. Addressing this knowledge gap, our study presents a data-driven approach to examining the demographic, attitudinal, and heterogeneous socio-behavioural drivers in decisions to participate in CRE, with the aim of designing evidence-based local energy policies. In our study, we leverage insights from a large-scale survey of 941 Australians, which investigated some possible non-economic and economic factors and employ unsupervised machine learning techniques. We introduce the Stratified Harmonic Clustering Framework (SHCF), a comprehensive analytical approach that examines five clustering classes across nine distinct methods, completing 235,420 hyperparameter tuning iterations to determine the optimal algorithm for identifying distinct groups. Here, we present our novel Adaptive Nested DBSCAN algorithm, which reveals three distinct clusters with varying priorities, motivations, and attitudes towards renewable energy (RE): a) Senior CRE Enthusiasts, b) Urban RE Adopters and Advocates, and c) Rural RE Investors and Sceptics. Our findings suggest that i) Tailoring outreach efforts to these different demographic clusters, ii) Prioritising community needs and concerns, iii) Fostering positive attitudes and trust, iv) Implementing supportive regulations, and v) Devising economic incentives, are all crucial for promoting CRE adoption. Based on these insights, we propose targeted CRE policies for each identified cluster, underscoring the importance of addressing the unique priorities and motivations of these various groups. The key benefit of this approach is the potential to address debates surrounding the changes in social formations arising from energy transition, and the opportunities they present for increased resilience.

1. Introduction

Renewable Energy (RE) plays a pivotal role in confronting the challenges of fossil fuel depletion and emissions based climate change, both of which present significant constraints on our existing energy production systems [1]. According to the International Energy Agency (IEA), RE is the sole energy source expected to experience growing demand over the next two decades and is hoped to account for over 90% of global electricity capacity by 2027 [2]. The IEA stated that "utility-scale solar Photovoltaic (PV) and onshore wind are the cheapest options for new electricity generation in a significant majority of countries" and "global solar PV capacity is set to almost triple from 2022 to 2027" [2]. Nevertheless, the transition to RE encounters considerable financial and social hurdles. These include: policy, regulation, financing, maintenance and support, billing and metering arrangements, optimisation of both distribution and benefits, community conflict, and the commitment and self-organisation of members, all of which have to be taken into account [3–5]. Non-government energy investors and producers, including businesses and citizens, must contribute to and invest in RE projects for them to become widespread. The successful evolution towards a low-carbon society and acceleration of viable energy transitions hinge on citizens' acceptance, support, and collective action [6].

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https://doi.org/10.1016/j.apenergy.2024.123007
Received 6 July 2023; Received in revised form 16 February 2024; Accepted 8 March 2024
Available online 19 March 2024

List of Abbreviations

ML	Machine Learning
PV	Photovoltaic
RE	Renewable Energy
CRE	Community Renewable Energy
SHCF	Stratified Harmonic Clustering Framework
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
CRE	Community Renewable Energy
GMM	Gaussian Mixture Model
IEA	International Energy Agency
PCA	Principal Component Analysis
BGMM	Bayesian Gaussian Mixture Model
FAMD	Factor Analysis of Mixed Data
UMAP	Uniform Manifold Approximation and Projection
fastICA	fast Independent Component Analysis

Given the challenges impeding the transition to RE, Community Renewable Energy (CRE) presents a promising approach for fostering investments in clean energy generation capacity at the local level [7], and for avoiding the necessity of large scale grid connections in countries like Australia. As an alternative to larger public and private entities, CRE initiatives involve cooperative arrangements among small-scale private investors, who participate in financing, planning, installing, and operating RE projects [8]. These local, citizen-led endeavours aim to bolster clean energy availability for the long term and enable people to participate in emissions reduction and action against climate change at a local level [9]. Although regional utilities and banks often fund CRE development, communities are intimately involved in various aspects of the development process [10]. Such involvement also fosters trust and ownership within the community, potentially leading to heightened engagement in the transition to RE. Community ownership can augment energy security by reducing dependence on centralised energy production, thereby enhancing community resilience to power outages and other energy-related disruptions, especially under climate change [11]. Supplies can be somewhat maintained even when the grid collapses due to extreme weather events or fossil fuel energy supply breaks down. CRE can also increase community engagement and connection, promote volunteerism, energy literacy, and political participation [12]. This approach encourages people to move from being ‘energy consumers’ to becoming ‘energy citizens’, embedding energy production in local society rather than in more distant companies [13]. Besides the environmental benefits of generating clean energy, CRE projects can also deliver significant economic and social advantages to local communities [14], such as fostering positive attitudes towards general energy transition [15], co-ownership, and benefit-sharing.

In Europe, community energy projects have grown rapidly in recent years, with Germany leading the way with over 1 million energy cooperative members [16,17]. By contrast, Australia lags behind, with only 100 CRE projects, generating around 60 MW of electricity [18]. Despite Australia’s high uptake of rooftop solar, according to the Minister for Energy, its participation in CRE is limited [19]. The Business Council of Australia, despite previous hostility, recognises the potential for RE to create over 395,000 clean export jobs [20]. Although the relative cheapness, modularity, and scalability of RE make it possible for groups and communities to build setups gradually, more effort is needed to boost the adoption of CRE in Australia [21–23]. Understanding the social and human factors that influence people’s preferences for CRE initiatives is essential for devising effective policies and mechanisms that encourage participation.

Previous literature has demonstrated that the reasons for engaging in a CRE project are just as multifaceted as the potential benefits they provide [5,24]. Numerous studies have emphasised the importance of financial considerations, such as return on investment or low electricity prices [25,26]. However, these may not be the sole factors shaping the decision to invest in CRE initiatives. In fact, behavioural economics has challenged the notion that individuals are solely motivated by their financial gain [27]. While economic factors carry weight, research has revealed that behavioural factors, including environmental concern, social and moral norms, interpersonal trust, and social identification, also significantly influence decisions to invest in CRE [28,29].

People may be motivated to invest in CRE to conform to the behaviour of those around them and to gain acceptance and recognition within their community. They can be influenced by social norms [30] and emotions such as pride, guilt, shame, and anger, and may adhere to these norms even if they do not directly benefit financially. Environmental concerns and intentions to support RE production may also drive participation [31]. Moreover, trust, a sense of belonging, and social responsibility to a group may influence a person’s decision to engage in these initiatives. Studies have shown that interpersonal trust and social identification can foster cooperative behaviour and a strong sense of community [32]. CRE can also be disrupted by previous social conflicts, and constrained by market organisation, or the presence of fossil fuel companies acting as a source of local income and influence [33].

Upon reviewing related literature, it becomes apparent that socio-cultural norms and behavioural change are instrumental in shaping pathways towards success in CRE transitions [34]. However, these factors have scarcely been recognised in designing policies and mechanisms, especially in the context of energy transition in regional areas with small populations and limited resources. The current literature inadequately addresses this issue, resulting in a significant gap between policy and people [35]. By expanding our knowledge of why people invest in RE at the community level, the kinds of people who invest, and the extent of their willingness to be involved, policymakers can develop targeted policies that more effectively increase participation. This social knowledge is rarely investigated empirically, which hinders the development of policy instruments designed to promote positive social change in decarbonisation [36]. Further research in this area is crucial for unlocking the full potential of community driven RE projects and facilitating a more sustainable energy future.

Various methods have been employed to analyse the motivations behind people’s participation in CRE projects, including surveys, interviews, focus groups, and case studies. Surveys have been used to quantify interest levels and willingness to participate in CRE initiatives, while interviews and focus groups have provided deeper insights into motivations and barriers to participation. Case studies have examined successful examples of CRE projects to identify factors that contributed to their success. However, Berka and Creamer [37] found that most studies of CRE are predominantly anecdotal and qualitative. There have been few sophisticated quantitative investigations of the contributions of socio-behavioural factors in motivating and reinforcing community participation in the energy transition [38]. Despite the growing qualitative literature on citizens’ motivations to join CRE initiatives [39], there is a pressing need for quantitative analyses to inform evidence-based policy design [40]. The application of analytics and machine learning (ML) in this field is still limited [41,42], presenting significant potential for translating analytical results to policymakers [43–45]. To address this gap, data-driven approaches are needed to develop informed policies that reinforce community participation in the energy transition.

In this study, we aim to explore the heterogeneity of people’s preferences for participating in CRE projects and design targeted policies accordingly. Our focus is on investigating Australia’s population and understanding the behavioural factors that motivate and reinforce their participation in the energy transition, an area that has been largely overlooked.

Firstly, a nationally distributed survey was conducted, with 941 residents responding to questions related to demographics, attitudes, and socio-cultural norms. Secondly, we introduced Stratified Harmonic Clustering Framework (SHCF). This framework represents a comprehensive approach in unsupervised learning, exploring five clustering classes through nine different methods to uncover patterns in data and identify distinct clusters of individuals sharing similar preferences. We hypothesised that SHCF allows us to go beyond the immediately obvious and extract useful and relevant empirical categories, which would then help to make focused policy recommendations that could not otherwise have been made. By conducting analyses using different algorithms and evaluating each algorithm's performance quantitatively, we aimed to make informed decisions about which method best suits our data, ensuring the most accurate results from our clustering analysis. It became clear that a more refined approach was needed to effectively reveal the clusters. Thus, we developed a modified version of the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm, named Adaptive Nested DBSCAN, specifically to reveal the clusters within clusters and identify subtle relationships that might not be evident with more basic clustering techniques. This enables us to design policies tailored to specific groups, addressing the unique motivations and barriers that exist within each cluster.

The use of ML methods for analysing socio-behavioural factors represents key theoretical and methodological contributions with significant potential for advancing knowledge about promoting sustainable energy transitions.

(i) This study, by identifying the unique priorities and motivations across diverse groups, lays the groundwork for the creation of market structures and organisations in line with community needs. Such alignment can foster greater trust and collaboration, promoting a cooperative energy environment.
(ii) Through mapping the social landscape, we offer insights that address resilience and energy transition challenges, providing a dynamic blueprint capable of adapting to community needs and formulating future energy policies.
(iii) The introduction of SHCF, a multifaceted clustering approach, refines traditional survey analysis. This framework can help other researchers utilising clustering methods by enhancing the efficiency and precision of segmentation across disciplines that require a deep understanding of complex datasets.
(iv) The development of the Adaptive Nested DBSCAN algorithm improves granularity in our analysis and unveils clusters that might have remained hidden. This advancement enables the crafting of targeted policies tailored to unique characteristics of each cluster, potentially leading to higher effectiveness and increased adoption rates.

2. Material and methods

This section details the three main components of SHCF to ensure a robust evaluation of the data (see Fig. 1). First, we start by discussing the data collection component (Section 2.1), where we gathered a mixed dataset containing both numerical and categorical variables from diverse sources. Next, we described the data pre-processing (Section 2.2), which involved cleaning and transforming the data to make it suitable for analysis. Third, the study focuses on unsupervised machine learning component (Section 2.3), specifically clustering algorithms, to identify patterns within the data. We tested four dimensionality reduction methods, adopted an exhaustive search approach by employing nine clustering algorithms, calibrated their parameters using a range of heuristics, and evaluated the performance of clustering using a set of validation metrics. This thorough and systematic approach allowed us to effectively identify and interpret underlying patterns and similarities within our dataset, ultimately leading to robust and reliable clustering results (see Fig. 4). More technical detail, about programs and practice can be found in Appendix 1.

2.1. Data collection

In collaboration with Geni. Energy and the Community Power Agency (https://cpagency.org.au/), an Australia wide not-for-profit research and advocacy organisation, we conducted an online survey which gathered opinions from 941 participants across Australia. The survey URL was distributed to potential subjects through online posts, CPA reach out, posts to Facebook groups and so on. This online format enabled a wide reach and enhanced the sample's representativeness. The survey aimed to understand individuals' preferences for participating in CRE projects, featuring 24 questions that gathered information on demographics, attitudes, and behaviours. We built the test survey based on Marshall's fieldwork experience, together with Geni.Energy to use their expertise and try out questions they found relevant, as well as questions of more general economic and sociological relevance. The online format did however limit the number of questions we could ask and expect to be answered without people withdrawing. We assessed the validity of the survey by testing it in Narrabri to explore local expectations of CRE, garnering responses from almost 70 respondents. We conducted various statistical tests, such as Cronbach's alpha (0.85) and factor analysis (ranging from 0.7 to 0.9), which confirmed the reliability and consistency of the survey instrument. These preliminary results provided a solid foundation for further data collection and analysis, allowing us to confidently proceed with the nationwide survey. We were concerned that the group was likely to be more pro-renewable and pro-community energy than the general population, but comparison with other surveys reveals this was not the case (see Appendix A2).

The first set of questions collected socio-demographic data related to community energy projects, including gender, age, and living area. These factors could potentially influence respondents' opinions, attitudes, and experiences, as well as their access to resources.

The second part of the survey assessed attitudes associated with RE and CRE. Participants were asked about their general views on community involvement, personal beliefs about climate change, energy, and pollution, and their preferred energy mix and target year for achieving it. They also chose options explaining their thoughts on attaining RE targets and potential obstacles created by certain groups or organisations. Furthermore, participants rated their agreement with statements about facilitators and barriers to community energy and expressed their degree of willingness to participate in a program managing their household's energy consumption.

The third section explored socio-behavioural variables by assessing participants' investment status and willingness to engage with RE and CRE. Questions covered topics such as investment status, satisfaction with current RE installations, and involvement in community energy groups, with participants' roles categorised as investors, volunteers, or landowners, among others. This section also evaluated attitudes towards brownouts or blackouts and the benefits of transitioning to RE on community and large-scale levels. Additionally, the survey inquired about participants' social networks, including whether their friends, neighbours, or acquaintances had household RE installations.

2.2. Data pre-processing

Data pre-processing is a crucial step in ML that involves cleaning and preparing raw data before applying algorithms to it. In this study, we carried out several pre-processing steps to prepare the survey data for analysis.

The first step involved dropping columns from the dataset that were deemed uninformative. We removed respondents who had not answered more than 70% of the questions and dropped columns that contained more than 85% missing values. These steps were taken to ensure that the analysis was based on complete and accurate data and to maintain the integrity of the analysis as recommended by [46]. We enriched the dataset with additional information related to the

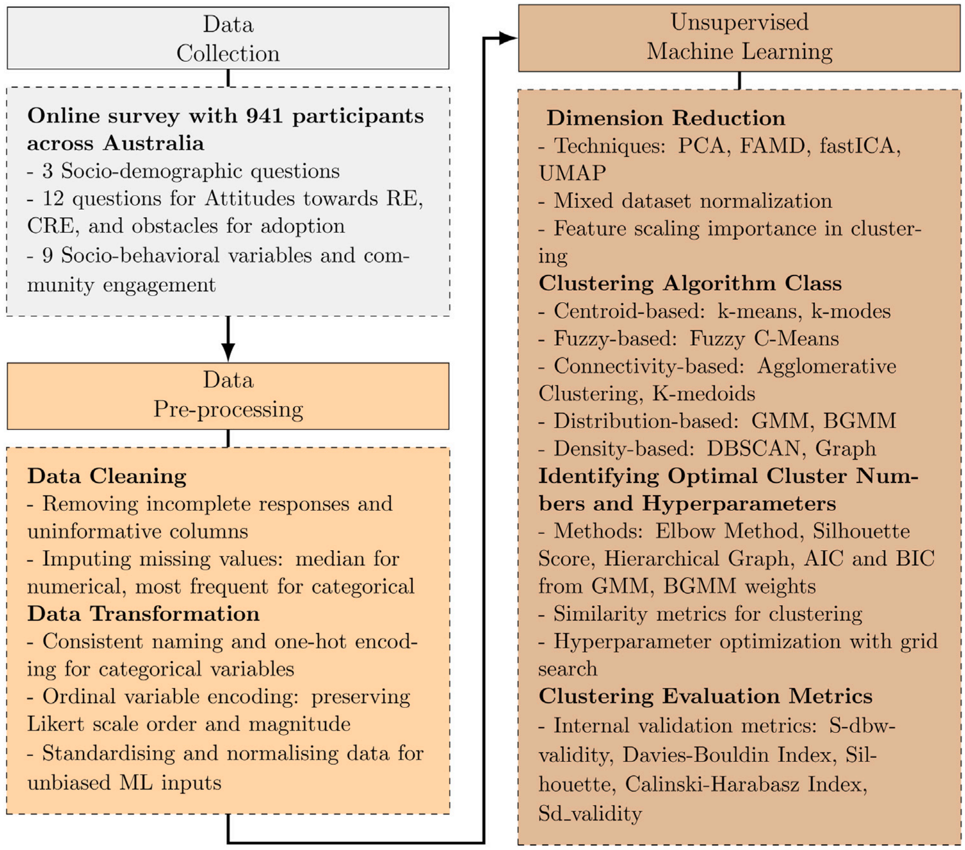


Fig. 1. An overview of Stratified Harmonic Clustering Framework (SHCF), from data collection to pre-processing and unsupervised learning.

postal code provided in the survey to enable data to be visualised on a map, providing additional insights into the distribution of the survey data. After these steps, 875 observations (out of 941 samples) with 89 features remained for further processing.

The next step in the data cleaning process involved imputing missing values [47]. To determine the best measure of the central tendency for imputing missing values in numerical columns, the data distribution was analysed using visualisation tools such as box plots and distribution plots. Since the data was found to be left-skewed with a long tail on the left, the median value was used for imputation rather than the mean value, which is more appropriate for symmetrical data distributions. For categorical columns, including nominal, ordinal, and Boolean variables, missing values were imputed using the "most frequent" strategy, which involved replacing missing values with the most frequently occurring value in each column [48]. To transform yes–no questions (Boolean variables), a technique was used [49] that imputed null values with zero, and transformed all other values to 1, ensuring that the data was in a numerical format and ready for analysis.

To standardise the remaining columns, we renamed them in a consistent format as q_xxx, where xxx represents the question ID assigned to each question in the questionnaire. This naming convention helped to clearly identify each question in the dataset and made the data easier to work with. Additionally, we created a metadata dataset that contained information about each question. The metadata included the text of the question, the possible answers, and the percentage of null values for each question, which can provide insights into the quality of the data and aid in the analysis. To convert six categorical variables in the dataset (Likert scale questions) into numerical data, we used the one-hot encoding technique [50]. This approach transforms each category into a binary vector that represents the presence or absence of a feature. One-hot encoding is a popular choice due to its simplicity and versatility, although it can result in increased data sparsity and reduced computational efficiency [51]. We also applied this technique to two nominal columns with a limited number of unique values, resulting in the creation of seven new Boolean columns.

We performed ordinal variable encoding to preserve the order and magnitude of the Likert scale used to measure attitudes and perceptions [52]. This encoding method is only applicable to variables where categories have a clear ordering. The resulting numeric form of the labels prepared the data for further analysis while retaining its ordinal nature. To ensure the ML algorithms focus on inherent relationships between data points rather than differences in scale, we standardised and normalised the data using standard scaling. This approach transforms the data distribution to centre around 0 and a standard deviation of 1 through standardisation. Normalisation is used to ensure all input variables have the same minimum and maximum values, and enhance algorithm convergence [53,54]. These transformations improve the meaning of the distance measure and provide unbiased inputs to the algorithms.

2.3. Unsupervised machine learning

Unsupervised machine learning techniques are widely used in data analysis to identify patterns and structures in data. In this study, we have applied clustering analysis to our high-dimensional mixed data with the aim of grouping similar respondents based on their answers to survey questions. Our intention is to identify hidden patterns and relationships in the data that may not be immediately apparent. The process involves several steps:

- Dimension Reduction: Techniques like principal component analysis (PCA) [55], factor analysis of mixed data (FAMD) [56], fast independent component analysis (fastICA) [57], and uniform manifold approximation and projection (UMAP) [58] are used

to transform the data into a lower/dimensional space while retaining as much information as possible. Feature scaling is also considered to ensure the unbiased nature of data distributions (refer to Appendix A1.1).
- Clustering Algorithms: Various clustering algorithms, including centroid/based (k/means, k/modes) [59], fuzzy/based (fuzzy C-/Means) [60], connectivity/based (agglomerative clustering, k-/medoids) [61], distribution-based (Gaussian Mixture Model (GMM), Bayesian Gaussian Mixture Model (BGMM)) [62], and density/based (DBSCAN) methods [63], are employed to handle different data types and features (refer to Appendix A1.2).
- Determining the Number of Clusters and Hyperparameters: The optimal number of clusters is identified using methods such as the Elbow Method [64], Silhouette Score [65], Hierarchical Graph [66], Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) from GMM [67], and BGMM weights [68]. A wide range of similarity metrics is used to generate similarity matrices, and hyperparameters are optimised using a grid search approach (refer to Appendix A1.3).
- Clustering Evaluation Metrics: Five internal validation metrics (S-Dbw Validity Index [69], Davies–Bouldin Index [70], Silhouette Coefficient [71], Calinski–Harabasz Index [72], and SD Validity Index [73]) are used to evaluate clustering quality based on the data's intrinsic characteristics (refer to Appendix A1.4).

Appendix A1 provides a comprehensive description of the analytical approach involving feature scaling, dimensionality reduction, clustering algorithms, and evaluation metrics. It ensures the robustness and reliability of the clustering results, ultimately helping to identify underlying patterns and similarities between respondents. Given the various combinations of scaled and unscaled features and dimensionality reduction methods applied to our dataset, we ended up with ten distinct versions of the input data for each clustering algorithm.

2.4. Adaptive nested DBSCAN

The SHFC results revealed that while traditional DBSCAN was the top performer among the existing methods, it did not fully meet our needs due to its reliance on global density parameters. To address this, we modified this algorithm to accommodate varying densities, implements a nested clustering strategy, and significantly improves noise differentiation.

The Adaptive Nested DBSCAN algorithm iteratively processes the data, applying the DBSCAN algorithm with parameters that are fine-tuned at each iteration. This fine-tuning is essential for the algorithm to align with the specific density characteristics of each subset of the data. Moreover, by using the outputs of one round of clustering as inputs for the next, the algorithm progressively reveals the complex structure of clusters within clusters. This methodical iteration refines the clustering parameters to better handle diverse densities within the dataset, a critical feature since our data exhibit non-uniform density patterns. The nested aspect of the algorithm allows a more granular examination of the data structure, enabling the identification of sub-clusters within larger clusters. Such a hierarchical approach proves invaluable for datasets with significant variations in cluster scale and scope. Furthermore, its improved noise handling ensures that the data points that do not belong to any cluster (noise) are not misclassified, leading to cleaner and more distinct clusters.

The original DBSCAN algorithm can be summarised by two key parameters:

- ϵ (epsilon): The maximum distance between two points for one to be considered as in the neighbourhood of the other.
- MinPts (minimum points): The minimum number of points required to form a dense region, i.e., a cluster.

A point p is considered a core point if:

$$N_\epsilon(p) \geq \text{MinPts}$$

where $N_\epsilon(p)$ represents the "neighbourhood" of point p, defined as the set of points within distance ϵ from p. The Adaptive Nested DBSCAN modifies these parameters iteratively:

(i) Initial Clustering:

- Apply DBSCAN with initial parameters ϵ_1 and MinPts_1 to obtain initial clusters.
- For each data point x in dataset D, if the number of neighbouring points within ϵ_1 is at least MinPts_1, mark x as a core point. Otherwise, mark it as a border or noise.

(ii) Adaptation Step:

- For each cluster $\mathtt{C}$ identified in the previous step, calculate new parameters $\epsilon_2(\mathtt{C})$ and $\text{MinPts}_2(\mathtt{C})$ that are adapted based on the density of $\mathtt{C}$.
- This adaptation can be defined through functions f and g, such that: $\text{MinPts}_2(\mathtt{C}) = g(\text{MinPts}_1, \mathtt{C})$.

(iii) Nested Clustering:

- Apply DBSCAN to each cluster $\mathtt{C}$ using the new parameters $\epsilon_2(\mathtt{C})$ and $\text{MinPts}_2(\mathtt{C})$.
- Iterate the process, defining $\text{MinPts}_{n+1}(\mathtt{C})$ for each subsequent level of clustering within each sub-cluster formed.

(iv) Termination Condition:

- The iterative clustering process persists until the size of a newly identified cluster $\mathtt{C}_{new}$ at any given level is smaller than the minimum size of the clusters identified at the first level of clustering, denoted as MinSize_1.
- Formally, the process concludes for a cluster $\mathtt{C}_{new}$ when: $|\mathtt{C}_{new}| < \text{MinSize}_1$.

In this condition, $|C_{new}|$ denotes the size of the new cluster C_{new}, and MinSize_1 is the minimum cluster size identified after the first iteration of DBSCAN. This ensures that the algorithm does not over-partition the data into clusters that are smaller than the smallest meaningful cluster detected in the initial pass.

3. Results and discussion

3.1. Respondent representation

The survey respondents closely reflect the demographic makeup of the Australian population [74], which suggests that the survey results are representative of the broader population. A Chi-Square Test of Independence was conducted to assess the association between gender distribution and living areas in the population (retrieved from Australia Bureau of Statistics (ABS)) and the survey sample. The results indicate no significant difference between the two groups (details in Appendix A2), with an even split between male and female respondents in both the population and the survey. Regarding living areas, the survey sample included 53% of respondents from capital city areas and 47% from rest of state/territory areas, which roughly aligns with the population data showing that 63% of Australians live in capital city areas. The state/territory areas distribution of the sample appears to be reasonably representative of the population, with only minor differences in the proportions for each state when compared to the overall Australian population.

In terms of attitudes towards renewable energy, the survey results correspond with polls from the Clean Energy Australia 2022 Report by Clean Energy Council [75] and Climate of the Nation 2022 report

Table 1
A summary of best performing methods in each clustering class.

Clustering class	Method	Number of iterations	Best performing method
Partition-based	K-means	352	K-means 3 clusters (PCA dimension reduction: and unscaled data) with and without using Euclidean distance.
	K-modes	12	K-modes (FAMD dimension reduction and unscaled data) with 3 clusters
Fuzzy-based	Fuzzy C-means	360	Fuzzy-PCA with 3 clusters with and without using Chebyshev distance.
	GMM	20	GMM-UMAP with 3 clusters.
	BGMM	20	BGMM-UMAP with 3 clusters.
Hierarchical-based	Agglomerative	1040	Agglomerative 3 clusters (UMAP dimension reduction and unscaled data) with and without using Chebyshev distance.
	K-medoids	1380	K-Medoids 3 clusters (PCA dimension reduction and unscaled data) with and without using squared Euclidean distance.
Density-based	DBSCAN	232,050	DBSCAN (UMAP dimension reduction and scaled data) with a sample size of 10 and epsilon 0.6, and DBSCAN (PCA dimension reduction and unscaled data) with a sample size of 85 and epsilon 0.16.
	Graph	186	Graph-PCA using cosine similarity and threshold value of 0.969.

by The Australia Institute about the broader population [76]. An Independent Samples t-test was conducted to compare attitudes towards renewable energy between the population and the survey respondents and the results revealed no significant difference which might have been unexpected (details in Appendix A2). A majority of Australians believe that increasing the use of RE is crucial for the country's future (79%), a sentiment reflected in the survey results where 72% of respondents agreed with this statement. Additionally, both the population and the survey respondents largely support phasing out fossil fuels (71% population versus 81% of respondents) and agree that RE is beneficial for the environment (82% of Australians, mirrored by 71% of respondents). The survey respondents were slightly more negative towards RE than the population as a whole, which lowers the chance that our sample has a bias towards RE.

The survey respondents also express robust support for CRE projects, consistent with national opinion [77]. Most Australians believe that CRE will create new jobs (71%), a view also reflected in the survey results, where 68% of respondents share this opinion. A significant proportion of Australians (70%) express a preference for sourcing their electricity from community-owned renewable energy projects. This preference is mirrored in the survey results, with 66% of respondents concurring with this statement and only 34% preferring to purchase green energy from retailers. Furthermore, the survey results reveal that a considerable proportion of respondents (53%) believe that CRE projects will positively impact community building and the local economy, aligning with the opinions of 66% of Australians. These findings suggest that the survey sample is representative of the broader Australian population, allowing us to make inferences about the attitudes and opinions of the Australian public concerning RE and CRE projects (more information on representativeness of the survey is available in Appendix A2).

3.2. Clustering algorithm selection

The evaluation of the optimal cluster quantity for various algorithms was conducted and scrutinised. The optimal cluster numbers for the chosen algorithms displayed variability, yet the most consistent outcomes were obtained with either two or three clusters (in a range of one to nine clusters). Utilising the Elbow method, it was discerned that the most substantial decline in the within-cluster sum of squares transpired at two clusters, accompanied by a relatively considerable decrease from three to ten clusters. Consequently, it was deduced that the optimal cluster quantity is likely two or three. The Silhouette Score similarly indicated the presence of two or three clusters, with the two-cluster model exhibiting the highest value, while the Hierarchical Graph proposed three or four clusters. Furthermore, the smallest AIC value was observed at three clusters, and the smallest BIC value corresponded to the two-cluster model, with the three-cluster model exhibiting a comparable value. This implies that the optimal cluster quantity is either two or three. Supplementary information for Tables 1 and 2 can be found in Appendix A3.

In order to juxtapose the outcomes of clustering algorithms for distinct variations of each method, an "inner benchmarking" process was executed. This procedure entailed comparing clustering results derived from the same algorithm, albeit with divergent input variations. The objective of conducting this inner benchmarking was to pinpoint the optimal pre-processing and dimensionality reduction techniques for each method, thereby guaranteeing the most precise and robust clustering outcomes feasible. This extensive analysis facilitated the refinement of our methodology, ultimately allowing for the selection of the most suitable clustering algorithm for our dataset, taking into account the implications of feature scaling and dimensionality reduction. Table 1 showcases the top-performing methods within each clustering algorithm category.

Upon identifying the optimal pre/processing and dimensionality reduction techniques for each clustering method, we initiated an "outer benchmarking" process. This subsequent step involved comparing the best-performing combinations from each method against one another. This involved using the same benchmarking function applied during inner benchmarking but now comparing the top-performing algorithms from each method based on their results (details in Appendix A3). Out of all the methods, DBSCAN-UMAP with a sample size of 10 and epsilon 0.6 has the highest S-Dbw Validity score of 0.93, indicating that it has the best overall clustering quality. It also has the lowest Davies–Bouldin score of 2.12, indicating that it has the most compact clusters and the least amount of overlap between them. By combining DBSCAN and UMAP, we can leverage the strengths of both techniques to obtain the best clustering results for non-linear datasets. UMAP can be used to reduce the dimensionality of the data while preserving the important non-linear relationships, and then DBSCAN can be applied to capture the underlying non-linear structure in the dataset.

Nevertheless, this method has a relatively low Silhouette score of 0.13, indicating that the clusters may not be well-separated. It also has a relatively high Calinski–Harabasz score of 53.07, indicating that the

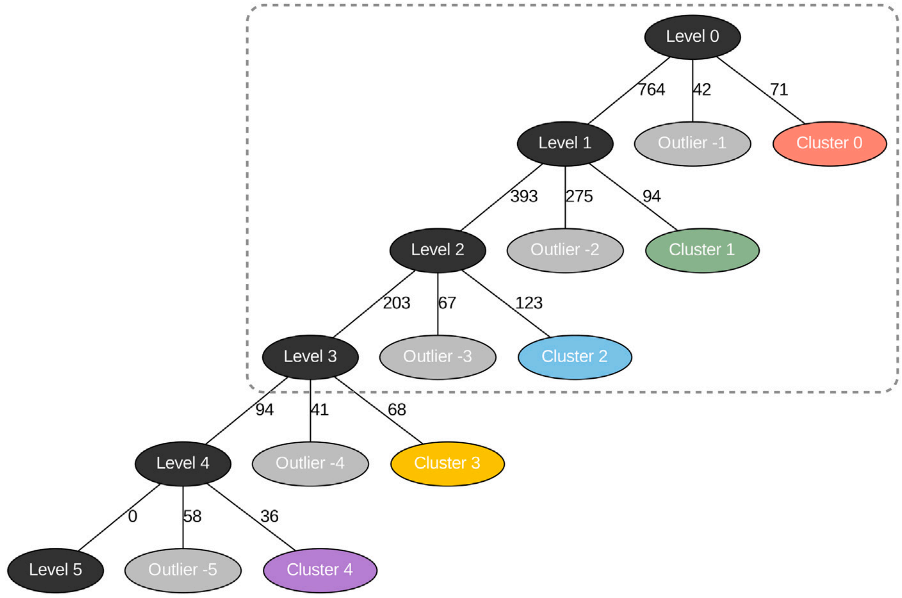


Fig. 2. Adaptive nested clustering approach using DBSCAN algorithm. Initially, three clusters are detected, including an outlier cluster, a larger cluster, and a smaller cluster.

clusters may be too large. On the other hand, GMM with 3 clusters has the highest Silhouette score of 0.000741, indicating that the clusters are well-separated. It also has a relatively low Calinski–Harabasz score of 11.28, meaning that the clusters are not too large. However, the low S-Dbw Validity score of 0.99 and a relatively high Davies–Bouldin score of 8.88, demonstrate that the clustering quality is not as good as DBSCAN.

The application of Adaptive Nested DBSCAN could further improve the performance of DBSCAN-UMAP on scaled data in terms of cluster compactness, separation, and size. This novel algorithm allowed us to break down the larger clusters into smaller, more defined sub-clusters automatically, thus enhancing the interpretability of our data and addressing issues related to cluster imbalance. Specifically, the initial DBSCAN phase identified three clusters: an outlier cluster (outlier -1), an initial cluster (cluster 0), and a large cluster (level 1) (See Fig. 2). Following this, we focused on the largest cluster (level 1) and applied our adaptive nesting approach. This iterative process involved re-clustering the points within the largest cluster, thereby generating sub-clusters with each iteration.

These sub-clusters are then used as input for another round of clustering, and the process was repeated until the size of the new cluster (cluster 3 in level 3, size 68) was smaller than the minimum size of original clusters (cluster 0 in level 0, size 71). Our results showed that this has improved the Silhouette score and reduced cluster size while maintaining good overall clustering quality (5% improvement on average, details in Table A4, Appendix A3). This outcome aligns with findings from other research, such as the study by Nagaraju, Kashyap [78], which underscored the efficacy of nested clustering in enhancing the performance of standard density-based clustering algorithms, especially for large datasets or those with complex structures.

3.3. Segment analysis

The segmentation analysis focuses on three primary factors: socio-/demographics, attitudes, and socio-behavioural variables. We offer a succinct and comprehensive summary of each segment, emphasising the distinctions among them. Appendix 4 discusses the features determined to be significant at levels 1 and 2, employing the Mann–Whitney U-test and the independent T-test [79] at a 0.1 significance level. Table A12 in Appendix A5 displays box plots of the critical variables responsible for most of the variation between clusters. Furthermore, we incorporated the percentage of most important socio-demographic, attitudes, and socio-behavioural variables corresponding to each cluster in Table 2. Table A13 in Appendix A5 presents the percentages for all significant demographics, attitude, and behavioural variables within each cluster. Complementary explanation is available in Appendix A5.

Fig. 3 illustrates the distribution of individuals across various states in Australia and their association with the three identified clusters:

- Cluster 0 (Senior CRE Enthusiasts, comprising 71 members),
- Cluster 1 (Urban RE Adopters and Advocates, with 94 members), and
- Cluster 2 (Rural RE Investors and Sceptics, consisting of 123 members).

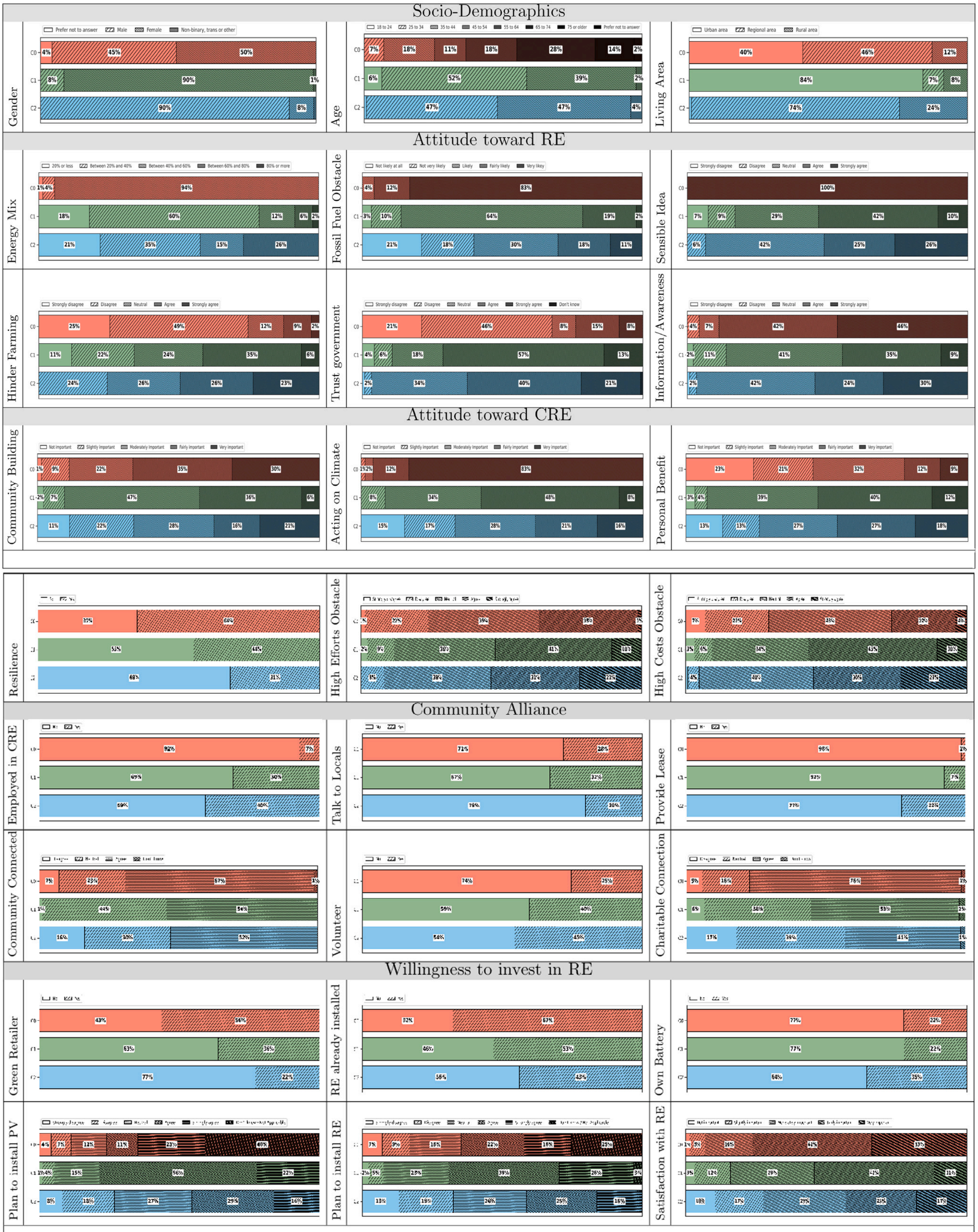
This representation underscores regional disparities in CRE priorities, motivations, and attitudes, which can be instrumental for stakeholders to take into account when designing and implementing policies. The percentages within each state signify the proportion of individuals associated with each cluster. The top two states with the highest representation in each cluster are as follows: Cluster 0: Victoria (49.4%) and New South Wales (20.6%); Cluster 1: Northern Territory (77.8%) and New South Wales (42.2%); and Cluster 2: Tasmania (100%) and Western Australia (55.6%).

3.3.1. Senior CRE enthusiasts (Cluster 0)

Demographically, this cluster comprised citizens aged between 55–75 years old, with the majority (46%) falling within the 65–75 age range. It is likely that this cluster consists of retired or semi-retired individuals who might have had different priorities and perspectives when compared to younger generations. The literature indicated that older individuals might be more focused on environmental concerns and community well-being, while younger individuals (raising families) might prioritise economic benefits [80]. They may also have more free time to be informed, or potentially to act and be more concerned with their legacy. 46% reside in regional areas, 40% in urban areas, and the remaining participants are from rural areas.

Attitudinally, participants in this cluster believed that Australia's future energy mix should consist of 40%–60% RE. To achieve this energy mix target, they considered retrofitting buildings for energy efficiency (94%), installing solar PV and batteries

Table 2
Most important demographic, attitude, and behavioural variables according to which the three clusters are segregated.



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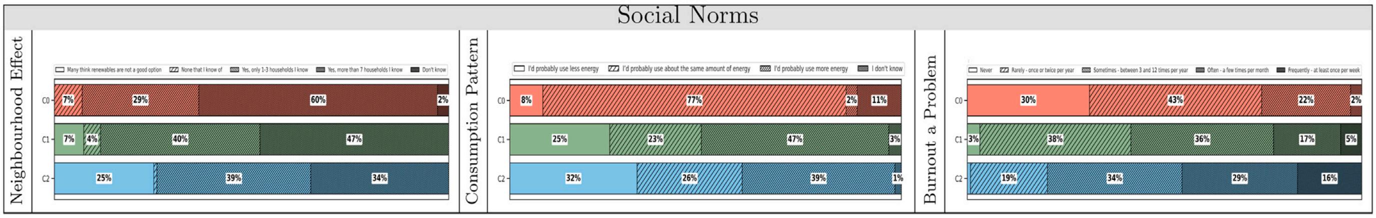

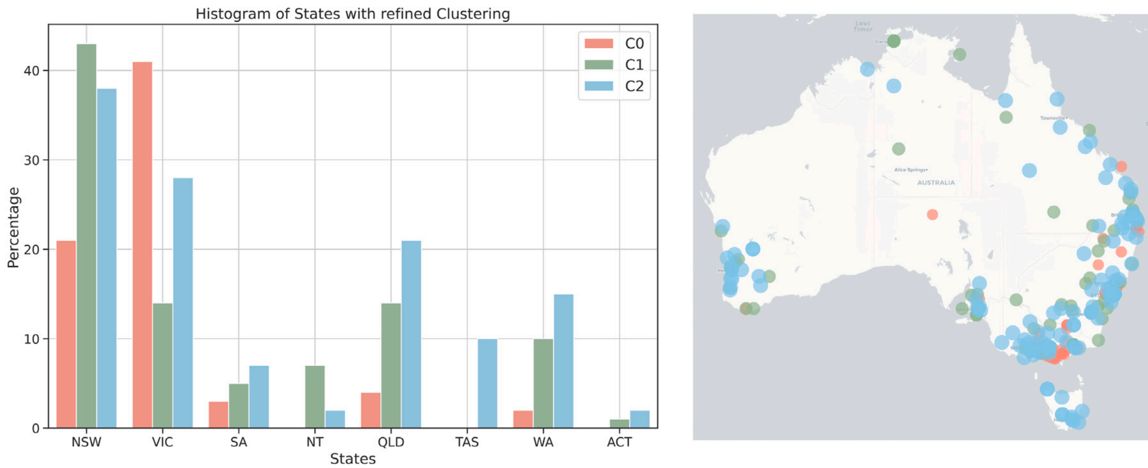

Fig. 3. Spatial distribution of three clusters in eight states of Australia.

at household and business levels (98%), implementing small to medium-scale (95%) and large-scale (95%) community-owned renewable projects, transitioning to electric vehicles (EV) (90%), fostering RE-powered manufacturing (98%), and phasing out fossil fuel power generation (97%) to be essential. Their strong support for RE, aligned with literature that suggested increased awareness and positive attitudes towards RE, could promote its adoption [81].

This cluster perceived the most significant obstacles to achieving their preferred RE target to be the fossil fuel sector (95%), grid transmission problems (61%), financial constraints (47%), large organisations (46%), and state (39%) and federal (33%) government policies, regulations, and politics. However, they did not believe that community opposition would be a significant barrier (more than 80% disagreed).

In terms of attitude towards RE, this cluster strongly agreed that RE was a reasonable approach and evoked positive feelings (99%), while also considering themselves well-informed on the subject (88%). They firmly disagreed with the notion that environmental issues were often exaggerated (94%). When it came to climate change sentiments, they accepted responsibility for climate change (72%) and disagreed that their personal energy use had no impact on pollution of land, water, air, and climate (82% disagreed). Additionally, they had the least trust in the government to take proactive measures in addressing pollution and climate change (87% disagreed). This might indicate that concern for the environment and climate change was a major factor in being in favour of RE and CRE as was distrust of the establishment.

Regarding knowledge about RE, they strongly disagreed with the notion that RE was available at night (94% disagreed), that jobs in RE were not local (80% disagreed), and that large-scale RE projects degraded the landscape's appearance (80% disagreed) and might hinder farming (74% disagreed). They were unsure about the statement that renewables undermined the gas and coal businesses (50% agreed vs. 36% disagreed). However, they strongly agreed that renewables supported regional development (95%). This cluster had the highest stated likelihood of participating in a program that managed their household's energy consumption remotely to benefit the grid and reduce their energy bills (78%).

In terms of CRE attitudes, individuals in this cluster considered, addressing climate change (95%), achieving independence from commercial energy providers (77%), and favourable government policy (75%), supporting the local economy (75%), and fostering community building and social connections (65%) as very important factors for participating in CRE. Personal financial benefits were deemed slightly important (only 21%). They strongly agreed that the idea of a community owning and controlling its energy supply was essential (94%). These positions align with the literature that highlighted the importance of recognising local involvement and decision-making as a motivation for engaging in CRE projects [36].

The main benefits of switching to RE were seen as creating well-paid, long-term jobs (78%), reducing the risk of land and water destruction (92%), providing more independence from providers, and granting more control over the energy system (84%), keeping money in regional communities (77%), enabling local participation in energy decision-making (76%), and empowering new businesses based on affordable energy (76%).

The perceived benefits of RE in this cluster, such as job creation and environmental protection, echoed findings in the literature that underscored these advantages [36], and perhaps indicates this cohort's concern for the future. Barriers to participating in CRE might be related to changes in government rules (46%) and the high individual effort required (36%), rather than the financial costs of joining CRE being too high (26%). Financial costs of joining a CRE project were less of an expected obstacle for Cluster 0 compared to Clusters 1 and 2.

Socio-behaviourally, this cluster played a minimal role in the community through negotiations with locals about the CRE project (28%). Despite this, they had the highest sense of community, with 67% feeling strongly connected to the community they lived in, and 91% considering their community a great place to live, while 83% volunteered in the community and 76% made charitable contributions. They might have purchased green energy through an electricity retailer (56%), while having the highest installation rate of RE systems (67%) among the clusters. This aligns with the literature that suggests consumers' willingness to pay for RE was influenced by environmental awareness and perceived personal benefits and adds to the supposition that people supporting RE were also concerned with community futures. Their satisfaction with installed solar systems, batteries, and purchased EVs remained unknown (44% neutral). When considering their future intentions, despite their support for RE, they exhibited the lowest intentions to install it (less than 20% plan to install RE), though 30% did not have RE. This might have been due to the fact that they already had the highest installation rate of RE systems, or they might have been concerned about changes in government rules (tax and subsidies), and the high individual effort required. Reports of high frequency of blackouts or brownouts was rare, occurring never or once or twice per year (73%), which indicates that energy reliability was not a significant concern for this group.

This cluster felt their opinions were influenced by their friends, neighbours, or acquaintances, who had already adopted household RE (89%). If energy bills were to decrease significantly due to the use of renewables or participation in a CRE project, this cluster said they would maintain their current energy usage (77%).

3.3.2. Urban RE adopters and advocates (Cluster 1)

Demographically, the majority of individuals in this cluster were female (90%) and fell within the age range of 25 to 34 (52%). Furthermore, participants primarily resided in urban areas (84%). Studies have shown that women tended to be more environmentally conscious and expressed greater concern for climate change than men (e.g., [82]). Additionally, younger individuals and urban residents might be more open to new technologies, making them more likely to engage in CRE projects [83]. However, their apparent support for RE and CRE seems less than in cluster 0 and their support for the current energy system seems much greater.

Attitudinally, for RE attitudes, 60% demonstrated a preference for an energy mix between 20% and 40%. To achieve energy mix targets, they held the strongest opposing view to the notion of transitioning towards RE-powered manufacturing (79% disagree). They disagreed with phasing out fossil fuel power generation (89% disagree), transition to EV (64% disagree), retrofitting buildings for energy efficiency (63% disagree), and medium and large-scale energy projects (61% disagree). They expressed uncertainty regarding installing solar PV and batteries at both household and business scales (52% disagree) and small and medium-scale commercial and residential energy projects (55% disagree).

This cluster held mixed opinions on RE obstacles. They were unsure about the fossil fuel sector and other large businesses being obstacles (less than 40%), while believing that federal government policies and financial constraints and considerations were likely to create obstacles (45%). Regarding attitude towards RE, this cluster considered themselves moderately informed about renewables and energy (neutral-agree). Just above half of them believe in their personal impacts on the environment and feel responsible for climate change. Only 52% agreed with RE being a sensible idea, while 61% felt good about it. This cluster had the highest trust in the government to take positive actions to address climate change (70%). They held a neutral stance (with opinions ranging from agreement to disagreement with a neutral median) regarding Knowledge about RE and were situated between the opinions of cluster 0 and 2. Their uncertainty regarding specific RE measures and moderate knowledge about renewables echoed the findings of other studies that have emphasised the importance of addressing misconceptions and uncertainties surrounding RE [84], and possibly of addressing the real uncertainties around established fossil fuels, such as peak oil, pollution and government subsidies, and surrender of power to corporate control.

In terms of CRE attitudes, factors that were fairly important (just above 50%) for participating in CRE projects include involvement in decision making, favourable government policies, supporting the local economy, personal financial benefits, taking action on climate change and reducing carbon emissions, and greater independence from commercial energy providers. They were unsure about the idea of the community owning and controlling its energy supply (50% agree vs 50% disagree).

Regarding the benefits of switching to RE, this cluster exhibited negative opinions, expressing the highest disagreement among the three clusters in terms of well-paid, long-term jobs (74% disagree), enabling new businesses with cheaper energy (79% disagree), creating local networks (89% disagree), and providing more independence from providers and greater control over the energy system (91% disagree). Their uncertainty about the benefits of switching to RE suggested a need for clearer communication and education about the potential advantages of RE itself and CRE projects [85]. 55% considered high costs as a barrier to joining CRE. The cluster was likely to participate in a program that remotely managed their household's energy consumption to benefit the grid and reduce their energy bills (63%), indicating openness to new energy solutions that could benefit both the grid and individual households. When compared to the first cluster, this group seemed more preoccupied with their own economic security, than with ecological and climate issues, or changes to society.

Socio-behaviourally, the cluster played roles in the community through partial involvement in advocating to the government (32%) and talking to locals (20%). This was supported by the literature that highlighted the importance of multi-stakeholder involvement in activity promoting the development and success of CRE initiatives [86]. For this cluster, the question of what community looks like yielded responses of "I do not know". Only half of them feel connected to the community, volunteered, or made charitable contributions.

63% of this cluster stated that they would not purchase renewable "green" energy through an electricity retailer and 53% had already installed RE. About 36% own a battery, and more than half were satisfied with the RE technology. As for future investment, they had the highest intentions to install a solar PV system (78%) and RE systems (wind, biofuel, battery, etc.) (45%) within the next 1–2 years. These points likely highlight the increasing interest in RE among consumers [87]. They also strongly agreed that having blackout protection was important to them (78%), while 41% responded that blackouts and brownouts were rarely a problem, occurring only once or twice per year. This suggested that energy reliability was a relatively important factor influencing their investment decisions aligned with the literature that identified energy security as a key driver for RE adoption [88]. One way of attacking renewables seems to have been based on insecure supply, so it may well be possible to point to insecurities of fossil fuel supply in times of extreme weather and grid collapse.

This cluster's opinion was influenced by their friends, neighbours, or acquaintances, who have already adopted household RE practices (87%). If their energy bills were to decrease significantly through the use of renewables or by participating in a CRE, 47% of this cluster think they would increase their energy consumption, while 25% and 23% would consume the same or less, respectively. The willingness to increase energy consumption in response to a decrease in energy bills highlighted the potential rebound effect (Jevons paradox [89]), which has been observed in some studies [90], and which could undermine emissions reduction, which is the whole point of RE.

3.3.3. Rural RE investors and sceptics (Cluster 2)

Demographically, this cluster primarily consisted of males (90%) within the 35 to 45 age range, predominantly residing in regional areas (74%). Research has suggested that males might place a higher emphasis on economic benefits and energy independence, while females might prioritise environmental and social benefits [91]. However, it appears that the high female percentage in Cluster 1 did not demonstrate this point strongly. Additionally, residents of regional areas could face unique challenges related to energy infrastructure and access, making them more interested in self-sufficiency and community-based energy solutions [92].

Attitudinally, for RE attitudes, this cluster's preferred proportion of RE in the Australian energy mix ranged from less than 20% to 60%, with a median preference of 40% to 60%. In terms of methods for achieving energy mix targets, this cluster showed the highest disagreement with the idea of phasing out fossil fuel power generation (94% disagree), transitioning to EVs (74% disagree), installing solar PV and batteries (73% disagree), small, medium, and large-scale commercial and residential energy projects (69% disagree), and retrofitting buildings to be energy efficient (66% disagree).

However, more than 40% of them indicated several obstacles to achieving this target, such as grid transmission problems, state and federal regulations and politics, community opposition, and financial constraints and considerations. The community opposition highlighted the importance of engaging with and addressing the concerns of local stakeholders in RE projects and being able to justify the idea of and necessity for transition itself. With respect to their attitude towards RE, individuals in this cluster had similar opinions about personal impacts, responsibility, and feelings to those of cluster 1.

While 61% believed that climate change was exaggerated, 54% perceived themselves as being well-informed about environmental issues. They showed relatively high trust in the government for taking actions to address climate change (61%). Their belief in their low personal impacts on climate change suggested that targeted education and communication efforts might be required to address these concerns [28], or that they might accept the notion of holding large producers of emissions responsible.

Regarding knowledge of RE, about half of this cluster agreed that RE is available at night (47%), jobs in RE are not local (45%), and profits from RE went to external investors (52%). On the other hand, they believed that RE could help with regional development (50%), but they were concerned that large-scale renewable projects might hinder farming (47%) and undermine the appearance of landscapes (46%). Additionally, 40% agreed that RE undermines the gas and coal industries, which were important to their communities. Their concerns about the negative impacts of RE on existing industries and landscapes aligned with literature on the potential barriers to RE adoption [93]. However, a stress on CRE with local labour, local use of energy, local control over places of installation and returns going to the community rather than to distance fossil fuel companies, might be supported by their recognition of the potential for regional development.

In terms of CRE attitudes, this cluster did not rate any of the listed factors as important for participating in CRE projects (less than 40%), indicating that targeted communication efforts, and community action, and outreach might be necessary to address concerns and misconceptions. In relation to attitudes towards CRE, they strongly agreed with the statement that policymakers and energy companies overlook their community when upgrading grid infrastructure (more than 60%), suggesting a potential lack of trust in external stakeholders, which could be a barrier to, or support for CRE project success [94], as they would be less subject to being ignored by external operators, and they might be open to ideas of community self-support through CRE.

When it comes to the benefits of transitioning to RE, respondents showed the highest disagreement (among the three clusters) with the statements that switching to RE would contribute to enhancing community spirit, cohesion, and resilience (68% disagree), well-paid, long-term jobs (74% disagree), participation in energy decision-making (74% disagree), enabling new businesses with cheaper energy (75% disagree), improving the community's image in the outside world (85% disagree), enabling local participation in energy decision-making, keeping money in regional communities (90% disagree), and enabling community sponsorship and grant opportunities (90% disagree). Since RE has primarily become commercial (sold to the grid rather than locals), it is unlikely to have helped local development. Transmission of electricity over the network in a centralised setting had huge infrastructure costs and non-trivial energy loss, which required excess power generation [95]. It would seem to be beneficial to encourage what seem to be correct ideas that CRE as opposed to pure RE, could be beneficial to local communities, and could be controlled by those communities, as there would be no one in between the community and its energy.

64% of individuals found changes in the government rules to be the most important risk factor for joining CRE. It was unlikely that this cluster would participate in a program that remotely manages their household's energy consumption (lowest likelihood at 39%). This possibly indicates the appeal of presenting RE as a means of community independence and self-control.

Socio-behaviourally, surprisingly, this cluster claimed to play the most significant role in CRE projects through facilitating the communication with government (33%) and with locals (18%). Many had been employed or contracted for such projects in the past (40%), provided/leased space for the projects (22%), and supplied other inputs (21%). These reflect the importance of active engagement and collaboration in successful CRE projects [96] but suggest this can still leave a sense of un-involvement. Interestingly, in response to the question of what your community looks like, they had the least sense of community, as more than 50% found significant divisions regarding the use of coal or gas, underlining the potential challenges of navigating differing opinions on energy sources in the community [97]. Their negative feelings for the community revealed that their apparent involvement in CRE projects did not necessarily translate to a strong sense of community, perhaps because it was primarily a matter of making money, not tackling energy problems or environmental destruction. Further research would be needed to see if the answers about their role in community energy and their lack of sense of community, are related.

77% were against purchasing green energy from the retailers. This might have been due to some of them having upfront investments in batteries for electricity storage, which indicated their interest in and commitment to RE, or it may have been due to hostility towards RE, or RE retailers. They had the highest adoption rate of batteries (37%) and EVs (36%), while they had the lowest RE installations among all clusters (43%). As for future RE investment, 65% of the cluster planned to install PV and RE systems soon. 43% expressed their satisfaction with installed solar and batteries. This suggests a degree of confusion about RE, and a relative lack of coherence in the hostility towards RE. 54% agreed that having blackout protection was important as they experienced burnouts or blackouts sometimes (36% 3–12 times a year) to often (22% a few times per month), suggesting that they valued energy reliability and the potential benefits of RE [98].

A majority of respondents reported knowing more than seven households that have already adopted RE systems (73%). Despite the prevalence of positive examples in their communities, a significant portion (25%) still did not view renewable energy as a favourable option. The presence of negative norms in this cluster (together with the high intentions to install RE) showed the need for a higher level of RE awareness within the community. The changes in energy consumption of this cluster due to RE was similar to those of cluster 1. The different responses to potential decreases in energy bills indicated that individuals may have had different priorities, such as environmental concerns or financial savings. This highlighted the role of individual values and preferences in shaping energy consumption behaviour [99].

3.3.4. Comparative analysis of clusters

The comparative analysis of the three clusters reveals distinct characteristics. Cluster 0, which is the group with the generally oldest members, is clearly the most pro RE and pro CRE. They are high in recognising responsibility for climate change and do not think environmental claims are exaggerated. They want to address climate change and think RE can do that. They have the most positive feelings towards RE for home, business and community and have the highest targets for energy mix, while almost all think fossil fuels must be phased out.

Cluster 1 is much younger and highly female, and surprisingly low in feelings of responsibility for climate change and is uninterested in high levels of RE in the energy mix. Cluster 2 has a large variety of different responses including a belief climate change is exaggerated and that they have little responsibility for it. However, Cluster 2 still has a greater median favouring of higher levels of RE than Cluster 1 even though it does not favour phasing out fossil fuels, and objects to EVs. Both groups other than Cluster 0 are against retrofitting buildings and to CRE in general, but claim to want to install personal solar PVs at a higher rate than the others — possibly because Cluster 0 have already largely installed theirs.

Individuals in Cluster 0 intend to encourage RE for manufacturing and are the most positive about retrofitting buildings as an important technique. In keeping with their apparent radicalism, Cluster 0 think that the main obstacles to CRE are the fossil fuel sector, grid problems and large organisations, but do not think the opposition will win out. They generally do not think the government will solve the problems, while clusters 1 and 2 are largely happy to leave things to government. Cluster 0 in keeping with their radicalism, are also keen on achieving independence from commercial energy providers, supporting the local economy, and fostering a community they already feel connected to. The other groups seem to indicate a larger proportion of their members do not feel connected to community, and Cluster 2 people tend to think that profits from RE will go to external people.

Hypothetically, and needing further research, we can see Cluster 0 as older people close to retirement or retired, wanting to leave a constructive legacy. Cluster 1 people will probably be engaged in child rearing, and perhaps wanting to leave the situation to other people's activities, perhaps Cluster 0. Cluster 2 would probably be must influenced by financial or personal benefits, arising from CRE, again without much effort as they generally do not believe in the urgency of avoiding climate turmoil, but may have experience with renewable energies. In terms of policy, Cluster 0, primarily seem to need encouragement or grants to give the sense that they can achieve their aims, instructions on procedure, or the active removal of obstacles such as hindering regulations. Cluster 1 and 2 may require help with their own solar as they seem less motivated by community concerns. For more detail, see Table A14.

4. Policy insights

Our findings have emphasised the importance of considering factors such as demographics, community needs and concerns, attitudes, and economic incentives when designing policies for promoting CRE. Our analysis may also suggest that steps taken to improve one group's participation might aggravate resistance from other groups. Care is needed, and the best policies may be ones that encourage local people to take action in their communities to support local CRE, engage with other groups locally, encourage community independence and self reliance, and get projects started.

This supports a position of tailoring outreach efforts to different demographic clusters: Different demographic clusters possess different priorities, motivations, and attitudes towards RE adoption, including distrust and hostility. Policymakers should consider these factors when designing outreach, and education efforts and community groups need to consider these problems and resistances when they are trying to encourage participation and interacting with these groups. For instance, engagement efforts directed at older adults (Cluster 0) might highlight practical benefits, such as cost savings and improved health outcomes, as well as to more idealistic factors such as community benefit and saving the Earth and their grandchildren, while outreach to younger adults could emphasise long-term benefits, like reducing carbon footprints and tackling climate change. The outreach could focus on inter-generational collaboration to foster community and inclusiveness, and perhaps mentorship from older people, or policies that encourage the concerned older groups to organise.

Engagement strategies for Cluster 1 could underscore the economic benefits of RE and CRE and highlight monetary incentives like rebates, tax credits, and access to low-interest loans. Educational efforts might illuminate how these energy sources lead to cost savings over time. Cluster 2 approaches could emphasise self-sufficiency, energy reliability, and local prosperity if the community is not depending on distant corporations for energy. Noting that a reasonable number of this group had engaged with RE for economic purposes, the message could reinforce the benefits of supporting rural communities through local ownership and control of energy resources. Gender-sensitive approaches can help in wider adoption of RE and CRE. Policies and interventions should also be tailored to the specific needs and circumstances of different regions, which is another reason to help local group initiatives, as they are familiar with local conditions and local social factors. It also seems that many people consider the current regulatory regime in Australia favours large scale commercial operations or the established mode of supplying energy, and that it effectively hinders CRE, or does not help CRE progress.

Prioritise community needs and concerns: Engaging with, addressing and encouraging local stakeholders' concerns is crucial for the adoption of CRE projects. This could involve community engagement efforts, like town halls or community meetings (together with local organisers, rather than just outside experts from on high), to educate residents, and address their concerns, about the benefits of CRE projects. Ensuring that community members have opportunities to participate in decision-making processes and benefit from these projects seems essential. This emphasis on local involvement and decision-making aligns with the encouragement of establishing community-based energy projects in urban settings, encouraging a sense of ownership and control among urban residents.

The local Community needs to be able to decide what kinds of benefits they will aim for, as the project progresses, and these may not be purely 'selfish' individual economic gains. They also may need to design and locate the RE themselves, to get buy-in and to account for objections, as placement and disruption of landscape seems to be important. It may be useful to encourage communities to consult with each other, without aiming for particular results so as to allow all people to speak and feel heard.

Promote positive attitude and trust: Developing community-led projects can emphasise the advantages of RE adoption, such as lowered energy expenses and greater energy independence. Providing transparent information on financial incentives, including tax credits and rebates, can further encourage adoption and reinforce trust in the government actions. We probably also need to encourage community groups, so the idea is present in the community. If it is not possible to organise CRE, it may be possible for such groups to do other work which spreads RE through the community, such as giving solar panels to public buildings such as schools, bowling clubs, and sporting associations [33]. This kind of involvement cannot be done from a distance, it has to arise from the community itself, and be encouraged. Action is a form of learning about local conditions and responses. One problem may be that actions die from lack of encouragement, time, or money.

Devise economic incentives: Stable financial incentives can increase adoption rates by encouraging individuals and communities to adopt RE and CRE. These incentives can include tax credits, subsidies, grants, paying local community labour, and other financial support. Policymakers should emphasise the benefits of RE for regional development, including job creation, economic growth, improved quality of life for residents, self-reliance and the use of money staying in the community rather than going to external electricity companies. Encouraging and incentivising energy-efficient building upgrades and addressing grid transmission problems and sharing through infrastructure investments, energy storage technology development and more favourable regulation, can also support CRE adoption, by making the environment, or context, more friendly to this development (Appendix A5 provides detailed information).

Based on the identified factors, in Fig. 4, we proposed three targeted RE policies for each cluster to promote adoption, increase participation, and investment in CRE (Appendix A5 provides the detailed information).

The interconnectedness and feedback loops among the three targeted policies can create a synergistic effect that amplifies the benefits of RE and CRE adoption. When Inter-generational Inclusive and Stable Incentives are promoted within Cluster 0, it can positively impact the Cluster 1 and 2. The exchange of knowledge and experiences between generations can inspire urban dwellers (Cluster 1) to adopt and advocate for RE and CRE technologies, leading to increased demand and awareness. This, in turn, can contribute to a stronger sense of community and trust in the Rural Investors (Cluster 2), as successful RE and CRE projects in urban settings can serve as examples for rural communities to follow.

Education Campaigns and Incentivised Adoption policy that are devised for Cluster 1 can create a ripple effect benefiting both Cluster 0 and 2. As urban populations become more informed and engaged in RE and CRE, their experiences and knowledge can be shared with senior enthusiasts and rural communities, further reinforcing the benefits of these technologies. Additionally, successful urban initiatives can lead to improved technologies and infrastructure that can be utilised in rural settings, enhancing energy security for rural communities. Lastly, the Rural CRE Empowerment and Energy Security policy, beside enhancing energy security in rural communities, can foster a stronger bond of trust and cooperation among community members, energy firms, and policymakers. This model of unity and collaborative effort can inspire urban areas and bridge generational divides, showcasing a scalable blueprint for partnership and collective action in RE and CRE ventures.

5. Conclusion

It is a reasonable hypothesis that understanding and facilitating community renewable energy (CRE) participation could both help accelerate viable energy transitions in Australia and generate 'co-benefits' for communities. This study advances our understanding of the factors influencing the adoption of CRE projects and provides policy insights for promoting renewable energy (RE), grounded in clusters discovered through our ML analysis. By seeking empirical evidence for the claims that CRE acts as a potentially socially transformative force, this research highlights the importance of customising CRE policies to suit diverse demographics, attitudes, perceptions, and sociocultural behaviours. In doing so, the focus is shifted to the investigation of sociocultural norms, diverging from the traditional emphasis on technical or economic factors. Using novel clustering techniques, we reveal previously unnoticed clusters, providing a new perspective on how to effectively foster sustainable energy transitions across different communities.

Our cluster findings demonstrate that different demographic groups possess different priorities, motivations, and attitudes towards RE adoption. As a result, outreach, education, and participation efforts should be tailored to these specific groups. We propose policies for three identified clusters: "Senior CRE Enthusiasts", "Urban RE Adopters and Advocates", and "Rural RE Investors and Sceptics". These policies aim to promote adoption, increase participation, and encourage investment in CRE projects. We hope to reveal the pathways that influence people's engagement and their success in energy transitions, while helping to predict and overcome the problems which arise.

This study has some limitations that offer avenues for future research. Primarily the reliance on cross-sectional data, which may not fully capture the evolving dynamics of RE adoption over time. Future studies could employ longitudinal data to capture these dynamics more accurately. Additionally, the analysis is limited to the factors and clusters identified in the study of a particular survey, and there may be other factors or demographic groups that have not been considered or found. Future research could explore the impact of policy changes on CRE adoption, as well as the role of innovative financing mechanisms, public–private partnerships, and the influence of local governments and community organisations. The impact of policy changes on CRE adoption, as well as the role of innovative financing mechanisms and public–private partnerships, are also worthwhile areas for further investigation. Another notable limitation is the potential bias in survey data, which could affect the accuracy and generalisability of the results. This underscores the need for future research to collect more field data, thereby enhancing the predictive power and applicability of the findings. While the survey did look for opinions on community dynamics and feelings, and we have reported some of these factors, community dynamics is not best studied through survey information but by longer-term observation and interview in particular communities, which we are hoping to be able to engage with later.

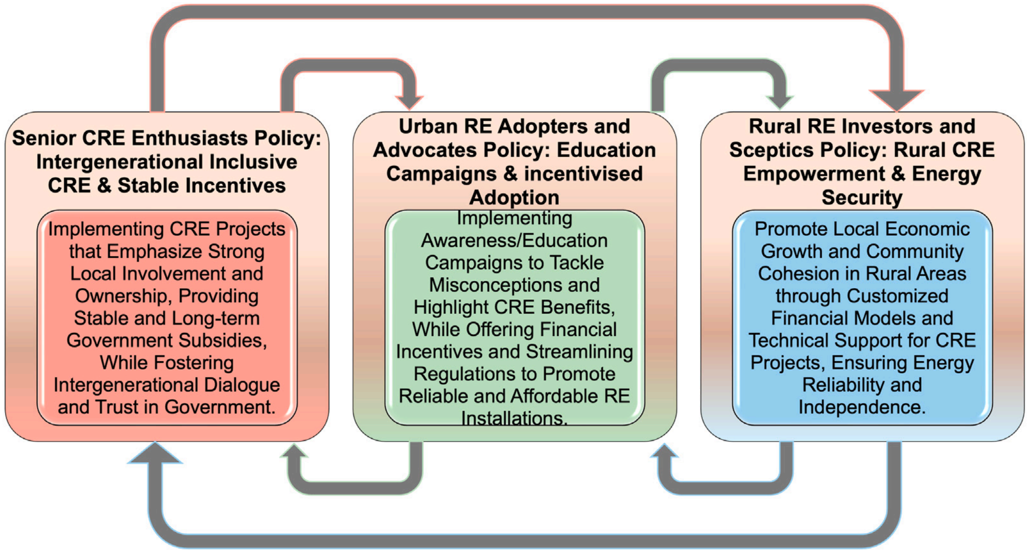

Fig. 4. Data-driven CRE policies for identified segments. The arrows indicate the interconnected feedback loops that facilitate synergistic effects among the different policy approaches.

Despite these limitations, the study makes important contributions to the understanding of CRE adoption and provides actionable policy recommendation. They encourage local involvement to promote RE adoption, foster community engagement, and work towards a more sustainable, low-carbon future. This study serves as a valuable resource for stakeholders seeking to advance the RE transition and combat the pressing challenges of climate change.

CRediT authorship contribution statement

Firouzeh Rosa Taghikhah: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Masoud Taghikhah:** Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Jonathan Paul Marshall:** Writing – review & editing, Validation, Supervision, Funding acquisition, Conceptualization. **Alexey Voinov:** Writing – review & editing, Validation, Supervision, Resources, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

This work was supported by Early Career Research Grant, Business School, University of Sydney, Australia [219050, 2023], An Australian Research Council Future Fellowship [FT160100301, 2016], and Cross Faculty Research Award, University of Technology Sydney. The authors extend their gratitude to the editor and three anonymous reviewers for their insightful comments and recommendations.

We would like to thank Geni.Energy, Community Power Agency, and the Narrabri Community for their help with data collection. Special thanks to Dr. Gnana Bharaty for facilitating access to essential datasets.

Appendix A. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.apenergy.2024.123007.

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