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Original research article

Solar energy surge: The socio-economic determinants of the photovoltaic systems growth in Australia

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ABSTRACT

The installation of solar photovoltaic (PV) systems on residential units is one of the measures that countries around the world are implementing to mitigate the impact of the global warming crisis. Australia has become the world leader in the solar PV sector since it introduced its solar-related program in 2001. The adoption was initially spurred by government-driven incentive schemes providing opportunities for early adopters to financially capitalise on the technology through feed-in tariffs. Over time, the growth was further propelled by the phenomenon often referred to as the neighbourhood effects. This paper conducted a statistical analysis to investigate the demographic composition, at postal area (POA) resolution, associated with the PV uptake in Australia. To detect the presence of the neighbourhood effects, a formula was developed to simplify its quantification, drawing analogies to kinematics. The results of the regression analysis reveal that gender, share of certain age groups, land area, and dwellings with a vehicle do not correlate with adoption. On the other hand, other variables such as marital status, weekly household income, number of bedrooms, population and dwellings densities, do have influences, positively and negatively. Furthermore, the "accelerated rate" determines a positive impact of the neighbourhood effects in the range of 15 to 20 additional PV units installed per year per POA. A publicly accessible tool was developed with this study that can aid policymakers in exploring the socio-economic indicators identified in this analysis as predictors of the diffusion of the technology for effective policies, regulations, and schemes.

1. Introduction

1.1. The Anthropogenic climate change and the world

The world is fighting a global battle – the fight against climate change. While the use of energy is essential for the normal functioning and the progress of nations, and is basically innate to our congenial life that we sometimes take for granted, it does leave an undesirable by-product that if left unchecked, would cause, bluntly speaking, sufferings to humanity. The greenhouse gas (GHG) emissions, after years of extensive scientific studies, are found to be the main cause of the increase in the Earth's average temperature in the last 250 years. These GHG emissions come primarily from the burning of fuels as sources of energy for both industrial and domestic usages [1]. In the European countries under the EU, for instance, more than 75% of the GHG emissions are reported to come from the energy sector [2].

Countries from all over the world have joined forces to combat climate change under the Paris Agreement, which came into effect in November 2016. Its main goal is to limit the increase of the average global temperature by 1.5 °C by the turn of the century, beyond which, the potential for the frequent occurrence of more severe floodings, droughts, and heatwaves increases. This can be achieved by limiting the GHG emissions [3].

In the energy sector, countries have started adopting renewable energy sources as a mitigation measure against climate change. Natural sources, such as solar irradiation, wind, and hydropower, are utilised to generate energy for the communities. Among the EU members, Sweden has the highest share of its energy consumption coming from renewable sources at 62.6% in 2021. This is followed by 43.1% of Finland and 42.1% of Latvia. Overall, in EU, the share of renewable energy has

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reached around 22% [2]. In the same year in the US, the share of renewables was around 21%. This grew to about 23% in 2022 [4]. Meanwhile in Australia, the mix of energy from sustainable sources was at 32.5% in 2021 and at about 36% in 2022 [5]. These but all are indicative of the concerted efforts that developed countries are doing and continued to be doing towards a sustainable future. Of the 36% share of renewable energy in Australia, about 15% comes from small to large scale solar power [6]. This is closely followed by wind power at approximately 13%. Further breakdown of the solar power energy reveals that 9.3% are generated from solar photovoltaic (PV) systems installed on residential units [5]. The country now ranks first globally both in the total solar electricity generation per capita, overtaking Spain in 2017 [7] (Fig. 1), and the installed solar PV capacity per capita [8]. The installation of PV systems on dwellings in Australia is the focal point of this study.

1.2. Solar PV adoption in Australia

Over the last decade, with the global maturity in the solar energy market, PV systems cost has declined by about 80% making it an affordable source of energy [9]. The technologies are modular and compact enough that they can be installed on dwellings, at the rooftop or on the ground, and on commercial establishments [9].

Australia has emerged as the global leader in the adoption of solar energy with capacity totalling close to 30 GW as of 2022 [10–12]. Small generating units, or those systems with rated capacity of <100 kW used in residential units and business establishments (units with capacity of 100 kW or more are considered as large-scale or power stations), constitute about two-thirds of that total or 19 GW, wherein, about 16 GW comes from residential units (systems with rated capacity of <10 kW). This feat was made possible by the installation of about 3.4 million systems (not taking into account the decommissioned systems) [10,11]. To date, about one in every three suitable dwellings in Australia is fitted with solar PV systems [13]. Fig. 2 shows the percentage status of installed solar PV in Australian states and territories as well as for the whole country. Countrywide, the average percentage of installed solar PV on Australian homes is about 33%, wherein, the highest percentage can be found in the state of South Australia (44%), followed by Queensland (40%), and with the lowest in the Northern Territory (19%).

To demonstrate the installation trend in a higher spatial resolution, Fig. 3 shows the “heatmap” of the installed solar PV systems across

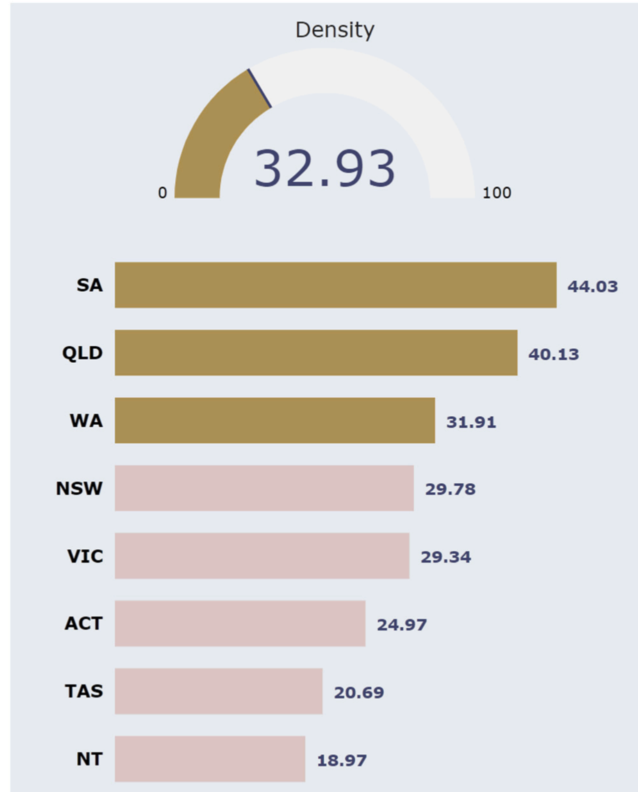

Fig. 2. Percentage of installed residential solar PV in Australia (32.93%) and its States and Territories (SA-South Australia, QLD-Queensland, WA-Western Australia, NSW-New South Wales, VIC-Victoria, ACT-Australian Capital Territory, TAS-Tasmania, NT-Northern Territory).
Source: Authors, data from [10] (see also Supplementary Section for the link to the dashboard developed by Authors).

Australia as a function of the PV-suitable dwellings per postal area (POA) based from the Australian PV Institute (APVI) Solar Map [10] data wherein the number of residential units was projected based on the 2011 and 2016 censuses. Depicted by colour-coding, the map provides a visualisation of the percentage of dwellings with installed PV systems

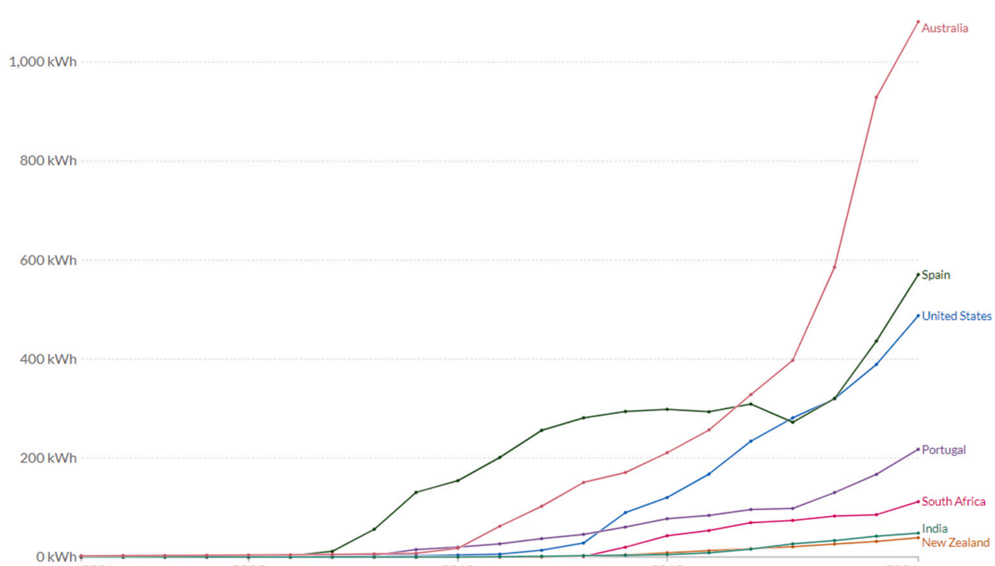

Fig. 1. Top ranking countries in the total solar electricity generation per capita. (Image: courtesy of OurWorldInData.org/energy under CC BY license)

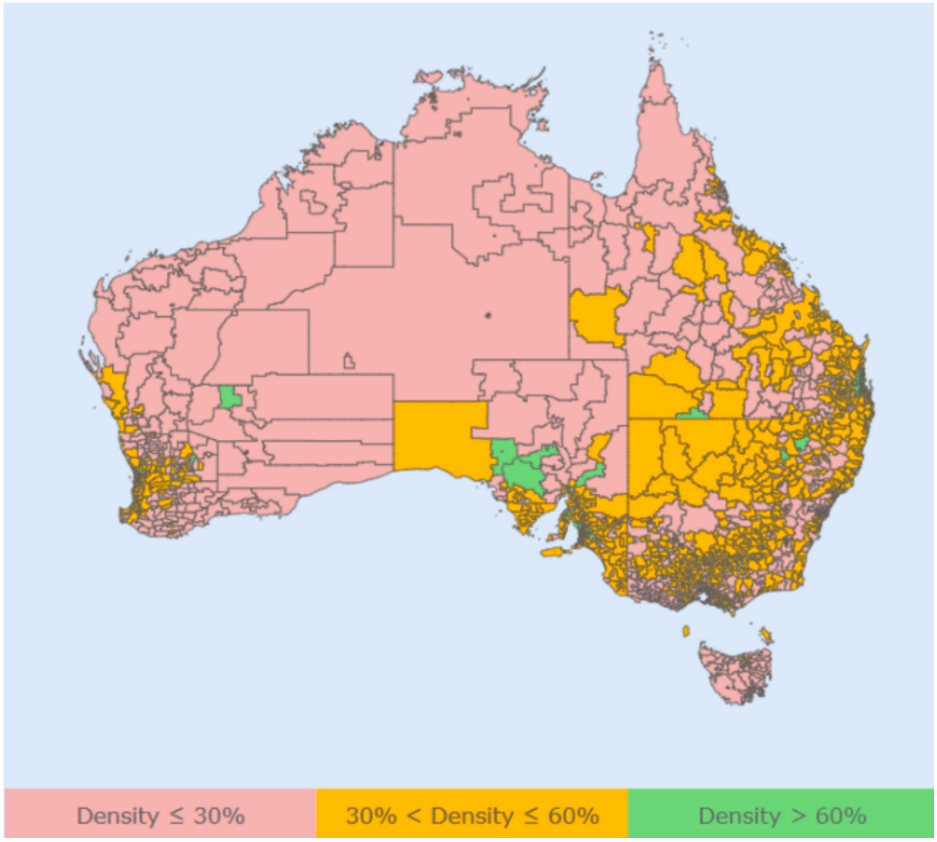

Fig. 3. Heatmap, per POA boundary, of the solar PV penetration on dwellings across Australia as of 2022.
Source: Authors, data from [10,14] (see also Supplementary Section for the link to the dashboard developed by Authors).

measured against the total PV-suitable dwellings in the POA or referred to as the "density" on the map. The map is dominated by the colour representing a density of less than or equal to 30% while a few small postal areas are shown to have a density in the order of at least 60%, particularly in the Queensland, New South Wales, South Australia, and Western Australia.

Table A.1 in Appendix A has the data on the rated output capacity and installation quantity of PV systems in Australia per year from 2001 to 2022. The same data is presented, but graphically, in Fig. 4 to visually demonstrate the longitudinal installation growth of PV systems over the last two decades. Here we have also mapped the timing of some critical government policies to highlight that diffusion of the solar PV technology in Australia, it can be argued, has not just happened organically. The government has taken a leading role in ensuring the augmentation of the country's transition to renewable energies through the Renewable Energy Target (RET) policy, erstwhile known as the Mandatory RET [15].

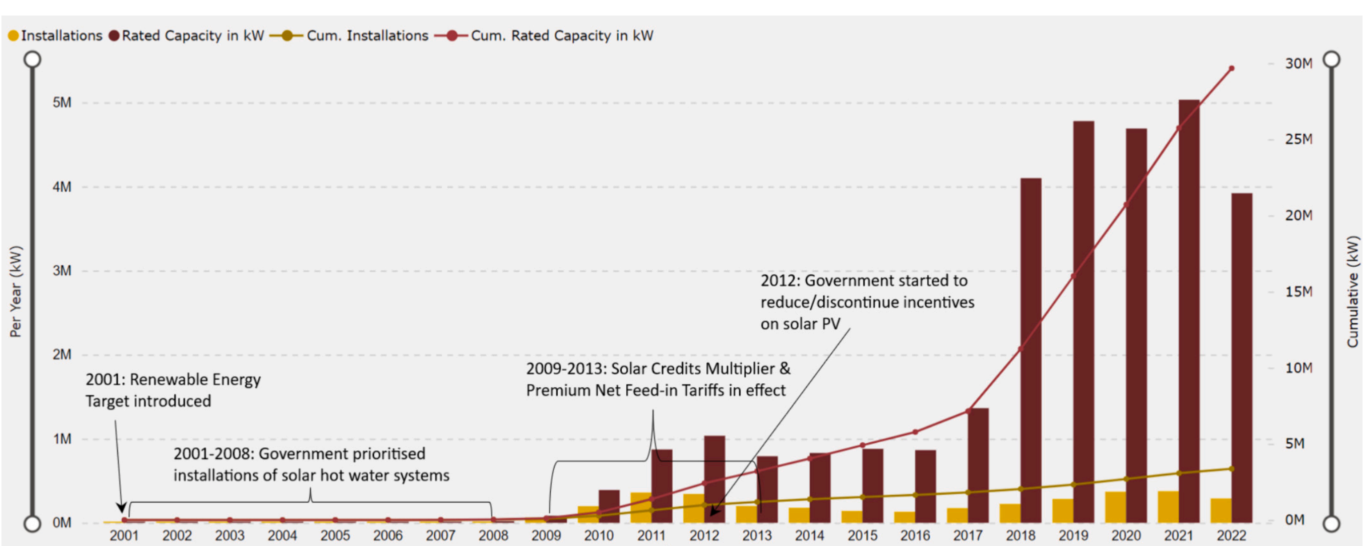

Fig. 4. PV systems installation quantity and rated output capacity in Australia from 2001 to 2022.
Source: Authors, data from [10,11,14] (see also Supplementary Section for the link to the dashboard developed by Authors).

The RET policy has been in effect since 2001 [15]. It has assisted communities in adopting the technology especially at the earlier stage when the cost of installing a PV system was substantial and doing so was economically non-sensical. Incentives, such as upfront capital costs rebates and feed-in tariffs, were made available to Australians. To jumpstart the program, a series of initiatives such as the Solar Credits Multiplier (SCM) and premium net feed-in tariffs, were introduced between 2009 and 2013 that greatly increased the appetite of the public to participate in the program by the installation of the PV systems. The generous feed-in tariffs (as high as $0.6/kWh in early days when the electricity tariff was less than $0.2/kWh) allowed the owners to sell the surplus electricity to the grid for consumption by others, thus, reducing the payback period on the initial investments. The flux of installations in 2009–2013 could be considered as driven by the infused incentives [12]. From 2001 to 2008, the government policy was centred around the installation of solar hot water systems. The incentives on solar PV were either scaled down or discontinued from circa 2012 [16]. Despite the feed-in tariffs reduction after 2013, the PV uptake continued at an increasing pace. The determinants to such uptake in terms of the various socio-economic factors are discussed in this paper.

1.3. Research purpose

The statistical analysis performed in this research is to understand the demographic make-up of solar PV adopters in Australia. This is accomplished by the application of the regression analysis correlating, based on pooled cross-sectional data from year 2001 to 2022, the number of small-generating units (SGU) installed on Australian homes (units with rated output capacity of <10 kW) with the socio-economic census data for the 2,641 Australia-wide postal areas (POA).

Postal areas or POA(s) are estimates of the geographic location of the Australia address postcodes [17]. The currently 2,644 POAs (including the three non-spatial POAs) covers the whole of Australia while postcodes are non-contiguous and only covers most, but not all (e.g., Western Tasmania does not have postcodes) [18,19]. As POAs are only approximations of the postcodes, POA census data may contain inaccuracies due to: respondents incorrectly reporting their postcodes; difficulty in appropriating the POA on respondents using post office boxes; respondents using the address at the time of census as opposed to their usual residency address; and the changes with the postcode boundaries over time causing difficulties in reconciling data from different periods of time [18] – some clear limitations of this data-intensive type of an analysis.

A total of 16 explanatory variables were used to analyse their associations with the 3,142,736 SGU solar PV systems installed on residential units in Australia in the last two decades. With the method employed and the results garnered in this paper, it aims to achieve the following:

- For Australia, it provides the opportunity to gain insights into the current underlying drivers in the solar PV market at the household level considering the technology's level of community penetration at this point, thereby, presenting policymakers and decision-makers with vital information to aid their actions.
- For other parts of the world, understanding that different countries have different geopolitical, social, and economic landscapes and that the results of the analysis herein may or may not directly resonate with them, it is the hope of this study, at the very least, that the demonstrated method can be reproduced to conduct a similar study utilising data and information intimate to that country.
- For everyone else, an openly accessible dashboard has been created wherein the data utilised and the results of the analysis in this paper were made available. The link to this dashboard can be found in the Supplementary section. By the dashboard's interactive feature and the richness of information, it gives everyone the opportunity to dissect a vast number of details pertaining to Australia's state of solar PV adoption. Furthermore, considering the data-intensive nature of this study, the dashboard itself in a way convey an implicit message of the vitality of ensuring robust collections of information, especially those conducted by government agencies, as these are crucial for current and future studies in the field.
- Lastly, the formula developed herein to detect and quantify the presence of the neighbourhood effects opens up the opportunity of its application to past and future researches, not just in the field of solar PV systems, but to similar new and innovative technologies as well.

Though several publications exist to ascertain the correlations of the solar PV adoption with gender [20,21], age [16,20], marital status [20], income [20,22,23], employment rate/status [24], education level [20,21,25], population density [26], dwellings density [23], land area [24], home ownership [22,23], ownership of a vehicle [21], persons per dwelling [26], and the number of bedrooms [16,25], they lack comprehensiveness in the variables considered, granularity of the applied spatial domain, and extent of data utilised. Specific to Australia, similar studies conducted by Simpson and Clifton [12] and Sommerfeld et al. [16] lack the extent of the geographic area covered and the demographic variables considered. With regard to the neighbourhood effects, several studies undertaken [24,27,28] have methods and underlying assumptions distinctive from the kinematics-based formula that was developed in this paper. The approach demonstrated here adds another dimension on how to diagnose for the existence of the neighbourhood effects given the available historical data packs. Therefore, the novelty of this manuscript can be summed up as follows: extended period coverage (from 2001 to 2022 historical PV installation information); vastness of geographic area covered (whole of Australia or for 2,641 POAs); large number of explanatory variables included in the regression analysis (16 socio-economic indicators); new formula developed to quantify the neighbourhood effects (based on kinematics in physics); and, a publicly-accessible dashboard (created with this study containing the data and results of this analysis).

The structure of this research paper is arranged as follows: Section 2 reviews the literature relevant to the topic of this study; Section 3 elaborates on the method employed to analyse the sourced data; Section 4 explains the results based on the pre-established methods; Section 5 discusses the insights on the generated results and their policy implications; and lastly, Section 6 provides the conclusion.

2. Literature review

Thematic to this research is identifying the demographics that might be associated with the solar PV installations on dwellings in Australia and to diagnose whether the neighbourhood effects do exist influencing the transactions.

2.1. The socio-economic factors

Over the recent decade, there has been a growing interest in studying the correlations between the socio-economic variables and the solar PV installations in a geographical context. For instance, in the survey conducted by Parkins et al. [29] on 2,065 residents in Canada, they found that the educational level was positively correlating with the intent to adopt the PV technology. By ordinary least squares (OLS) technique, Balta-Ozkan et al. [30] were able to estimate that population density and income impacted the PV adoption negatively in UK while employment, and population percentage with higher qualifications had a positive influence. Also in UK, Balta-Ozkan et al. [26] identified that income, education level, rented dwellings, and the number of separated houses have a positive effect on the PV uptake while population density, and the number of persons in dwellings had the opposite effect. In a similar study conducted by Davidson et al. [25] in the state of California in the US, they identified that the number of rooms, education, and ownership of a hybrid car were having a positive correlation with the number of PVs installed.

Meanwhile in Greece, the investigations conducted by Sardianou and Genoudi [31] using probit regression analysis showed that income and the higher level of education were positively correlated with the adoption of renewable energy sources. This was also the trend with the adoption pattern among middle-aged populace. Marital status and gender, however, were found to be statistically insignificant. In the city of Tehran in Iran, where energy prices were relatively low, Bashiri and Alizadeh [20] concluded from their studies that income had an inverse impact on PV adoption. Females were more likely to adopt the systems than males. The household size as well as the education level had a positive impact. Home ownership was also found as possibly influencing the PV acceptance such that rented properties were found to be less likely to adopt. Surprisingly, the analysis yielded a result against the number of dwellings in that the more dwellings there were, the less were the likelihood of adoption.

In the research made by Briguglio and Formosa [22] in the country of Malta, they found that younger age households were more prone to PV uptake and that the higher the unemployment rate is, the lower is the likelihood of adoption. Property ownership was deemed to positively relate to the PV adoption. Education, however, was not an explanatory variable in the analysis. In Germany, the exploration conducted by Schaffer and Brun [23] yielded results on the correspondence of high house density, high property ownership ratio, and high income with the higher uptake of PV panels.

In Australia, Sommerfeld et al. [16] made an in-depth look to identify the demographic variables impacting the PV adoption in Brisbane in the state of Queensland. The geographic span of their study was for 117 postal areas and using the publicly available demographic information to relate these data with the PV installations. They employed statistical modelling as the method of analysis. Their study revealed that home ownership and being of age over 55 years had positive correlations with solar installations. Income and education were not found to affect the PV uptake. In the Western Australia, the survey conducted by Simpson and Clifton [12] revealed that majority of the respondents (70%) had the government financial incentives as their primary motivator in deciding to adopt the PV technology.

Although the aforementioned studies do include other explanatory variables in their respective analyses, highlighted are the ones that have been considered in our analysis. In other words, this research encompasses more socio-economic variables in a single analysis to better assess what they relate to and the extent of their association with the solar PV uptake in Australia. Table 1 summarises the explanatory variables used in our regression model vis-à-vis their recognition in various literature in an attempt to explain their associations with the residential solar panel installations. The tick mark (✓) denotes a match in terms of being included in both our and the corresponding study's analysis. It should be noted, however, that the context and meaning of these variables in similar studies may not exactly correspond with how we have defined ours. For instance, although Bollinger and Gillingham [21] included car ownership in their modelling, they have defined such variable to mean ownership of a hybrid vehicle while ours refer to ownership of a vehicle in general (i.e., regardless of the engine classification). We have grouped age by their generation designation, but no grouping was made for such a variable in Bashiri and Alizadeh [20].

As is evident from Table 1, there is no single study that tick across all variables that we have considered in our modelling. Moreover, differences also exist in the location where the study pertains to and the analysis method. In Australia, for instance, the research conducted by Simpson and Clifton [12] and Sommerfeld et al. [16] encompass only the Western Australia and Queensland states, respectively. Although Lan et al. [32] covered the whole of Australia also at the POA resolution, they employed a different methodology in machine learning approach compared to ours which was by regression analysis. Although the variables in Table 1 were not all ticked, they have included other determinants such as the people who were Australian citizens and the mortgage payments. Other variables were also modelled in the various

Table 1
Explanatory variables considered in various existing solar household PV adoption studies (and their geographical coverage) vis-à-vis the ones evaluated in this study as denoted by a tick mark (✓).

Study	Location	Gender	Age	Marital status	Income	Employment	Education	Population density	Dwellings density	Land area	Home ownership	Car ownership	Number of occupants	Number of bedrooms
Simpson and Clifton [12]	WA, Australia				✓		✓							
Sommerfeld et al. [16]	Queensland, Australia		✓		✓		✓				✓		✓	✓
Lan et al. [32]	Australia		✓		✓		✓	✓	✓	✓	✓		✓	✓
Bashiri and Alizadeh [20]	Tehran, Iran	✓	✓		✓		✓				✓		✓	
Bollinger and Gillingham [21]	California, USA	✓	✓		✓			✓				✓		
Briguglio and Formosa [22]	Malta		✓		✓	✓	✓	✓					✓	
Schaffer and Brun [23]	Germany				✓				✓		✓			
Davidson et al. [25]	California, USA		✓		✓		✓					✓	✓	✓
Sardianou and Genoudi [31]	Greece	✓	✓	✓	✓		✓				✓			
Balta-Ozkan et al. [26]	United Kingdom				✓		✓	✓	✓		✓		✓	
Balta-Ozkan et al. [30]	United Kingdom	✓			✓		✓	✓	✓		✓	✓	✓	✓
Parkins et al. [29]	Canada	✓	✓		✓		✓	✓						
Karjalainen and Ahvenniemi [33]	Finland		✓		✓		✓	✓	✓	✓	✓		✓	✓

Source: Authors.

studies on Table 1 apart from those crosschecked (e.g., irradiation level and electricity sales in [26]; political orientation in [29]; availability of roof space, commuting distance, share of green votes, electricity demand, and pollution levels in [30]).

While a number of studies have already been made pertaining to demographic variables and their influences on solar PV installations, this research is not simply to further crowd the extant literature. The analysis broadens the extent of existing studies such as covering the whole of Australia in contrast to the geographical limitations in, for instance, Sommerfeld et al. [16]. Further, the rigour of the analysis includes data of PV installations for about two decades (2001 to 2022). The regression analysis, while it has been utilised in many studies (for instance, Bashiri and Alizadeh [20]), includes more explanatory variables than what were previously explored. Moreover, the spatial scale and location of the analysis adds nuances to the field. This study is a dissection at postal areas (POA) level.

Different countries have different socio-economic factors influencing PV uptake, and this research gives insights into those influences in Australia. Fig. 5 provides a graphical representation of the complete list of socio-economic factors assessed in this study. The temporal and spatial considerations, combined with the techniques utilised, are all contributories to the uniqueness of this paper. Finally, while the results of this research may align with or differ from others, this was not meant to validate or invalidate previous publications. This was conducted to supplement the existing pool of literature, not as a means to supplant any.

2.2. The neighbourhood effects

There have been numerous empirical studies that point to the close relationship between product visibility and technology adoption, such as solar PV systems [29]. More commonly known as the "neighbourhood effects," they were thought to play a vital role in the diffusion of technologies through direct communications between individuals or by the sensory effects of seeing the technology in the neighbourhood [28]. Bollinger and Gillingham [21] claimed that the neighbourhood effects have something to do with the increase of PV installations among residents in California in the US. They argued that effects were stronger at the street level compared to the study area at the zip code level, implying that neighbourhood effects increase with the proximity of the subject communities. Inhoffen et al. [24] attempted to quantify the effects on the PV installations in Germany. Their approach was using the propensity score matching, wherein two or more municipalities of identical size and demography were compared. For the municipality with at least one PV installed in the year, it was compared with its matching municipality and measured against the time when the next installations occurred. They concluded that the neighbourhood effects increased the probability and the number of new installations by up to 50%. Neighbourhood effects as a function of geographic distance were also a common approach, as what Balta-Ozkan et al. [26] utilised with spatial econometric method for the installation cases in the UK. The empirical study conducted by Parkins et al. [29] supported the claim of the influence of social interactions on the diffusion of solar technology among the surveyed residents of Canada.

Although the number of studies concerning the neighbourhood effects on PV installations is not lacking to the extent that quantitative attempts have even been made, the methods and the underlying workings are still poorly understood. It has been recognised that the presence of social effects does affect the effectiveness of the existing policies [24]. This research attempts to pragmatically assess the presence of the neighbourhood effects to the case of solar PV installations on Australian homes. The method used draws parallels to the field of kinematics in physics. The underlying assumption is that in the absence of significant changes in the community demography (i.e., one- to two-year timeframe) and external stimulus (e.g., changes to solar PV incentives), the growth of installed PV systems should be constant. Any "accelerated" rate determined could be attributed as the influence of the neighbourhood effects. Based on the literature reviewed, this approach has not been done before.

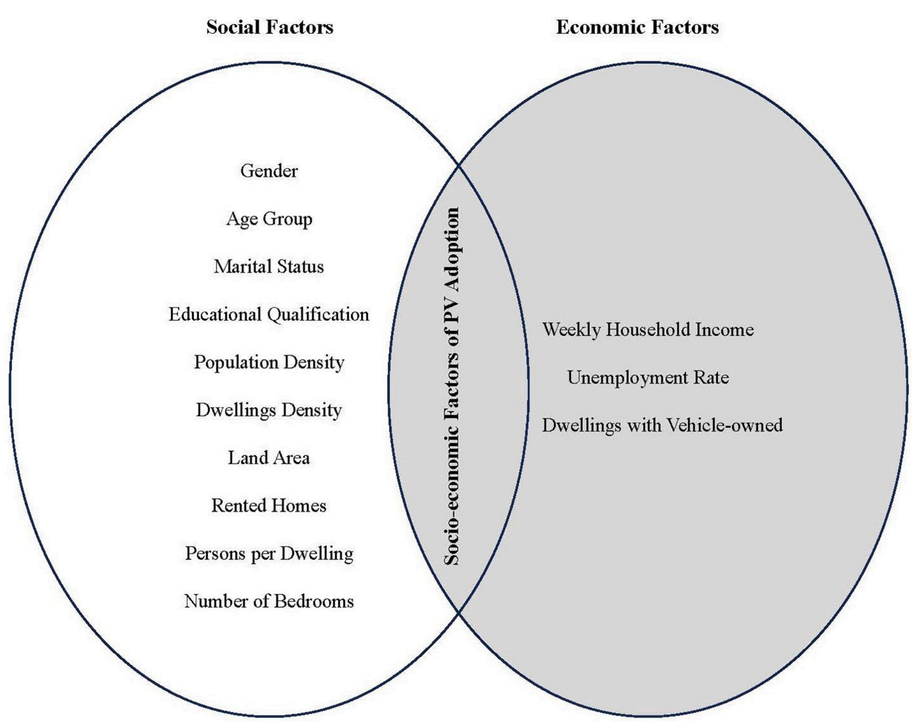

Fig. 5. The socio-economic factors assessed in this study.
Source: Authors.

Table 2
Response and explanatory variables used in the regression analysis.

Variable	Unit	Description
Response		
PV Installation	Number	Installed PV systems on residential units; small generating units with capacity of <10 kW
Explanatory		
Male	Percentage	Percentage of male against the general population age 15 years old and older in the POA
Gen Z (15–24)[a]	Percentage	Percentage of persons in the POA age 15 to 24 or those falling under the Generation Z grouping
Millennials (25–40)[a]	Percentage	Percentage of persons in the POA age 25 to 40 or those falling under the Generation Millennials grouping
Gen X (41–56)[a]	Percentage	Percentage of persons in the POA age 41 to 56 or those falling under the Generation X grouping
Boomers (≥57)[a]	Percentage	Percentage of persons in the POA age 57 and older or those falling under the Generations Boomers, Post War, and WWII
Married	Percentage	Percentage of the POA population age 15 years old and older who have a marital status under registered marriage or de facto marriage
Weekly household income	Number	Weighted average of the weekly household income by coding in the POA; excludes data from partially stated income and all income not stated; includes family and non-family households (lone person or group households); coding of income bracket is as follows:
		Negative/Nil income 1
		$1–$149 2
		$150–$299 3
		$300–$399 4
		$400–$499 5
		$500–$649 6
		$650–$799 7
		$800–$999 8
		$1,000–$1,249 9
		$1,250–$1,499 10
		$1,500–$1,749 11
		$1,750–$1,999 12
		$2,000–$2,499 13
		$2,500–$2,999 14
		$3,000–$3,499 15
		$3,500–$3,999 16
		$4,000 or more 17
Unemployment rate	Percentage	The number of unemployed persons against the total labour force
Non-school qualification	Number	Total number of persons aged 15+ years with a non-school qualification: certificate level, advance diploma and diploma level, bachelor's degree level, graduate diploma and graduate certificate level, postgraduate degree level
Population density	Number/km^2	Number of population age 15 years old and older per land size of the postal area
Dwellings density	Number/km^2	Number of residential units per land size of the postal area; residential units are counted only for occupied private dwellings of type separate house, and one or more storey semi-detached, row or terrace house, townhouse. Excludes the likes of flats or apartments or dwellings where a PV installation is not immediately feasible
Land area	km^2	Land size of the postal area (POA)
Rented	Number	Total number of rented dwellings for type separate house, and one or more storey semi-detached, row or terrace house, townhouse
Dwellings with vehicle	Number	Average of the binary numbering of dwellings with no vehicle (binary code 0) and dwellings with at least 1 vehicle (code 1)
Persons per dwelling	Number/Number	Total number of occupants per dwelling of type separate house, and one or more storey semi-detached, row or terrace house, townhouse
Bedrooms	Number	Average number of bedrooms per dwelling of type separate house, and one or more storey semi-detached, row or terrace house, townhouse

[a] Age at the time of census (2021).
Source: Authors.

3. Data and methodology

3.1. Data modelling

The geographic unit of analysis is at the postal areas (POA) level. The response or dependent variable is the number of installed PV units classified as small generating units (SGU), that is, systems with a rated output of <100 kW. This SGU is normally used for residential and commercial purposes. The data used is the cumulative figure from 2001 to 2022 for all the installations across Australia. The explanatory or independent variables are obtained from the latest census data published by the Australian Bureau of Statistics [34]. The 2021 census data provide a pack of community profiling information per postal area. Among these variables, the ones picked for this analysis are based on their deemed relationships to the response variable. Their actual connections, however, are determined by the *p-values* in the regression analysis.

For the neighbourhood effects, the datasets are processed and analysed to come up with formula-based determinations. These include calculating the monthly installations at POAs, determining the rate of change of the installation rate, and getting the average of the change of the installation rate per selected period.

3.2. Response variable

Data on small-scale installations of solar PV systems for the whole of Australia are sourced from Clean Energy Regulator [11]. The agency has comprehensive data files of the number of PV systems installed and their rated capacity in kW per postal area and at per month breakdown from 2001 to 2022. The updated listing of POA, as well as their corresponding land size, is based on the Australian Statistical Geography Standard (ASGS) Edition 3 which is readily available from the Australian Bureau of Statistics [14]. The encoding of solar PV installations per month per POA from 2001 to 2022 generated a total of 731,580 data entries.

Since the focus of this research is on the PV systems installed on dwellings, the installation counts (excluding those installed on business establishments) are extracted from the raw data by calculating the rated capacity per installation. That is, for the installed capacity of <10 kW, the system is assumed to have been placed on a residential unit. Otherwise, it is considered to have been placed on a business establishment. These are necessary steps to extract the records of interest considering that the raw data from the Clean Energy Regulator [11] do not discriminate whether the installations were made for a place of dwelling or on a commercial building [10].

3.3. Explanatory variables

The variables chosen from the Australian Bureau of Statistics [34] data packs are based on those mostly identified in several studies as seemingly correlating to PV installations on dwellings. These include the POA land size, age groupings, marital status, gender, and income, among others. Table 2 has the complete list of variables considered, including their descriptions. The significance of these explanatory variables to the PV system installations is determined by their statistical measurements in the regression analysis.

While some of the variables in Table 2 are self-explanatory, others need further explanations as to their interpretations and/or inclusions to the modelling. For instance, the income grouping ($1–$149, $150–$299, etc.) was directly adopted from Australian Bureau of Statistics [34]. A corresponding numerical figure from 1 to 17 was subsequently added for ease in interpreting the regression analysis results.

Age was grouped (Generation Z, Millennials, Generation X, Boomers) based on generational cohort theory first introduced by Mannheim [35] and then later on advanced by Strauss and Howe [36]. The theory asserts that people born during the same period experience similar major events and experiences. Consequentially, they exhibit similar behaviour, preferences, values, and beliefs throughout their lives. Therefore, rather than denoting the unmerited increase or decrease in age in relation to solar PV uptake, the grouping posited by the generational cohort theory provides more rationality in the sociological context.

Population density and dwellings density were both considered in the analysis as they do not refer to the same thing – one is a function of people living within the POA (regardless of the type of their homes), and the other is a function of the number of homes within the POA suitable for PV system installations (i.e., flats and units are excluded). Furthermore, the former might provide insights into the urbanity of an area (higher population density), while the latter might be intuitive about the community's wealthiness (low density, for instance, on houses with relatively large land properties).

Similarly, persons per dwelling and the number of bedrooms were both form part of the analysis as they might be indicative of the social status, wealth, characteristics (family, single, number of children), and energy consumption of the household.

3.4. Regression analysis

The relationship, if there exists, between the response variable and the explanatory variables are explored using the regression analysis. This technique uses statistical inference to ascertain the causal effect of a single or multiple variables (explanatory) onto another variable (response) [37]. Regression equation takes the form of:

$$Y = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \varepsilon \tag{1}$$

where, Y is the independent or response variable, β_0 is a constant term and commonly referred to as the y-intercept, X_i refers to the i^{th} explanatory variable, β_i measures the impact of X_i to the Y variable, and ε denotes the random error term.

The steps followed in data modelling and performing the regression analysis are illustrated in Fig. 6. The analysis is data-intensive, and having a structured approach in processing information from different sources is essential to ensuring that the quality of results is acceptable and committing blunders is avoided. At some point along the process, iterations are needed to verify the validity of the results against the inputs and vice versa. The steps in Fig. 6 are further elucidated as follows:

Step Al: Collect data.

As earlier mentioned, the analysis is data-driven, and these data come from various sources. Information on SGU PV systems are collected from the Clean Energy Regulator [11], POA demographics from the 2021 census on the Australian Bureau of Statistics [34], and updated POA and their land sizes from the Australian Bureau of Statistics [14]. Though processed data on the PV installations made on dwellings is available at the Australian PV Institute (APVI) Solar Map [10], this was based on projecting the 2021 POA demographics from the 2016 and 2011 census information. With the 2021 census already released at the time of this study, a reprocessing of information is needed to capture the latest information.

Step A2: Aggregate data.

The various collected data are aggregated and linked-up through the POA code. This collection of data makes up the explanatory variables that will later be used in the analysis.

Step A3: Sum-up PV installations per postal area.

While the explanatory variables were set-up in the previous step, this step starts to shape-up the response variable, which is the number of solar PV systems installed on dwellings. The Clean Energy Regulator [11] installation records from 2001 to 2022 are totalled to determine the cumulative count of the SGU installed per POA.

Step A4: Determine PV installations on dwellings.

The total figures derived from the previous steps need to be further digested to extract the number of installations on dwellings. This is done by dividing the total rated capacity of the installed units for a particular POA by the number of systems placed per month. If the result is $<$10 kW per installation, then the installation quantity for that month is assumed to have been made on residential units. Otherwise, it is assumed to have been done on commercial establishments. This assumption is necessary to filter in the PV systems on dwellings, as the data from the Clean Energy Regulator [11] do not take into account this delineation. The records are for small-scale generation units under 100 kW capacity, and these can be installed either on residential places or on business units.

Step A5: Include installation records in the analysis.

If the PV systems are deemed to have been placed on dwellings, then this number of installations is included in the analysis.

Step A6: Exclude installation records in the analysis.

If the PV systems are deemed to have been placed on units other than residentials, then this number of installations is excluded from the analysis.

Step A7: Select variables to be included in the analysis.

While the 2021 census on the Australian Bureau of Statistics [34] has a bit of everything profiling the POA, not all information can be used to reasonably explain the number of PV installations. Hence, careful considerations should be made to include only the ones that make sense for such. Note that this step may have to be undertaken again if necessitated due to the presence of multicollinearity of variables, the insignificance of the function, or the insignificance of a multitude of variables, or a combination of those grounds.

Step A8: Perform regression analysis.

The general form of the function for multiple regression is shown in Eq. (1). The Y response variable in the analysis is the number of PV installations on dwellings and the Xs explanatory variables are the selected characteristics of the POA. The parameters βs are not explicitly observable and these are derived using the given sets of data. The random error ε is assumed to be constant, independent, normally distributed, and takes a mean value of zero [38]. The complete list of variables for this study is listed in Table 2.

Using OLS approximations, the equation that best depicts the relationships between variables is selected by minimising the squared difference between the estimated and the actual values of the independent variable Y [38]. Eq. (1) can therefore be expressed as the average PV installation as a function of the average values of the defined POA characteristics, or:

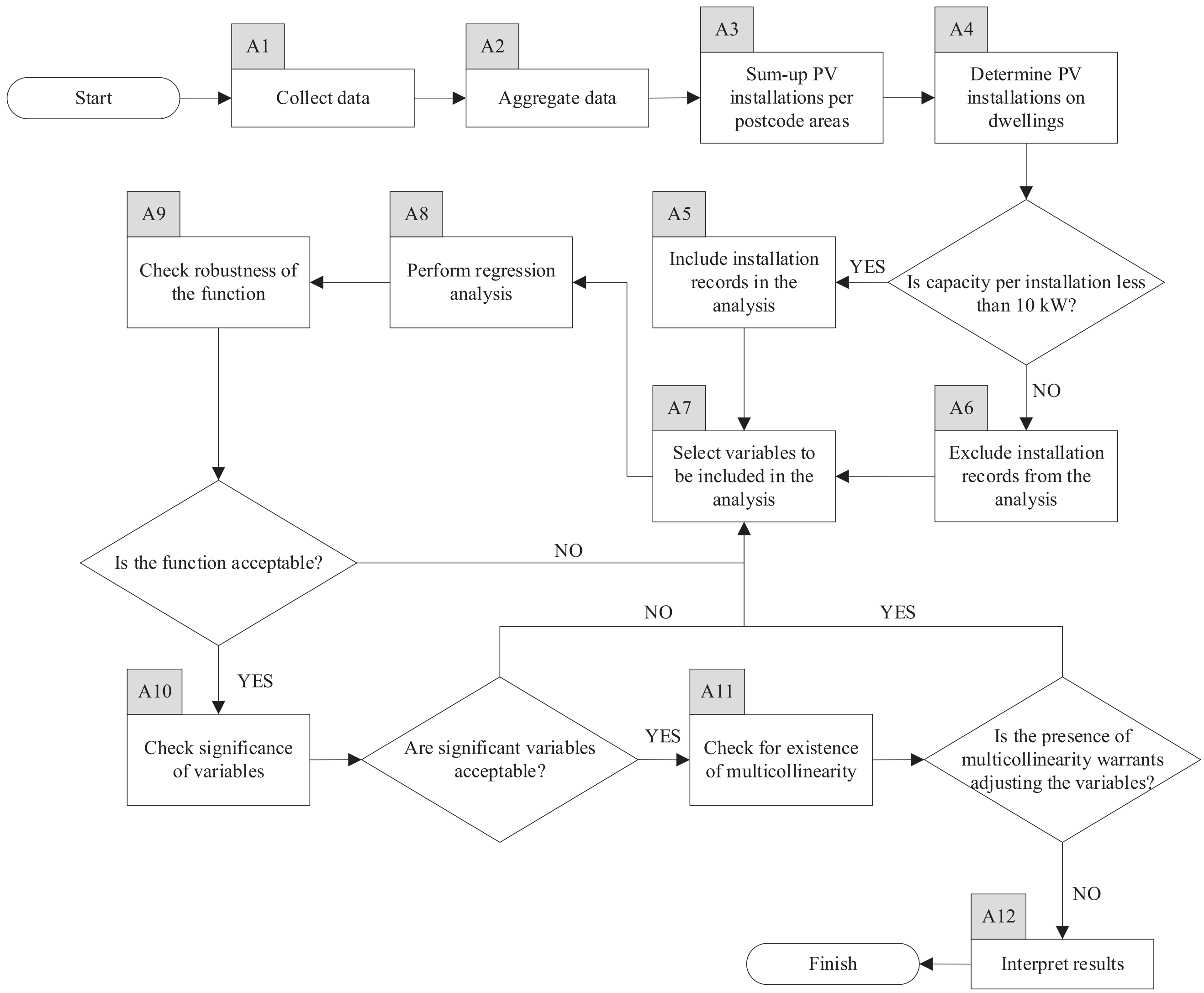

Fig. 6. Steps in data modelling for regression analysis.
Source: Authors.

$$\begin{aligned} \textit{PV Installation} = {} & \beta_0 + \beta_1 \textit{Male} + \beta_2 \textit{GenZ} + \beta_3 \textit{Millenials} + \beta_4 \textit{GenX} \\ & + \beta_5 \textit{Boomers} + \beta_6 \textit{Married} + \beta_7 \textit{WeeklyIncome} \\ & + \beta_8 \textit{UnemploymentRate} + \beta_9 \textit{Qualification} \\ & + \beta_{10} \textit{PopulationDensity} + \beta_{11} \textit{DwellingsDensity} \\ & + \beta_{12} \textit{LandArea} + \beta_{13} \textit{Rented} + \beta_{14} \textit{WithVehicle} \\ & + \beta_{15} \textit{PersonsPerDwelling} + \beta_{16} \textit{Bedrooms} \end{aligned} \tag{2}$$

Considering the size of the data and the number of variables considered in Eq. (2), it will need the sophistication of statistical software to effectively compute the values of the β parameters. The regression analysis is performed using Microsoft Excel's Analysis ToolPak.

Step A9: Check robustness of the function.

The significance of the function considering the collective impact of the independent variables is assessed by performing the analysis of variance (ANOVA). This is handily returned when performing the analysis in Excel and is termed *Significance F*. The value of *Significance F* would need to be less than the prescribed certainty of the approximation in order for that function to be statistically significant at that certainty degree. For instance, *Significance F* should be <0.01 for the model to be significant at 1%, <0.05 for 5% significance, and so on [39]. Moreover, the goodness of fit of the model is measured by the coefficient of determination, r^2. It takes a value between 0 and 1 with values closer to the latter indicative of a better relationship between the variables. For instance, an $r^2 = 0.78$ denotes that 78% of the changes in the dependent variable are explained by the independent variables. With more independent variables included in the model, r^2 would just continue to increase. To keep this in check and to ensure that the resulting values are not distorted by artificially bloating the r^2 with more variables, the adjusted r^2 (r^2_{adj}) is used instead. r^2_{adj} reduces the r^2 for every variable added into the model [38]. If the model exhibits a reasonably high *Significance F* or a remarkably low r^2_{adj} or both, then the analysis needs to be re-ran with new variables introduced and/or existing ones altered or omitted.

Step A10: Check significance of variables.

Aside from checking the significance of the function holistically as in the previous step, the significance of each explanatory variable needs to be individually checked as well. While the test for the model is signified by the *Significance F* value, the criterion for the independent variables is set forth by their respective *p-values*. Similar to the approach with *Significance F*, a lower *p-value* denotes a higher degree of certainty in regard to the relationship between the explanatory and response variables [38]. For instance, a *p-value* of <0.01 means that the particular variable has a 1% chance of being wrong in terms of its presumptive relationship to the response variable.

Step A11: Check for existence of multicollinearity.

Multicollinearity refers to the high degree of linear relationship between two or more independent variables. Its existence causes the model to be unreliable [40]. Having "redundant" variables included in the model results to higher *p-values*, therefore indicating that those variables are insignificant, though that might incorrectly be the case. The robustness of the function is not affected by the presence of multicollinear variables and might even provide indications of a good fit of a model. However, the individual variables are insignificant, and this is an indication of the existence of multicollinear variables. One way to assess its presence is the variance inflation factor (VIF) [38]. Another way to diagnose for it is by generating the coefficient of determination between independent variables in Excel. This is the method employed in this analysis with the coefficient of 0.90 or more between variables considered to be the multicollinearity threshold.

If there is multicollinearity, the model needs to be re-calibrated to drop off the collinear variables or combine them.

Step A12: Interpret the results.

The final step in this analysis is interpreting the generated results. This is explored aptly in Section 4 (Results).

3.5. Neighbourhood effects

Data collected and processed in the previous section are also utilised to determine the neighbourhood effects in the PV installations. The underlying assumption in detecting the presence of these effects is that the rate of change of the installation rate would not be zero in the presence of perceived changes in the existing stimuli. This stimulus could be changes to the existing incentives for installing the PV system that might potentially influence the number of installations in a given timeframe compared to the previous period. The other way to frame this is that when there are no policy changes or other external influences for installing the PV systems, the first derivative of the installation rate should be zero. Otherwise, a positive derivative of the installation rate is perceived to be the influence of the neighbourhood effects. It is thus crucial in this process to identify and select periods of time wherein changes in regulations, policies, and other external influences related to PV installation are minimal or are discerned to be non-driving factors. The steps taken to conduct this diagnostic are shown in Fig. 7. To wit:

Step Bl: Select the period to analyse.

The period in terms of year to select is based on the perceived latency of PV installation policies and regulations, for instance, in terms of introducing new ones or amending the provisions of the existing stipulations, and/or disruptions to the prevailing socio-economic conditions impacting the decisions on installing PV systems. This is an important qualification as the analysis is based on the premise that, sans external factors mentioned in the foregoing, the rate of change of the installation rate should be zero. A positive value on which is presumed to be the impact of the neighbourhood effects.

Step B2: Calculate the installation per month across the POA.

With the data available on the number of PV installations per month per postal area, the installation rate is calculated for the year immediately before the period under consideration by dividing the total installations by 12 (months), or

$$R_{T-1} = \frac{I_{T-1}}{t_{T-1}} \tag{3}$$

where, R is the number of PV systems installed per month in a particular postal area, I refers to the number of PV systems installed in the period, t denotes the number of months in the period which has a value of 12 for the full one year period, and the subscript *T-1* denotes that the values are taken one year immediately before the period being analysed, such as, for analysis on year 2022, data supplied to Eq. (3) is from year 2021.

Step B3: Determine the rate of change of the installation rate across the POA.

The rate of change of the installation rate is the second derivative of the number of installations with respect to time, or the first derivative of the installation rate with respect to time, or simply from Eq. (3)

$$R' = \frac{dR}{dt} \tag{4}$$

where, R' is the rate of change of the installation rate, or simply, the accelerated rate, and the term dR/dt is the derivative of the installation rate with respect to time. From Eq. (3) and Eq. (4), the formula to compute the accelerated rate can be derived by integration. The integral formula is shown in Eq. (5) while the simplified expression to calculate the accelerated rate is provided in Eq. (6).

$$\int_{I_{T-1}}^{I_T} dI = \int_0^{t_T} \left(R_{T-1} + R'_T t\right) dt \tag{5}$$

$$R'_T = \frac{2\left[\left(I_T - I_0\right) - R_{T-1} t_T\right]}{t_T^2} \tag{6}$$

I_0 is the quantity of installed PV systems at the beginning of the analysed period, which is generally equal to zero. I_T is the number of units installed after, say, a year. t_T is the number of months comprising the period being analysed, which is equal to 12.

Step B4: Compute the average of the rate of change of the installation rate per period.

This step is simply the averaging of the calculated accelerated rate across the postal area for the period analysed.

Step B5: Interpret the results.

The final step in this analysis is interpreting the generated results. The exposition of this is covered in the next section.

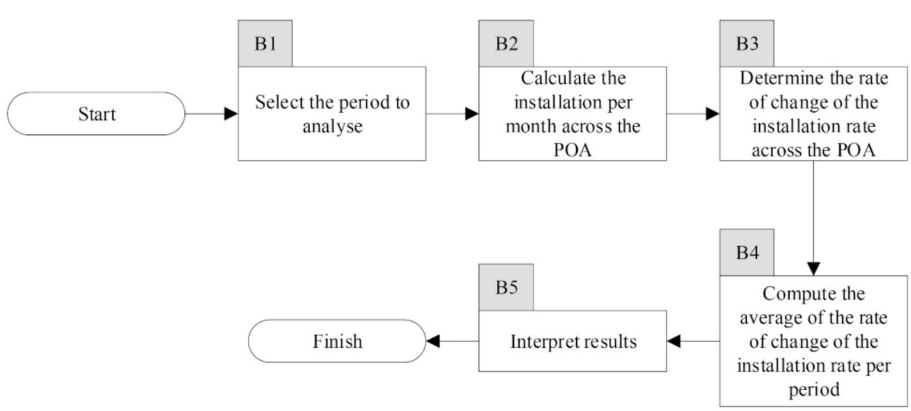

Fig. 7. Steps in the determination of the neighbourhood effects.
Source: Authors.

4. Results

4.1. The regression analysis

The latest listing of the postal areas (POA) and their land sizes from the Australian Bureau of Statistics [14] reveals a total of 2,644 unique codes. Excluding POAs ZZZZ – "outside Australia", 9494 – "no usual address", and POA 9797 – "migratory-offshore-shipping" leaves the count at 2,641. The POA serves as the anchor point connecting all the other gathered information such as the community demography and the solar PV installation details. It is the geographical unit upon which the parametric measurements are referred to.

From the monthly PV installation records per POA of Clean Energy Regulator [11] in Australia spanning from 2001 to 2022, a total of 44,277 out of 729,975 (~6.07%) data entries relating to small-scale generating unit installations were needed to be omitted. This constitutes a total of 173 unique POA data records, 1,801 small generating unit (SGU) installations (out of a total of 3,363,822 or ~0.05%), and about 9,800 kW rated capacity (out of a total of 19,031,823 kW or ~0.05%). The omission was mainly because of the changes in the POA through the years and that the updated POA vocabulary did not include them anymore.

Table 3 has the statistical information on the variables and parameters considered in the regression model. Effectively, the number of POAs is the size of the observation. The table is provided with information on how the variable is measured (i.e., unit). This provides the contextual degree of how the explanatory variable impacts the dependent variable (i.e., an increase in the "percentage" of the married population increases the "number" of PV installations).

Gender is measured as the percentage of males in the population aged 15 years and older.

Rather than averaging the age of the general population 15 years old and above, they are classified based on their distinctive generation [41]. With this approach, all age groupings are considered in the analysis to identify which ones might be influencing the PV uptake, if there is any, instead of simply relating to the age increase or decrease the PV adoption. The classification (Generation Z for 15 to 24 years old, Millennials for 25 to 40, Generation X for 41 to 56, and Boomers for those aged 57 and older) is based on the age of the individuals at the time of census. The percentage measure is based on the number of people identified within the grouping against the total population considered (age 15 years and older).

Table 3
Statistical summary of variables at POA level.

Variable/parameter	Unit	Total	Mean	Standard deviation
POA (Observations)	Number	2,641		
PV installation quantity	Number	3,141,090	1,189.36	1,979.96
Male	Percentage		50.57	5.30
Gen Z (15–24)	Percentage		12.80	6.10
Millennials (25–40)	Percentage		23.36	9.39
Gen X (41–56)	Percentage		25.15	6.70
Boomers (≥57)	Percentage		38.42	12.97
Married	Percentage		60.42	8.96
Weekly household income	Number		10.47	1.77
Unemployment rate	Percentage		4.57	2.79
Non-school qualification	Number		4,300.18	6,157.34
Population density	Number/km^2		628.37	1,343.99
Dwellings density	Number/km^2		185.46	312.27
Land area	km^2		2,911.05	24,175.80
Rented	Number		752.07	1,261.50
Dwellings with vehicle	Number		0.94	0.10
Persons per dwelling	Number/ Number		2.51	0.41
Bedrooms	Number		3.23	0.42

Source: Authors.

Marital status is counted for individuals in registered or de facto marriages. It is measured in percentage against the population set of 15 years and older.

The weekly household income is bracketed from 1 to 17 based on the range of the household's total weekly income. The income range and the equivalent numbering is provided in Table 2. This means that in the analysis, a unit increase in the weekly household income means a jump in the income range, not a jump in the income value itself.

The unemployment rate, in percentage, is directly based on the figures provided in the extracted census data per POA. It was calculated as the ratio of the unemployed individuals against the total labour force in the POA.

The non-school qualification is the number of individuals who identified themselves as having obtained education at certificate level, advance diploma and diploma level, bachelor's degree level, graduate diploma and graduate certificate level, or postgraduate degree level.

The population density is simply the total population divided by the land size of the POA. Likewise, dwellings density is the count of dwellings against the land area of the POA. The dwellings considered are those of type separate house, semi-detached, and townhouse, or those residential units where PV panel installations are feasible.

The land area of the POA is based on the figures made available from the Australian Bureau of Statistics [14] data.

The rented variable counts the number of separate house, semi-detached, and townhouse dwellings considered to be rented out.

Dwellings with vehicles are calculated based on the weighted average of the binary values 0 (dwellings without a vehicle) and 1 (dwellings with at least one vehicle).

Persons per dwelling refers to the number of individuals living in a separate house, semi-detached, or townhouse dwellings.

Finally, the bedrooms variable counts the number of bedrooms in dwelling types suitable for PV installations.

The results of the analysis based on the regression model in Eq. (2) are shown in Table 4. The calculated coefficients (β_1, β_2, β_3, …, β_{16}) of the explanatory variables, along with their corresponding *p-values*, are shown on the table. Other information includes the *Significance F* and r^2_{adj}, which are determinants of the robustness of the model, and the constant β_0 or the y-intercept. The highlighted items are the variables that are considered statistically insignificant. That is, with *p-values* >0.05 (5%). They do not provide explanations to the number of PV installations on dwellings. For instance, the Male variable has a *p-value* of 17.3%. This denotes the same percentage chance of making a mistake in explaining the PV uptake taking into account the percentage of the male population, hence, it is not significant in the expressed model. Other variables identified as insignificant are Gen Z, Gen X, Boomers, Land Area, and Dwellings with vehicle. The rest of the explanatory variables are considered significant.

Of the age groupings, only one is significant – the Millennials for ages between 25 and 40. Its negative coefficient denotes that the growth of PV installed quantity acts opposite of that percent share of Millennials in the population. That is, for an average 1% increase in the share of Millennials, the installed PV is reduced by an average of about 911 units, holding all the other variables constant. On the other hand, the marital status tends to go along with the quantity of PV installed. Holding all the other variables constant, an average 1% increase in the share of the married population results in an average increase of about 659 PV installed. The move in the weekly income bracket negatively influences the installed panels, holding all the other variables constant. Surprisingly, the increase in the unemployment rate has a positive effect on the PV uptake, holding all the other variables constant. On the education aspect, populations with non-school qualifications are more inclined to adopt the solar PV, holding all the other variables constant. Both the population and the dwellings densities have an opposite relationship with the PV uptake. Another surprising result is in the rented dwellings.

Table 4
Regression analysis results (shaded parameters are deemed insignificant).

Parameters	Coefficients	P-value
Significance F		0.000
Adjusted R square, r^2_{adj}	0.794	
Intercept, β_0	-287.17	0.476
Male	-510.19	0.173
Gen Z (15-24)	419.52	0.366
Millennials (25-40)	-911.28	0.036
Gen X (41-56)	-162.16	0.720
Boomers (≥57)	-507.36	0.194
Married	658.55	0.018
Weekly Household Income	-60.47	0.000
Unemployment Rate	2,544.40	0.001
Non-school Qualification	0.19	0.000
Population Density	-0.27	0.000
Dwellings Density	-0.26	0.009
Land Area	0.00	0.457
Rented	0.62	0.000
Dwellings with Vehicle	184.90	0.508
Persons per Dwelling	-383.34	0.000
Bedrooms	614.23	0.000

Source: Authors.

The analysis garnered a positive relationship between the number of rented dwellings and the PV installation. This means that the more dwellings are rented out in the POA, the greater the number of installed PV that can be found. In regard to the number of occupants in the dwellings, as more people are residing in the dwelling, the average PV uptake is reduced, holding all the other variables constant. Finally, the number of bedrooms has a positive effect on PV adoption. An increase of one bedroom impacts the average PV installations by about 614 units.

4.2. Robustness of the model

Checking the significance of each variable is made through its corresponding *p-value*. Checking the significance of the model as a whole, on the other hand, is done via the *Significance F* value. This value is also provided in Table 4, and it shows that the model is highly significant (*Significance F* ~0.000).

The goodness of the fit of the variables to the model function is indicated by the adjusted R square, r^2_{adj}, with values closest to 1 signifying a good outcome of the analysis. The resulting r^2_{adj} in this investigation is 0.794, which is a fairly good value. This means that about 80% of the behaviour of individuals in adopting the PV technology is explained by variables considered in the modelling. What about the remaining 20% then? Part of that might be from the neighbourhood effects, which are analysed in the next sub-section.

Another crucial aspect of the analysis is detecting multicollinearities, as discussed in Step A11 of Section 3. Their presence results to the unreliability and instability of the regression model by artificially inflating the r^2_{adj} while potentially causing some explanatory variables to be wrongfully considered as insignificant. Independent variables that are perfectly and positively collinear would have a value of $+1$ (-1 if the variables act in opposite directions). In this analysis, the threshold is set at ± 0.90. The plot of the collinearity coefficients among the explanatory variables is shown in Table 5. There are no two variables breaching the threshold (with the coefficients of 1 only returned when the variable is related to itself, which should understandably be the case). The maximum coefficient is 0.87, which occurs between the variables Rented and Non-school qualification. In the initial iteration of the model, the number of dwellings was found to be highly collinear with the number of rented homes and the non-school qualification, with coefficients of 0.95 and 0.93, respectively. The dwellings count was eventually dropped to form the final configuration of the model as being dissected herein.

4.3. The accelerated rate

The neighbourhood effects are derived from Eq. (6) and expressed as the accelerated rate. Table 6 has the calculated average accelerated rate across the POA in Australia in the last five years, along with the other functional values. The underlying assumptions in detecting the neighbourhood effects are that no substantial changes occurred in the demographic profile within the POA and the non-existence of external influences affecting the motivation of individuals to adopt the technology (i.e., incentives and regulation changes that may or may not be necessarily related to the PV systems).

It should be noted that while the regression analysis utilises the pooled cross-sectional data up to year 2022, that is, the aggregate data from 2001 to 2022, the application of the accelerated rate formula to detect the neighbourhood effects is on the panel data. Ideally, the accelerated rate is calculated for the year 2022. However, due to its limitations in satisfying the prescribed assumptions, a sample of the last five years is instead assessed in an effort to find the period(s) closest to 2022, unmarred by external factors that might have impacted the solar PV adoption.

In March 2020, the World Health Organization [42] declared COVID-19 a pandemic, ensuing lockdowns around the world, including Australia. Hence, the accelerated rate from 2020 to 2022 cannot be assumed to be purely attributed to neighbourhood effects due to the presumed impacts of the pandemic. Even though 2020 still reflects a positive accelerated rate, this might be due to the carried over effect of the installations in the prior years. Excluding 2020 from the controlled year is a more conservative approach. 2021 and 2022 show deceleration rates (negative acceleration rate) reflecting, perhaps, the effect of the pandemic lockdowns. This leaves 2018 and 2019 as the controlled years to assess the presence of the neighbourhood effects by the accelerated rate. In Table 6, these values are 0.21 and 0.28, respectively. The positive values indicate the presence of neighbourhood effects. In context, a 0.21 accelerated rate translates to an addition of about 15 PV systems installed in 12 months per POA, on average, while the 0.28 rate is about 20 extra units per POA. Fig. 8 shows the monthly impact of the accelerated rates in terms of the average additional units installed per POA.

5. Discussion and policy implications

The salient points of the preceding analysis outcomes are as follows:

- Gender (share of male population), share of population ages 15–24, share of population ages 41–56, share of population 57 years and older, land area, and dwellings with a vehicle do not correlate (i.e., are insignificant) to the PV adoption in the POA.
- Share of married population, unemployment rate, population with non-school qualifications, number of rented residential units, and the number of bedrooms do influence, positively, the PV uptake.
- Share of population ages 25–40, weekly household income, population density, dwellings density, and the number of occupants per dwelling do influence, negatively, the PV uptake.
- The neighbourhood effects increase the PV adoption, on average, by about 15 to 20 units per year per POA based on controlled years 2018

Table 5
Multicollinearity matrix of explanatory variables.

	Male	Gen Z (15–24)	Millennials (25–40)	Gen X (41–56)	Boomers (≥57)	Married	Weekly household income	Unemployment rate	Non-school qualification	Population density	Dwellings density	Land area	Rented	Dwellings with vehicle	Persons per dwelling	Bedrooms
Male	1.000															
Gen Z (15–24)	−0.034	1.000														
Millennials (25–40)	−0.006	0.241	1.000													
Gen X (41–56)	0.133	−0.134	−0.101	1.000												
Boomers (≥57)	−0.004	−0.533	−0.735	−0.304	1.000											
Married	−0.135	−0.184	−0.222	0.142	0.210	1.000										
Weekly household income	−0.241	0.125	0.350	0.206	−0.326	0.341	1.000									
Unemployment rate	−0.046	0.166	0.061	−0.115	−0.041	−0.423	−0.304	1.000								
Non-school qualification	−0.235	0.205	0.373	−0.032	−0.336	−0.169	0.289	0.118	1.000							
Population density	−0.150	0.150	0.473	−0.091	−0.357	−0.287	0.283	0.117	0.440	1.000						
Dwellings density	−0.228	0.167	0.399	−0.021	−0.344	−0.257	0.329	0.115	0.507	0.785	1.000					
Land area	0.081	0.058	0.089	0.002	−0.093	−0.093	−0.050	0.136	−0.055	−0.056	−0.071	1.000				
Rented	−0.197	0.188	0.312	−0.047	−0.278	−0.205	0.138	0.190	0.869	0.206	0.367	−0.004	1.000			
Dwellings with vehicle	−0.064	−0.231	−0.259	0.241	0.278	0.557	0.302	−0.285	−0.117	−0.377	−0.218	−0.158	−0.068	1.000		
Persons per dwelling	−0.170	0.245	0.369	0.188	−0.407	0.236	0.585	0.052	0.302	0.187	0.254	0.144	0.218	0.252	1.000	
Bedrooms	−0.207	−0.038	0.021	0.228	−0.008	0.499	0.626	−0.253	0.175	−0.033	0.040	−0.073	0.095	0.591	0.643	1.000

Source: Authors.

Table 6
Average PV installation quantity, installation rate, and accelerated rate across POA.

Year	Installed quantity, I	Installation rate, R	Accelerated rate, R'
2017	61.29	5.11	
2018	76.72	6.39	0.21
2019	96.97	8.08	0.28
2020	125.30	10.44	0.39
2021	122.78	10.23	−0.03
2022			−0.42

Source: Authors.

and 2019 (closest to the pooled cross-sectional data year 2022 used in the regression model), respectively.

The increased share of population between the ages of 25 and 40 has a negative impact in predicting PV adoption. Age was also one of the determinants in Canada identified by Parkins et al. [29] as having an opposite influence on PV uptake, although their measure was directly based on the individual's age and not on the share of the population grouped by age. In Greece, significant to PV adoption was identified by Sardianou and Genoudi [31] as those belonging in the middle-age. In the study conducted by Sommerfeld et al. [16] in Australia, the likelihood of solar adoption was found to come from people aged 55 years and older. Bashiri and Alizadeh [20] concluded in their study of the PV adoption case in Tehran, Iran that as the individual becomes older, his likelihood of adoption is reduced. This was in contrast to the results garnered by Briguglio and Formosa [22] in Malta, wherein the younger the individual is, the higher the potential for PV uptake. In Finland, the likelihood of adoption is increased between ages 45 and 65, according to the research made by Karjalainen and Ahvenniemi [33].

The marital state is found to be a positive predictor of PV acceptance. This may be attributed to the change in the spending behaviour of married individuals with PV systems perceived to be an economical option to source electricity. The result is inline with the findings uncovered by Davidson et al. [25] for the state of California in the US, and Sommerfeld et al. [16] in Australia, while the analysis made by Sardianou and Genoudi [31] in Greece found this variable to be statistically not a significant factor.

The average weekly household income and the PV adoption act in the opposite direction. With more disposable income in the household, the inclination to install the PV system drops, and vice versa. The lower level of income is no longer a deterrent but rather a motivator in acquiring for the solar energy source because of its perceived economic benefits [22,43]. This could especially be true considering that the cost of the solar technology has substantially decreased by as much as 82% in the last decade [9]. This agrees with the findings of Balta-Ozkan et al. [30] for the study case in the UK. In contrast, the research made by Parkins et al. [29], and Balta-Ozkan et al. [26] yielded income as not a predictor of adoption intent, while Sardianou and Genoudi [31] argued income to have a positive effect.

The effect of the unemployment rate comes as a surprise, as this means that as the unemployment rate goes up, the pick-up of solar technology goes up. The acquisition of the panels entails money, and this resource, intuitively, comes from employment. The shock is somehow alleviated considering that income acts in the opposite direction with adoption too. Moreover, subsidies were also provided by the Australian governments to reduce the initial upfront costs and the feed-in tariffs to reduce the payback period [12]. In a similar principle, Balta-Ozkan et al. [30] claimed that self-employment has a positive effect on adoption. Balta-Ozkan et al. [26] posit that households that utilise more daytime electricity, such as those unemployed, retired, or home-based parents, are more attracted to the cost advantage of using solar energy. The research conducted by Briguglio and Formosa [22], however, proved that unemployment has a negative effect.

The education level (obtaining a non-school qualification) is a positive predictor. This is consistent with the findings of other studies [21,25,26,29,30] while other studies do not find it statistically significant [16]. Education might be helpful in evaluating the costs and benefits of the PV systems [20]. Moreover, environmental awareness is closely knitted with educational attainment, wherein concerns about it could lead to the solar adoption [22].

Population density is showing a negative influence on solar technology uptake. This is in agreement with other studies, such as those

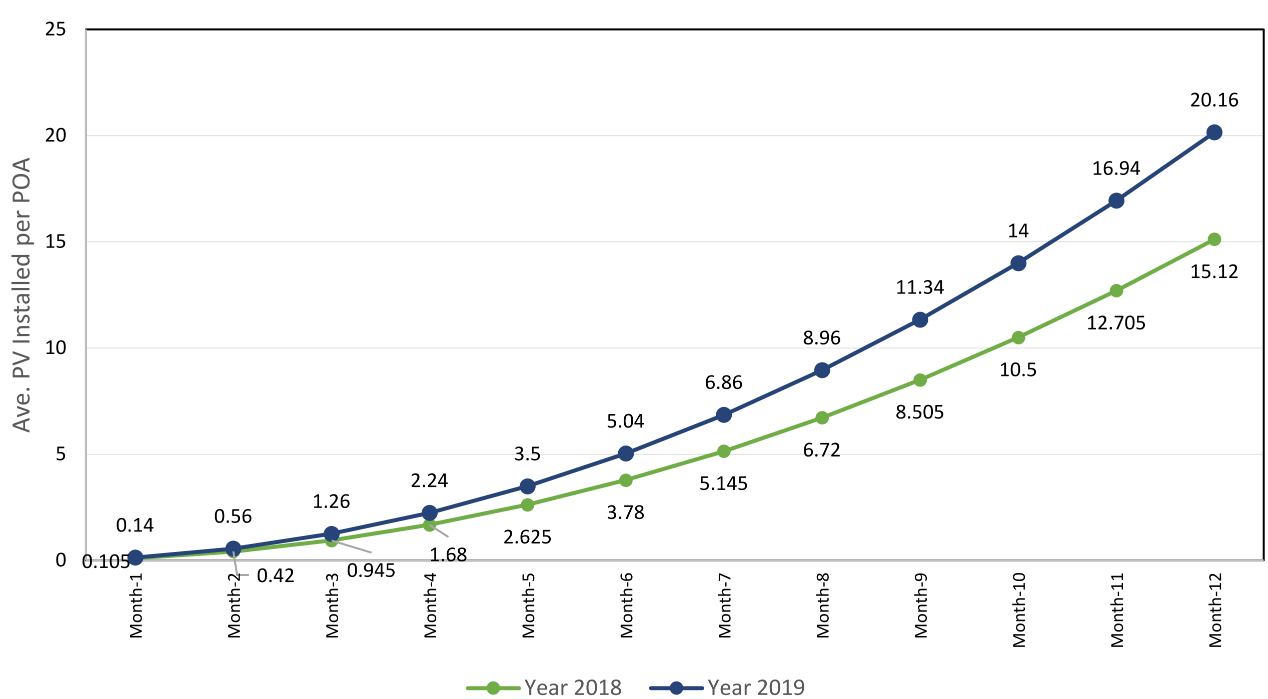

Fig. 8. Accelerated rate in 2018 and 2019.
Source: Authors.

conducted by Balta-Ozkan et al. [26], and Lan et al. [32]. Less densely populated areas are typically characterised by separated houses or dwellings that could be readily installed with PV systems [26]. In contrast, highly urbanised areas are typically situated with building apartments, relatively crowding the area for a denser space, that are mostly not suitable to be installed with the PV technologies. The results of this analysis do make sense from that perspective.

Almost having the same coefficient as the population density is the dwellings density. The result is consistent with some other publications [26] but in disagreement with the study made by Schaffer and Brun [23]. On one hand, lower dwellings density could imply presence of bigger houses whereby the utilisation of solar energy would make sense economically and ergonomically (i.e., roof size). On the other hand, greater dwellings density might mean more homes that can be installed with PV systems. Hence, this variable should be interpreted carefully.

Rented houses show a positive influence on PV uptake. This result, somewhat, comes as a surprise considering that the flexibility and choice of modifying the house, of which the PV installation includes, if it has not yet been fixed with, generally come with the homeowners, not the renters. Moreover, the solar panels could be treated as fixed capital investments enticing more the homeowners [16,22,23]. This could be true in some other countries or on some parts of the world where the PV adoption has yet to pick up, but it might not necessarily apply to Australia, where the PV saturation level has already gone up. The degree of penetration of the PV technology in Australia (30% to 40%) might have already reached the rented homes. Moreover, the 0.62 coefficient means that, holding all other variables constant, there is about a 60% probability that a newly rented house would have a PV system installed (or already have a PV system for dwellings that were previously occupied by owners and then rented out). This figure does not seem to come as an exaggeration though.

The number of house occupants correlates negatively with solar energy adoption. This is consistent with the investigations conducted by Balta-Ozkan et al. [26] and Davidson et al. [25] on UK households and residents of California, respectively. They argued that larger families have less flexibility in cash flows restricting their capability to invest in the PV technology [25], especially for early adopters. For wealthy households, they seemed to care more about the aesthetics of not installing a PV system on their house than for its energy savings [26].

The number of bedrooms follows the same direction with the adoption as what Sommerfeld et al. [16] also discovered. Unbeknown of the economic status of the household, larger homes consume more electricity, thereby attracting more residents to adopt the technology for cost savings [16,25].

The social or neighbourhood effects in relation to PV adoption have already been exposed in a number of studies [24,26,28,29], albeit with varying methods. In the analysis here, the neighbourhood effects translate to an extra 15 to 20 PV installations per year per POA based on controlled years 2018 and 2019, respectively. As much as decisions in adopting are made based on economic sense, decisions borne of emotions do occur [44–46] to the extent that they become integral to organisations in dealing with complex situations [47]. Finland PV adopters enjoy the pleasure of contributing to the environmental cause and disseminating information about the technology, or that "pleasure is the profit" [33]. As much as emotions impact decisions, decisions also affect the emotional state of individuals. This bi-directional effect makes emotional decisions last longer [48]. Individuals act by logic of appropriateness, not by logic of consequences [49]. More dominant to decision-making is the influence of surroundings, and not the perceived assessment of outcomes [49]. These phenomena, emotions, and the influence of surroundings, can best explain the prevalence of neighbourhood effects in technology adoptions, such as solar PV installations.

5.1. Policy implications

Governments in developed countries played a pivotal role in financially jumpstarting the solar energy market. Australia has been successful in its implementation of its renewable energy program that it has taken the lead as the top generator of solar energy. It was able to overcome the barrier imposed by its comfortable use, cheap cost, and abundant reserves of fossil fuel to transition to the technologically challenging use of renewable energy [50]. Aside from the benefit of producing renewable energy, the program may have also affected the behaviour of the Australian households towards efficient electricity usage, such as shifting the load during the peak PV energy generation [27,51].

However, as the program matures, policymakers in Australia, and in other developed countries in general, should consider balancing the monetary and non-monetary incentives of installing the PV systems. For example, not all are driven by the financial benefits of the technology. Others might have other motivations, such as being able to generate their own electricity grid independently or contributing to a greener environment. In this way, the program would be able to widen the spectrum of its demographic reach [51]. Initiatives could be framed targeting households that were identified, for example, as having negative associations with PV adoption.

For sustainable programs to be sustainable, governments should continue to engage, in a meaningful way, with the community, as the public's perception and attitude towards renewable energy programs such as the solar PV may change over time [52]. They should be careful not to break the trust of the community or plant a seed of scepticism towards an energy program by overpromising and underdelivering. Failures, perceived or real, may lead to the public's distrust of the government and resistance to adopting the technological change [53].

Meanwhile, developing countries are faced mainly with financial constraints to even initiate, and more so, support the drive towards renewable energy [54]. Even though funds are pouring from developed to developing countries, rampant corruptions and misuse of these funds by the receiving government could only mean program ineffectiveness and failures. Hence, there are underlying socio-political, cultural, and economic aspects that developing countries may need to address [55] before they can start following the trajectory of rich nations in renewable energy programs. Regardless of the degree of the development of a country, each poses unique geographic and demographic features. The results of the analysis per se presented in this study may probably not resonate in countries other than Australia, but the method is something that others can certainly follow, utilising its own datasets. Moreover, the methodology can be applied to expand future studies tackling the impact of energy battery storage on solar PV adoption [56] or in other fields such as the proliferation of hybrid or electric vehicles [57,58].

Having quality data is tantamount to having robust results. Government and other centralised agencies need to invest enough resources to ensure quality collection and synthesis of data for possible current and future analyses. Academic and non-academic researchers alike can certainly get the benefit of these data for possible policy altering studies by making them available to public such as the one made available with this research (see the Supplementary section for the link to access the dashboard).

Lastly, the formula developed, introduced, and demonstrated here to detect neighbourhood effects can certainly be used for both past and future studies. Neighbourhood effects are not easily ascertained primarily because of their abstract nature. Literatures that we have reviewed present various complex concepts just to arrive at an estimated quantitative figure. This prompted us to simplify the calculation while drawing a parallel idea with a rather more familiar field – kinematics. The formula can be applied not only to the solar PV adoption but also to other “visibly” disruptive technologies.

6. Conclusion and future works

Countries from all over the world are making concerted efforts to mitigate the impact of climate change. Initiatives include the transition towards the use of low-carbon emitting energy from renewable sources, such as the solar PV technology. Spurred by government policies and financial incentives, Australia has made a significant leap in the residential solar PV market since its program inception in 2001, to the extent that it currently stands as the world leader in terms of its capacity to generate solar energy.

This paper analysed the socio-economic factors that might be associated with the solar PV uptake in Australian households. Data tracking solar panel installations per month per postal area (POA) across the country from 2001 to 2022 were pooled for a cross sectional regression analysis against the census data pack from the Australian Bureau of Statistics [34]. The results of the analysis depicted that:

- Gender (share of male population), share of population ages 15–24, share of population ages 41–56, share of population 57 years and older, land area, and dwellings with a vehicle do not correlate (i.e., are insignificant) to the PV adoption in the POA.
- Share of married population, unemployment rate, population with non-school qualifications, number of rented residential units, and the number of bedrooms do influence, positively, the PV uptake.
- Share of population ages 25–40, weekly household income, population density, dwellings density, and the number of occupants per dwelling do influence, negatively, the PV uptake.

Furthermore, the formula developed herewith to detect and quantify the presence of the neighbourhood effects returned results that this phenomenon increased PV adoption by an average of about 15 to 20 units per year per POA in the controlled years 2018 and 2019, respectively. In as much as the neighbourhood effects should have been calculated for the year 2022, the requisite requirement of the “accelerated rate” entailed finding the latest year wherein there were no perceived or real external stimuli that might have impacted the solar PV uptake (i.e., no sudden change in the government policy concerning the solar renewable energy program, social events such as the COVID pandemic). The method used in determining the neighbourhood effects is something that has not been done before to the best knowledge of these authors.

The findings from this paper provide the opportunity for policymakers in Australia to gain fresh insights on the solar PV market in the country with the use of the latest socio-economic data. Behaviour and technology perception by the public change over time, and although Australia has achieved success in its renewable energy program, policies, new and existing, need to be adapted to the present conditions to sustain the sustainability programs.

For other parts of the world, the findings in the context of Australia may not resonate with them, and this should be understandable. Different countries have different social, economic, geographic, and other settings that would certainly affect the outcome of the analysis. The method employed here, including the formula developed to assess the neighbourhood effects, however, is something that others can replicate using their respective country-specific datasets. Moreover, data and findings can be made available and accessible for public information, for instance, and for further scrutiny by scholars, as demonstrated in this study with the dashboard developed with this research (see Supplementary section for the link) benefiting the energy study fields in general.

An apparent limitation of this study is its overreliance on publicly available data. The robustness of the outcome is dependent on the accuracy of the collected data. Certainly, there is nothing wrong with using these data assuming its rightful level of accuracy. This point is made to convey a message to the centralised data collecting agencies the importance of having reliable data for current and future research works. Moreover, the analysis results were highly dependent on the method used. In this study, the method used was regression analysis, which assumed linear relationships between the explanatory and the response variables. This relationship might not necessarily hold true or could be better represented by using a different approach. One such technique is the use of machine learning, which has the distinctive advantages of dealing with non-linear relationships between variables and the interplay between the variables themselves [32,59,60]. Scholars are certainly welcome to explore that avenue, utilising the data dealt with here.

Finally, the techniques explored here are not limited for applications with solar PV adoptions. They can be implemented for research concerning the adoption of other technological breakthroughs, such as the burgeoning of electric vehicles, or solar panels on building facades [61].

Supplementary

The link to the open access dashboard developed in this study: https://app.powerbi.com/view?r=eyJrIjoiZDg2YzJlZjYtOWEzZi00MWUxLWJlYjktMmI2YzYzYmM2NzQ1IiwidCI6IjNkMzM2ODI2LWViOWYtNGUxMC05NWRhLWE2ZGM4ZGIxNjk4YSJ9.

CRediT authorship contribution statement

Paul Marty Jordan Fuentes: Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization, Validation. **Kaveh Khalilpour:** Writing – review & editing, Supervision, Resources, Project administration, Conceptualization. **Alexey Voinov:** Writing – review & editing, Validation.

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.

Appendix A

Table A.1
PV systems installation quantity and rated output capacity in Australia from 2001 to 2022.

Year	SGU* rated output capacity in kW			Large-scale rated output capacity in kW	Rated output capacity in kW total	SGU installation quantity		
	Dwellings (<10 kW)	Business (10 to <100 kW)	Total for the year	(100 kW or more)		Dwellings (<10 kW)	Business (10 to <100 kW)	Total for the year
2001	182.80	0.00	**182.80**	0.00	**182.80**	118	0	**118**
2002	427.08	0.00	**427.08**	0.00	**427.08**	251	0	**251**
2003	952.58	0.00	**952.58**	0.00	**952.58**	664	0	**664**
2004	1,318.02	0.00	**1,318.02**	0.00	**1,318.02**	1,089	0	**1,089**
2005	1,860.99	45.01	**1,906.00**	0.00	**1,906.00**	1,403	3	**1,406**
2006	1,676.59	136.81	**1,813.40**	0.00	**1,813.40**	1,106	9	**1,115**
2007	5,394.07	292.12	**5,686.19**	0.00	**5,686.19**	3,462	18	**3,480**
2008	19,611.50	435.47	**20,046.97**	0.00	**20,046.97**	14,038	26	**14,064**
2009	83,757.08	715.45	**84,472.53**	0.00	**84,472.53**	62,880	36	**62,916**
2010	385,298.39	4,455.24	**389,753.63**	0.00	**389,753.63**	197,951	257	**198,208**
2011	859,399.07	12,856.65	**872,255.72**	0.00	**872,255.72**	360,015	730	**360,745**
2012	1,027,699.29	8,069.64	**1,035,768.93**	0.00	**1,035,768.93**	342,796	524	**343,320**
2013	761,843.18	30,355.37	**792,198.55**	0.00	**792,198.55**	198,457	1,950	**200,407**
2014	738,409.30	61,860.52	**800,269.82**	30,309.50	**830,579.32**	176,281	3,887	**180,139**
2015	619,044.13	86,889.11	**705,933.24**	174,008.90	**879,942.14**	136,163	5,368	**141,490**
2016	626,089.18	121,743.33	**747,832.51**	117,042.90	**864,875.41**	125,359	7,387	**132,677**
2017	912,351.94	206,710.72	**1,119,062.66**	245,159.50	**1,364,222.16**	161,920	13,138	**174,941**
2018	1,288,209.89	329,297.23	**1,617,507.12**	2,482,324.10	**4,099,831.22**	202,677	22,505	**224,850**
2019	1,759,410.15	405,450.01	**2,164,860.16**	2,614,306.70	**4,779,166.86**	256,122	28,245	**283,991**
2020	2,424,350.11	540,237.44	**2,964,587.55**	1,726,014.40	**4,690,601.95**	330,953	39,664	**370,302**
2021	2,487,119.03	704,231.34	**3,191,350.37**	1,841,392.80	**5,032,743.17**	324,301	53,357	**377,408**
2022	1,937,941.00	575,695.78	**2,513,636.78**	1,407,384.70	**3,921,021.48**	244,730	45,587	**290,241**
Total of all time	**15,942,345.37**	**3,089,477.24**	**19,031,822.61**	**10,637,943.50**	**29,669,766.11**	**3,142,736**	**222,691**	**3,363,822**

SGU*: small generating units.
Source: Authors, data from [11].

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