Systematic map of determinants of buildings’ energy demand and CO₂ emissions shows need for decoupling

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Abstract

Buildings are responsible for a major share of global final energy consumption and carbon dioxide (CO₂) emissions. An analysis of the worldwide observed drivers of demand can highlight the policy actions most suited to drive the decarbonization of the building sector. To contribute to such an analysis, we carry out a mapping of the literature on determinants of energy demand and CO₂ emissions from buildings. The work includes a list and classification of relevant studies in an on-line geographical map, a description of trends and gaps, and a narrative review. We identify 4080 articles in the Scopus and the Web of Science databases, of which 712 are relevant after screening at the title and abstract level, and 376 are included for data extraction. The literature base mostly addresses electricity and water use, in North America and Europe (57% of the literature) and Asia (27%). Econometric modeling approaches using panel data to calculate demand elasticities, dominate. These findings highlight gaps in terms of the studied variables (only 5% focus on CO₂ emissions while a mere 1% have a lifecycle perspective), geographical scope (only 5% of the articles focus on Africa, 7% on Latin America and the Caribbean, and 5% on Oceania), and methodological approach (only 5% use qualitative methods). We confirm that worldwide, income, energy price and outdoor temperature are unequivocal drivers of buildings energy demand and CO₂ emissions, followed by other indicators of scale such as population or heated floor area. Our analysis makes it clear that decoupling from rising wealth levels has not been observed. This will continue to challenge reductions in energy use and CO₂ emissions from buildings in line with climate targets. Macroeconomic policies focusing on the impacts of income, energy price, population and growing floor area are needed in combination with technical policy to reduce the impact of outdoor climate.

1. Introduction

Buildings account for 35% of global final energy consumption and almost 38% of total direct and indirect CO₂ emissions (UNEP 2020). Buildings use energy for space heating, hot water, cooking, lighting, and electrical appliances. Whereas part of the consumption is linked to the building itself (e.g. insulation levels, type of fuel use, efficiency of the technical services), the consumption patterns of the occupants are also key (e.g. preferences for indoor temperatures and illumination levels, choice and use of appliances) as is the impact of the local climate. Transforming the building sector in line with ambitious climate targets, requires high energy-renovations rates and deployment of decentralized renewable energy sources, including electrification and demand-side responses (Eom et al 2012, Zhou et al 2014, Wang et al 2018). The implementation of this transformation has to date not been achieved. While rational real estate markets are expected to support the implementation of energy efficiency improvements, and life cycle cost has long been used to communicate the costs and net benefits of investments in energy efficiency (Hutton and Wilkie 1980) decisions on profitable investments have mostly been delayed (Jaffe et al 2004). Significant
techno-economic potentials for energy savings have been reported (Urge-Vorsatz and Novikova 2008), however, these have not been realized to any great degree (Mata et al 2020).

A prerequisite to designing successful decarbonization strategies in the building sector worldwide, is to understand what drives buildings’ energy use and climate impact. However, there is still no comprehensive systematic understanding of such drivers or their comparative weight or the influence of difference contexts.

Even though studies on key determinants have been published extensively in the literature, they are implemented with different methodologies, perspectives and fields of research.

For instance, qualitative research aims to understand how people perceive facts, and in consequence how they act, using interviews to collect perceptions and experiences, participant observation for collecting data on naturally occurring behaviors in their usual contexts and focus groups for eliciting data on the cultural norms of a group. Quantitative methods aim to understand how and why people act in the way they do, applying systematic empirical investigation of observable phenomena and behavior using statistics and mathematics usually assisted by computational techniques. Measurement is central to quantitative research because it provides the fundamental connection between empirical observation and mathematical expression of quantitative relationships.

There have been a number of focused reviews using different approaches from around the world. For example, the human dimension of the energy-related behaviors of key stakeholders that affect energy use over the building life cycle have been reviewed (D’Oca et al 2018). Sociological perspectives investigate energy consumption within its socio-cultural context, for which consumption is a byproduct of everyday practices that are structured by differences in past experience embodied as routines and habits (Shove 2010, Hansen 2016). A sectorial bottom-up modeling approach has calculated for residential buildings of four European countries (with a normalized sensitivity analysis) that the input parameters that most determine total final energy demand are indoor temperature, the properties of the building envelope, the heated floor area, the ventilation flow and the demand for hot water (Mata et al 2014). Similar approaches are compiled by Tian et al (2016). An economic approach tries to understand responsiveness to energy price changes, thereby helping to predict future energy needs and to design pricing and taxation policies, e.g. by combining electricity tariff data from the regulator with expenditure survey data from households and it is found that household income and electricity price are major demand determinants (Ye et al 2018). Similar approaches are compiled by (Fazeli et al 2016, Bissiri et al 2019).

An analysis of CO₂ emissions of buildings in China using the STIRPAT model shows that per capita floor space of residential buildings, floor space of buildings and CO₂ emissions of unit building area have a larger impact on CO₂ emissions than the household consumption level and output value of tertiary industry (Cong et al 2015).

Moreover, significant differences exist across countries in term of commitments, financial potential and market conditions for current regulation and policy instruments, not to mention climate, as summarized for European buildings (Bertoldi and Mosconi 2020) and worldwide (Mata et al 2020).

While existing studies certainly provide valuable insights into buildings energy use and CO₂ emissions, to date they have been limited in scope being implemented with different methodologies and perspectives and focused on different regions. A systematic understanding of the key factors behind buildings’ energy use can serve as a basis to define the policy actions most suited to steer measures for increased demand reductions and decarbonization of the building sector.

In order to compile the state of knowledge on this topic, we conduct a systematic map of the peer-reviewed literature on the subject. The novelty of the work lies, to start with, in the systematic map methodology itself. Second, in the comprehensiveness of the scope, as we include all perspectives and methodologies and world regions. Finally, we synthesize the findings both quantitively and narratively.

2. Aim

The aim of this systematic map is to address the following primary research question:

What is the state of recent evidence on the determinants of buildings’ energy demand and CO₂ emissions?

This paper also addresses the following set of secondary research questions:

(a) What is the state and distribution of the evidence base on determinants of buildings’ energy demand and CO₂ emissions in terms of quantity of articles, methodological approaches, intervention types, outcomes measured, and geographical location?

(b) What are the key determinants of buildings’ energy demand and CO₂ emissions being examined?

(c) What are the major trends and gaps in knowledge?

(d) Although our results aim to be used in the formulation of energy policy that could guide decarbonization of the building sector worldwide, an analysis of policy implications, or effects of policies, is beyond the scope of our paper.
3. Method

We generally follow the methodology guidelines of the Collaboration for Environmental Evidence (CEE) (2018) in conducting systematic evidence mapping as well as the ROSES reporting standards for systematic maps (Haddaway et al. 2018). The one deviation from these guidelines is that we have conducted the search only for scientific literature in two databases, Scopus and Web of Science (WOS) core collection. We include both of these databases because a recent comparative analysis which shows that there is only a 12% overlap between them (Cabeza et al. 2020b). Nevertheless, we are aware that the number of documents that our search string would retrieve from additional databases could be quite different. Furthermore, Konno and Pullin (2020) find that restricting searches to a few, widely used, bibliographic platforms may lead to provision of biased estimates of effect sizes. We take this limitation into account when discussing the distribution and extent of the evidence base and its implications.

We have used the articles contained in Scopus as a pilot study to develop our search query, screening and coding strategy (explained in sections 3.1–3.3), and then applied the developed method to the WOS.

3.1. Search

We review the literature published from 2011 onwards, in order to capture the most recent published findings. For a summary of earlier works, see e.g. Fazeli et al. (2016), Bissiri et al. (2019) and Liang et al. (2019).

We use PICO guidelines to identify keywords for searches. According to James et al. (2016), in environmental sciences, the most common question to answer is ‘what type of impact an intervention or exposure has on the environment’, and generally four key elements must be specified: what is the affected population (P), what is the intervention/exposure (I/E), what is the comparator (C), and what is the outcome (O)? Elements of our primary question were: Population: Buildings sector; Intervention: Determinants; Outcome: Energy demand and CO₂ emissions; the comparator is not relevant in this case.

Our search terms are as follows:

3.1.1. Buildings sector

(‘hou*’ OR ‘building’’ OR ‘resident’’ OR ‘dwelling’’ OR ‘home’’ OR ‘domestic’’ OR ‘tertiary’ OR ‘commercial’ OR ‘hotel’ OR ‘education’’ OR ‘school’’ OR ‘sport’’ OR ‘service’’ OR ‘religio’’ OR ‘facility’) AND (‘building’’ OR ‘facility’ OR ‘sector’’ OR ‘demand’’)

3.1.2. Determinants

(‘determinant’’ OR factor OR driver OR effect OR cause OR reason OR source OR role OR ‘understand’’ OR ‘characteristic’’ OR ‘pattern’’ OR ‘projection’’ OR estimate OR status) AND (‘econometr’’ OR ‘regression’’ OR ‘Kuznets curve’’ OR ‘EKC’ OR review OR ‘elasticity’’ OR ‘decomposition’’)

3.1.3. Energy consumption and CO₂ emissions

(‘energy’’ OR ‘demand’’ OR ‘heating’ OR ‘electricity’ OR consumption OR ‘cooling’ OR ‘emission’’ OR ‘climate’’ OR ‘impact’’ OR ‘CO₂’ OR ‘GHG’ OR ‘environment’’ OR ‘carbon’ OR ‘life cycle’ OR ‘LCA’ OR ‘embodied’)

We have combined the three sets above with the Boolean operator AND, as well as identified keywords that lead to unsuitable documents. The latter, which we have combined with the Boolean operator AND NOT, can be seen in the search string provided as (supplementary material 1 (available online at stacks.iop.org/ERL/16/055011/mmedia)).

The final search has been conducted in the Scopus database, excluding irrelevant fields (agriculture, earth sciences, biochemistry, nursery, physics, chemistry, immunology, health, pharmacy, neurology, veterinary, dentistry, or ‘Undefined’) and resulted in 1851 articles being retrieved. Additionally, a total of 466 documents had already been identified while developing the final search query. A further 2119 articles are identified in the WOS of which 190 are duplicates. We can therefore confirm the literature estimates (Cabeza et al. 2020b) that there is only ~10% overlap between the content of Scopus and WOS in the investigated subject.

3.2. Article screening

The definitive 4080 search results are screened at title and abstract level, following criteria for inclusion and exclusion developed on the basis of the PICO framework described previously. The inclusion criteria are relevant population (building sector), intervention (determinants), and outcome (energy demand or CO₂ emissions). The number of articles excluded and the justification for their being so at each stage are described (figure 1). The articles from Scopus were reviewed using the APSIS tool (MCC 2018) whereas those from WOS were reviewed using the EPPI-reviewer app.

A total of 712 articles were selected for uploading into the EPPI-reviewer app. Of these, 683 full texts could be retrieved (25 documents were not accessible). The full texts have been then screened for relevance against the above-mentioned inclusion criteria.

A total of 332 articles are disregarded after full text screening (table 1). Some papers are disregarded

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4 Although our focus is on CO₂ emissions, in the search string we try to capture all possible wording in the literature. In figures 2–4, however, the more general term ‘carbon emissions’ is used, as the focus of the studies in the literature varies while the amount of papers for each is not significant to deserve a disaggregated visualization. For a recent review of non-CO₂ buildings sector GHG emissions, see (Hu et al. 2020).

5 EPPI-Reviewer 4: systematic review software. [online] https://eppi.ioe.ac.uk/eppireviewer-web/home.
Table 1. Summary of the number of documents \((N)\) disregarded at full text screening, with reasons.

| Reasons for exclusion                        | \(N\) |
|---------------------------------------------|-------|
| No buildings sector                        | 61    |
| No energy or climate                       | 28    |
| No determinants:                           | 72    |
| Access to energy, poverty or equity        | 3     |
| Broad LCA, emissions                       | 34    |
| Demand response or short-term forecast     | 35    |
| Rebound                                     | 13    |
| Consumption                                | 55    |
| Trends                                      | 27    |
| Adoption or uptake of energy saving measures| 45    |
| Study design issues:                       | 25    |
| One building/study case only               | 22    |
| Method not sound or unclear                | 3     |

for mismatching population or outcome, however, the majority of the disregarded papers do not address the same intervention, but focus on adjacent topics. Finally, some documents are disregarded due to study design issues.

A total of 376 documents are selected for data extraction.

3.3. Coding strategy

Four reviewers conducted the coding in EPPI Reviewer. We checked for consistency of coding by coding 10% of full text parallel and discussed in detail any disagreements. We extracted (by screening the full texts) four key categories of data:

- Variables studied: demands for services (space and water heating, cooling, lighting, cooking, appliances), demands for fuels (electricity, gas, propane, district heating, biomass, all fuels, fuel mix, green power) or energy expenditure, or broader environmental assessments (CO\(_2\) and GHG emissions, life-cycle assessment (LCA) and embodied carbon, ecological footprint).

- World regions, following 5 regions and 22 sub-regions\(^6\): Africa and Middle East (Eastern Africa, Middle Africa, Northern Africa, Southern Africa, Western Africa), Asia and developing Pacific (Central Asia, Eastern Asia, South-Eastern Asia, Southern Asia, Western Asia), Eastern Europe (Eastern Europe and West-Central Asia), Latin America and the Caribbean (Caribbean, Central America, South America), and more developed regions (North America: USA and Canada, Greenland and Bermuda + Others; Europe: Northern and Western Europe, Southern and Eastern Europe; Asia-Pacific developed: Australia and New Zealand, Others).

- Methodological approach, distinguishing qualitative (interviews and surveys) or quantitative (simulation, decomposition, statistical methods, econometric modeling, and surveys).

- Key determinants (of the variable studied), grouped in the following categories: household

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\(^6\) Following IPCC classification, with very similar world regions to the M49 Standard or ISO 3166.
characteristics, building characteristics, physical surrounding environment, climate factors, behavioral aspects, technological efficiency, macro-economic factors, energy prices, non-pricing policies. In all three categories of variable, the number of key variables has been selected in an iterative inductive process, by developing a list of all determinants identified in the papers during screening at both abstract and title level, then grouping them in larger categories.

3.4. Mapping and presentation

We provide statistical and narrative descriptions of various characteristics (the filters in our visual map in the supplementary material 2-4), namely: variables studied, geographical scope, methodological approach and key determinants. We also visually present our map by using an evidence mapping software Wizzard. By such visualization we can identify evidence gaps (underrepresented sub-topics that warrant primary studies) and clusters (well-represented sub-topics that indicate a potential for synthesis via full systematic reviews). In the evidence assessment of this review, the visualization serves to quickly direct the readers toward the information they may be looking for.

4. Results

4.1. Literature map

4.1.1. Statistical description

The coding shows the following number of articles (n), in descending order:

Variables studied: electricity demand (n = 162), water use (n = 63), total energy demand (n = 74), fuel demand gas (n = 31), space heating demand (n = 25), cooling demand (n = 10), CO2 emissions (n = 18), space and water heating demand (n = 6), lighting demand (5), cooking demand (n = 5), energy expenditure (n = 5), ecological footprint (n = 1), appliances demand (n = 2), hot water demand (n = 0), fuel demand biomass (n = 4), LCA embodied carbon (n = 4), green power demand (n = 1), fuel demand cooking (n = 1), fuel demand propane (n = 2). In all, 48% of the articles focus on services, 48% focus on fuels, 5% focus on emissions, and 1% use a lifecycle perspective.

World regions: Western Europe (n = 132), Northern America (n = 82), Eastern Asia (n = 92), Oceania (n = 18), Western Asia (n = 12), South America (n = 17), Eastern Europe (n = 7), Southern Asia (n = 14), South-Eastern Asia (n = 16), Central America (n = 7), Eastern Africa (n = 5), Western Africa (n = 5), Northern Africa (n = 4), Southern Africa (n = 5), Caribbean (n = 3), Central Asia (n = 2). In all, 5% of the articles focus on Africa, 27% focus on Asia, 7% focus on Latin America and the Caribbean, 59% focus on more developed regions and 5% focus on Oceania.

Methodological approach: econometric models (n = 323), interviews (n = 20), statistical analysis (n = 32), decomposition analysis (n = 26), simulation models (n = 17), experiments (n = 6). In all, 5% of the literature uses qualitative methods and 99% quantitative methods, percentages that do not add up to 100% as 5% of the articles use both methods.

4.1.2. Clusters and gaps

Figure 2 presents the distribution of variables over different world regions. Much of the literature focuses on the determinants of electricity or water use in Europe or North America. A gap can be identified in terms of variable studied, as there is a lack of studies with focus on CO2 emissions and with a life-cycle perspective. The few studies that investigate these variables will be presented in the narrative review of section 4.2.3. Quite a number of articles (n = 55) were disregarded after full text screening, because they address all consumption categories with limited details about building-related emissions, e.g. Xia et al (2019) contains a recent summary of studies that investigate households consumption.

Whereas the LCA studies disregarded at abstract level were typically optimization methodologies or tools for decision making for one building, at full text level, a number of studies address LCA broadly (n = 34). These include, for instance, comparative LCA analyses for typologies or materials that have a limited relevance when scaled up, as well as structural decompositions with focus on a component (e.g. inequality, urbanization) or where the operational life-cycle phase is disregarded. As it is well known that decarbonization pathways for the buildings sector have to be supported by large scale, sectorial studies with a life-cycle perspective including synergies/trade-offs among sectors as well as lock-in effects (Urge-Vorsatz et al 2014, Cabeza et al 2020a, Mata et al 2020, Urge-Vorsatz et al 2020), we conclude that there is a further need for such studies.

A second gap can be identified in terms of geographical scope: the literature on Africa, Latin America and Caribbean, and Oceania is scarce.

Figure 3 presents the distribution of the literature per variable studied and methodological approach. Overall, linear and non-linear regression analysis are the most common methods and they are used for studying electricity demand (n = 53), water use (n = 24), space heating demand (n = 10) and total

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7 http://eppimapper.digitalsolutionfoundry.co.za/#/

8 The list of references supporting this statement is endless, here only a limited selection of worldwide or very recent reviews is given.
energy demand ($n = 9$). Among those articles a significant share use panel data ($n = 22$). Regression analysis is the most common method applied on Western Europe ($n = 42$), Northern America ($n = 26$) and Eastern Asia ($n = 21$). A third gap can be therefore identified in the lack of qualitative approaches.

As the literature on electricity and water use (the latter is also less relevant for energy and CO$_2$ emissions) is more extensive and recent reviews are available (Labandeira et al 2012, Romero-Jordán et al 2016, Jones et al 2015, Khan et al 2019), these variables will generally be excluded from the narrative review which follows.

### 4.2. Literature review: key determinants

Figure 4 presents the key determinants of buildings energy demand and CO$_2$ emissions, for the different types of variables studied, i.e. services, fuels, environmental impact or energy expenditures\(^9\). Factors studied include macroeconomic factors, household and building characteristics, climate, physical surrounding environment, as well as technological and behavioral factors that will be presented in the subsections below.

Macroeconomic studies cover the structure, behavior and decision-making of an economy as a whole, which could be a region, a country or even the global scale. Microeconomic studies, on the other hand, specifically focus at the behavior of individuals and organizations\(^9\) in making decisions. Thus, microeconomic studies can provide further insights, since...
the level of detail is higher and they often cover the interactions between individuals and organizations to a larger extent. In corresponding subsections below, we will review results from macro and micro studies on determinants for energy demand for all end-uses (sections 4.2.1 and 4.2.2) as well as those for broader environmental assessments, including climate impacts, LCA and ecological footprint (section 4.2.3).

To address the challenge of presenting the data extracted from all 376 papers, we have strategically selected the references among the six topics (the
subsections of section 4.2) and five world regions, trying to give priority to more comprehensive studies. Additionally, we give less attention to the well-researched clusters. The results should be interpreted with a degree of caution, as details on regional variations could be missed (notably for electricity demand which could include HVAC and non-HVAC end uses) and we do not conduct critical appraisal on the specific set of studies covered in the narrative review.

4.2.1. Results from macroeconomic studies
Worldwide, we find that income, energy price and outdoor temperature are unequivocal drivers of buildings energy demand and CO$_2$ emissions, followed by other indicators of scale such as population and conditioned floor area. The latter two, together with income and GDP, are indicators of wealth. Therefore, following the observed trends, increased wealth will inhibit reductions in buildings’ energy use and CO$_2$ emissions. We have only found two cases of decoupling. A decomposition and decoupling approach confirms that CO$_2$ intensity decouples from per capita income for the residential building sector of China and its four megacities between 2000 and 2016, and shows that the inflection point of CO$_2$ emission per floor space has occurred at the level of the nation and three of the megacities (Liang et al 2019). A comparison of space and water heating demand at household level in Germany and in the UK between 1991 and 2015 shows that, upon reaching a certain income threshold, heating demand decreases as income increases in German households whereas demand rises with higher incomes in the UK. Negative income values in Germany suggest that consumption does not rise with disposable incomes, as typically expected, for German households, probably owing to more efficient dwellings in higher income households (Bissiri et al 2019).

The demand for natural gas in the residential sector of 12 European countries from 1978 to 2002 is explained by the lagged consumption term (an econometric modelling proxy for the incumbent heating system), the heating degree days (HDDs) index and the contemporary natural gas price (Brounen et al 2012). A thorough examination of the impact of prices on electricity demand in German households using data from Germany’s Residential Energy Consumption Survey, shows that only those households that are informed about prices are sensitive to price changes, whereas the electricity demand of uninformed households is entirely price-inelastic (Frondel and Kussel 2016, 2019, Frondel et al 2019a). In the residential sector of the Nordic countries, outdoor temperature and interfuel substitution are identified as key factors for projecting fuel demand (Fazeli et al 2016).

In the US, for residential energy efficiency for a panel of 48 states, income, price, population, average household size, and HDDs are significant (Alberini and Filippini 2011, Filippini and Hunt 2012), and using the U.S. Residential Energy Consumption Survey for 2001 and 2005 to estimate household energy demand as a function of a composite energy price, a short-run price elasticity of $-0.6$ and a short-run income elasticity of $0.04$ is found, with poverty-level households having slightly higher price elasticities and lower income elasticities (Ahmed et al 2013).

For Arthur et al (2012) calculated the price and the income elasticities of demand for domestic energy for urban households, and found the following energy ladders (by their desirability and affordability): firewood–charcoal–electricity for urban households and firewood–kerosene–candles for rural households (charcoal and electricity are mostly urban sources in Mozambique, and electricity and kerosene are mutually exclusive). In Nigeria the price of cooking gas has negative significant impact on its demand, and prices of the alternatives to kerosene and cooking gas have positive but insignificant impact on the demand for the respective products (Arawomo 2019). In South Africa, using data from 2010/2011 income, energy prices, and the number of persons per household (and floor space, outdoor temperature, and level of urbanisation), are found to be determinants of household electricity consumption (Ye et al 2018). In Algeria, using an ARDL econometric model with time series data from 1970 to 2013, Bouznit et al (2018) find GDP/capita and energy prices to have been determinants of energy demand. A study of the determinants of household use of clean and renewable energy sources in Ethiopia, Tanzania, and Malawi, using multinomial logit and ordered probit models, finds income and education level and whether dwellings are located in urban or rural areas to be key (Behera and Ali 2017).

In Indonesia the determinants of energy demand (by fuel) are driven predominantly by the triple interaction of demographics, income growth, and change in demand/supply parameters (Chen and Pitt 2017). In Saudi Arabia using an ARDL Bounds Model, urbanization is found to have increased energy demand between 1971 and 2012 (Belloumi and Alshehry 2016).

In China, rising income levels contributed most to households energy usage, improved energy efficiency offset the rising effects of heightened household consumption in most regions, and rural-to-urban migration played an important role in enhancing energy use in all regions from 2002 to 2012 (Zhang and Lahr 2018).

4.2.2. Results from micro data
4.2.2.1. Households characteristics
Refer to the sociodemographic data of the building occupants such as income, age, education level and family composition. There is full agreement in the literature that, together with energy price, household
characteristics are significant influencers of buildings energy use. For instance, structural factors have the largest impact on appliance energy efficiency of 4231 Irish buildings, followed by socio-economic factors and behavioral factors (Kavousian et al 2015); the demand for space and water heating in single-family detached houses in Denmark is influenced by sociocultural differences between households such as income, education, occupation, and immigration status (Hansen 2016); a study of a sample of 1181 Irish households provides evidence that, together with weather, the structural characteristics of the dwellings and the socio-economic characteristics of the households are significant factors in explaining residential gas demand (Harold et al 2015); the choice of household’s energy mix in France is determined by the income and the socio-economic characteristics of households such as the age of the head of the household, socio-professional category or the type of housing (Couture et al 2012); the main drivers of household fuel choice in urban areas of southwest Nigeria are household size, level of education, occupation of the consumer and the price of the energy good (Ajayi 2018); for domestic energy consumption in Kerala, a state in the southern part of India, the data analysis reveals significant influence of socio-economic, demographic, geographic, and family attributes (Sreekanth et al 2011). Although none of the references above examine embodied energy, an analysis of both direct and embodied energy for Swiss households finds that both cases are driven by the same determinants, with no evidence for significant substitution between them, and an increasing effect of income on both, with particularly important effects on embodied energy (Tilov et al 2019). A summary of the evidence on detailed contributions by the various factors follows in subsequent paragraphs of this section.

Generally, income has a direct positive correlation with energy demand and an indirect influence via other variables, as higher-income households tend to have larger homes and lots, live in certain types of buildings and have certain household compositions (Hansen 2016, Singh et al 2017). On average across all the OECD countries, the long run elasticities of price and income are found to be −0.51 and 0.94 respectively, with Ireland being the most elastic (Bernstein and Madlener 2012, MacNaughton et al 2018). Notably, household fuelwood demand in France is found to have a negative link to income, and the highest income households are likely to use wood as a backup source of heating energy or for pleasure (Couture et al 2012).

Varying effects are found for household size, age, and gender. The energy use for heating of 472 multi-family buildings containing 7554 dwellings in Stockholm, is determined by ownership form, proportion of females and proportion of occupants expressing thermal discomfort (Engvall et al 2014). Single-parent and elderly households consume more and gender has no significant effect (Brounen et al 2012, Harold et al 2015). Immigrant households in Danish detached houses consume less energy for space and water heating than Danish families (Hansen 2016). For domestic energy consumption in the southern Indian state of Kerala, per capita income level is identified as the most important explanatory variable; among the higher income group the models demonstrate the influence of per capita land area, and residential area, while among the lower income groups, average age and literacy form significant variables (Sreekanth et al 2011). Household size and age of the household has a positive significant impact on the demand for kerosene and cooking gas in Ondo State in Nigeria (Arawomo 2019). All this would suggest that families in a later stage of the family life cycle have higher electricity demand than do younger families suggesting that the development of an aged society may increase electricity consumption (Huang 2015) as also described in previous section. At the same time, among all individual housing units in the city of Amsterdam, the Netherlands, larger households with children consume more gas (Rafiee et al 2019). This effect is however not linear as, larger families show economies-of-scale in that consumption per capita diminishes proportionally to the number of occupants (Andr and Carvalho 2014, Ouyang et al 2014a).

In South Korea, using interviews and multiple linear regression, Lee et al (2019) find that persons per household and their age to be determinants of energy demand (in addition to outdoor temperature, sunshine incidence, and floor area). In Indonesia, using interviews and multiple linear regression, Akil et al (2018), find the education level and age of household occupants (and consumer behavior) to be among determinants of the level of efficiency of refrigerators used; Mustapa et al (2017) find the occupancy of University buildings to be determinants of electricity use (and the outdoor temperature).

The results on patterns of occupation are therefore mixed. In all, families with kids who have full-time employment and are highly educated are more efficient compared to families with no kids, or families with retirees or unemployed members (Kavousian et al 2015). The consumption for space and water heating in single-family detached houses in Denmark, households with lower occupational status is lower than for households with higher statuses (Hansen 2016). The same argument could explain why households with unemployed persons also consume less, although the default explanation is that the unemployed spend more time at home and thereby consume more.

Mixed results are found for the impact of education levels. Some literature finds that households with higher educational levels are consuming more electricity and gas for heating and cooking (Huang
2015, Hidalgo et al 2018, Arawomo 2019), whereas it is also found that households with higher education levels are on average 1.3% more efficient than their peers (Kavousian et al 2015). A possible explanation here is the trade-off between efficiency and affluence: although high-income households tend to use more efficient water-using appliances and are likely to be more educated and therefore more environmentally sensitive, their higher living standards require more energy (Makki et al 2013).

Some behavioral factors have been found to have significant impact on use of appliances, e.g. households that track their energy savings are on average 0.4% more efficient than others, and households that expressed interest in making major energy-saving lifestyle changes scored higher efficiency ranks on average (Kavousian et al 2015). In Malaysia, Jalalkamali and Abbas (2014) find that behavioral practises relating to lighting, cooling and appliance use to be a determinant of Residential sector electricity demand. In Kuwait, using a survey and regression analysis Jaffar et al (2018) find that occupant driven cooling behavior i.e. air-conditioning thermostat temperature set points, are the major driver of electricity use, followed by the number of rooms and the number of occupants.

Heating expenditure tends to be higher for home owners than for renters (Meier et al 2013, Harold et al 2015). Owner-occupied households tend to have more efficient electrical appliances but also consume more electricity than renter-occupied households (Huang 2015, Kavousian et al 2015). In the U.S. Public housing residents use about 10% less energy than non-residents (Ahmed et al 2013).

The literature on non-residential buildings is more scarce. Surmann and Hirsch (2016) find considerably increased energy consumption of single-tenant compared to multi-tenant office buildings. Molinos-Senante et al (2016) decompose the energy performances of 34 office buildings in Santiago, Chile, into two indices: the management energy efficiency index (explained by type of renter and market classification) and the architectural energy efficiency index (see section 4.2.2.2). Using multiple linear regression, Ntsaluba and Malatji (2018) find the number of persons staying in South African University residences to determine energy use (along with outdoor temperature). In Korea, for the period 1970–2011, long term price and income elasticities for the service sector are −1 and 1 respectively (Lim et al 2014).

4.2.2.2. Characteristics of the building and its technological systems

Building typology, construction year and dwellings’ floor area (or other variables that measure physical size, e.g. number of bedrooms, or lot size) are positively correlated to energy demand. In Australia, for space heating and cooling energy requirements of representative dwelling types, airtightness, window-to-wall ratio, window types, as well as insulation levels of ceiling, wall and floor are identified as having high influence coefficients (Aghdæi et al 2017). Households with efficient lightbulbs and double-glazed windows were on average 4% and 3.5% more efficient than others; furthermore, installing heater timers, wall insulation, and living in owned residences were correlated with higher efficiency (Kavousian et al 2015). From 567 UK dwellings with 118 000 d of gas and electricity data, energy use for heating was significantly related to the building age, type of building and ventilation, length of time since the last heating adjustment; power temperature gradient10 was predicted by dwelling characteristics such as number of bedrooms and floors, dwelling type and age (Summerfield et al 2015). With a data sample of 206 occupied facilities owned and operated by public-sector institutions located in Germany, Lashhof and Stoy (2016) identify seven significant predictor variables on heating energy cost (type of facility, share of defective heat supply systems, number of floors, floor size, type of heating energy source, share of heated gross floor area and share of defective building envelope) and five predictor variables on electricity cost indicators (type of facility, share of ventilated and air-conditioned area, floor size, number of elevator stops and share of defective electrical installations).

For various Chinese building types and using a variety of analytical methods, floor area is found to be a determinant of energy demand (Khanna et al 2016, Shen et al 2017, Ding et al 2018).

In the city of Tianjin, China, gross floor area, heating energy source and canteen had a close relationship with the total primary energy consumption of 270 schools (Xing et al 2015). In Santiago, Chile, (Molinos-Senante et al 2016) assess the energy performance of 34 office buildings, and decompose overall energy efficiency into three indices: the architectural energy efficiency index (the sum of the surface areas of all facades), the total floor area of the building and the shape factor of the building.

Multi-family apartments have the lowest daily maximum electricity consumption in the winter, followed by town houses and detached houses (Kavousian et al 2013). Engvall et al (2014) found, for 472 multi-family buildings with 7554 dwellings in Stockholm, that energy use for heating was significantly related to the building age, type of building and ventilation and length of time since the last heating adjustment. Very large office buildings consume significantly more energy per square meter that their smaller peers (Surmann and Hirsch 2016).

For all typologies and end-uses, vintage has a negative correlation, as recently built buildings must comply with increasingly strict standards (Brounen

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et al 2012, Kavousian et al 2013, 2015, Harold et al 2015). Using data from the 2012 Australian Household Energy Consumption Survey and regression, Cao et al (2015) find dwelling typology and age to be determinants of energy demand (in addition to income, price and outdoor temperature). Only for the case of electricity consumption is no significant correlation observed with building age (Kavousian et al 2013). Gas consumption of all individual housing units in the city of Amsterdam, the Netherlands, is determined by size and age of the housing: older houses have a higher energy consumption, but a rebound effect was found for the newest dwellings (Rafiee et al 2019). However, the older buildings may have been extensively retrofitted. That is the case for 288 office buildings in Europe from 2008 to 2012, of which buildings of higher age turn out to be of lower energy consumption, as lower additional energy consumption was found for buildings with more recent extensive refurbishment, compared to those with refurbishment several years ago (Surmann and Hirsch 2016).

4.2.2.3. Climate factors
Are highly determinant of energy demand. Outdoor temperature, sunshine hours and rainfall are all significant.

Oil, gas and electricity use decrease with rising temperatures due to a reduced demand for energy for heating purposes, but the speed of that decrease declines with rising temperature levels (for an unbalanced panel of 62 countries over three decades) (Tol et al 2012). Although the same study finds no significant impact of temperature on the demand for cooling energy globally, greater impacts are observed for cooling-dominated locations. For instance, daily and monthly HVAC runtime fractions increase with both increasing or decreasing temperature in Texas, USA (Cetin and Novoselac 2015). CDD have the highest statistical significance in the demand for air conditioning home appliances in the USA (Rapson 2014) and temperature clearly correlates to average daily electrical cooling load for the entire city of Abu Dhabi (Ali et al 2011). An analysis of the daily gas consumption from Ireland’s Smart Metering Gas Consumer Behavioral Trial using panel data suggests that sunshine hours have a negative effect on residential gas demand, whereas cloud cover has the opposite effect (Harold et al 2015).

For 31 OECD and non-OECD countries, using an error correction model of residential energy demand from 1978 to 2000, De Cian et al (2013) show the impact of outdoor temperature. For Norway, a regression analysis of daily measurements of total electricity consumption of 45 households during a year in combination with information of daylight and measured temperatures at the same time and location, shows that the seasonal difference in daylight is reflected in the seasonal variation in electricity use, and a correlation between daylight and out-door temperature (Rosenberg 2014); for offices and schools, the most important explanatory variables for electricity consumption were identified to be outdoor temperature, daylight dummies, day dummies and monthly dummies, dummies being an econometric modelling proxy for time related effects (Lindberg et al 2019).

In Malaysia, using a regression model, Aris et al (2015) find outdoor temperature, room occupancy and number of working days to be the most significant determinants of electricity demand for some Government buildings. In Iran, using a panel data model of household energy demand from 2002 to 2008, Barkhordar and Saboohi (2014) find outdoor temperature to be a driver of useful energy demand.

4.2.2.4. Urbanization and physical surrounding environment
The physical environment is studied in terms of density, capacity, and spatial effects. Urbanization is implicit in the building and urban typologies, with single family houses and rural areas generally being less compact than apartment buildings and urban areas. Urban households consume more electricity than rural households (Feng et al 2011, Miah et al 2011, Chun-sheng et al 2012, Huang 2015), as urban residents usually have a relatively affluent lifestyle (Niu et al 2012). A regression analysis explaining the yearly gas consumption of all individual housing units in the city of Amsterdam, the Netherlands, finds that denser neighborhoods with less open space, as well as buildings with higher numbers of housing units and less exposed perimeters have lower heating demand, and that trees limit gas consumption for heating in Amsterdam when they are located on the colder northwest side of building units (Rafiee et al 2019).

Density is also studied in terms of building-related indicators such as the ratio of surface to volume (SV), ratio of perimeter to area (PA), or window to wall ratio (WWR), as well as context-related indicators such as orientation of building (O), ratio of obstruction height to canyon width (HCW) or horizontal obstruction angle (HOA), external painting reflectivity percentage (REF%), area of shadow cast on building surfaces. HOA, REF% and WWR are the most influential variables on the building performance of residential buildings in the hot-desert hybrid settlements of Egypt (Ayoub 2019). SV, PA, O, HCW are significant for energy consumption of buildings in Seoul. Furthermore, SV was proved as better indicator that could describe heating and cooling load while PA is found to be more appropriate for lighting load (Oh and Kim 2019).

Using Spatial Regression Models on monthly data for energy consumption for the year 2010 from the City of Chicago, Li et al (2019) confirm that urban
forms e.g. porosity and geomorphometry affect residential electricity usage intensity, and that proximity to large water body (Lake Michigan) impacts on summer electricity usage intensity. Li et al (2018) use a multi linear regression model on a data set of 534 dwellings across several neighborhoods in Ningbo, China in 2015, and find that for electricity consumption during summer months, neighborhood density has a positive association for tower and slab apartments and a negative association with single-family houses. Using a variety of analytical approaches, no less than eight works find the level of urbanization to be a key determinant of energy demand in China (Feng et al 2012, Ding et al 2016, Jiang 2016, Khanna et al 2016, Ma et al 2017a, Li et al 2018, Lin and Chen 2018, Wang et al 2019).

4.2.3. Determinants of environmental impact

Studies that address buildings’ climate impact include CO\textsubscript{2} emissions from operational energy use, carbon footprint, PM\textsubscript{2.5} concentrations and embodied carbon. The literature focuses on China, including national and regional analyses, and covers residential and commercial buildings using mostly econometric modeling. In this vein and using a variety of empirical and decomposition methods, eight additional works analyze the determinants of CO\textsubscript{2} emissions from buildings in China (Feng et al 2012, Cong et al 2015, Lin and Liu 2015, Liu et al 2015, Chen et al 2016, Jiang 2016, Ma et al 2017a, 2017b, Wang et al 2019) and find income, floor space, education, outdoor temperature, dwelling typology, fuel intensity, persons per household, urbanization to be key.

Using the STIRPAT model to identify the socioeconomic determinants of PM\textsubscript{2.5} concentrations for 12 different regions, across China from 1999 to 2011, (Luo et al 2018) find the influencing factors can be ranked in descending order of importance as: proportion of secondary sector of the economy, GDP per capita, urbanization, population, energy intensity, and proportion of tertiary sector. Although no results are shown for the building sector, accelerating urbanization is identified as the most important CO\textsubscript{2} emission reduction measure in Northeast China and Northwest China. An analysis of the carbon abatement values in China’s commercial buildings indicates that mainly three types of drivers (i.e. floor space demand per unit of GDP in Service Industry, population density in commercial building sector, and comprehensive emission factor of commercial building sector) contributed negatively to the carbon intensity of commercial buildings from 2000 to 2015 (Ma et al 2018). Similar results are found in an analysis of ecological footprint of historical patterns in the three main consumption clusters (housing, food and mobility) in Latvia, demonstrates that the growth effect and the increasing infrastructure (construction boom, increased hot water demand and number of electric appliances) are the main drivers behind increasing efficiency in the housing sector and offset efficiency improvements (Brizga 2012). However, changes in the energy mix—households switching from fossil fuels to biomass—and milder winters have contributed to a decline in the housing ecological footprint.

The only analysis of embodied carbon found identifies, using a regression analysis of historical data of office buildings in the UK from four different data sources, wall to floor ratio and the number of base-ments as predictors of embodied carbon (Victoria and Perera 2018). In addition, the need for standardizing embodied carbon measurements and to develop embodied carbon benchmarks to facilitate embodied carbon estimating throughout the project lifecycle are emphasized.

5. Conclusions

We perform a mapping of the literature on determinants for energy demand and CO\textsubscript{2} emissions from buildings. The map, available online, includes a list and classification of relevant studies, a description of gaps, and a narrative review. We identify 4080 articles from Scopus and WOS, of which 712 are relevant after screening at abstract level, and 387 documents are, after screening at full text level, selected for data extraction and narrative synthesis. Although there are limitations to mapping the state of evidence based on just two Scientific publications databases—given the broad scope of the questions around building demand studies—we are confident that this map gives a comprehensive overview of the relative distribution of research effort across various spaces within the sector. Thus, while the insights gleaned in this work could have been broader had some studies from other databases not been missed, they are still reliable for providing an exploratory picture of where likely evidence gaps exist.

The literature has an overwhelming focus on demand for electricity and water, with a major focus on North America and Europe. Econometric models applying regression on panel data, usually to analyze demand elasticities, dominate the literature across regions. Factors studied include household and building characteristics, climate, physical surrounding environment, as well as technological, behavioral and macroeconomic factors.

We identify gaps in terms of studies with a lifecycle perspective, in terms of geographical scope (Africa, Latin America and Caribbean, and Oceania) and of method (qualitative).

Worldwide, income, energy price and outdoor temperature are found to be the unequivocal drivers of buildings energy demand and CO\textsubscript{2} emissions, followed by other indicators of scale such as population or heated floor area. Increased wealth can therefore damper climate mitigation from buildings. Although a policy focused analysis is beyond the scope of the
paper, our analysis makes it clear that to reduce CO₂ emissions from buildings requires macroeconomic policies focusing on the impacts of income, energy price, population and growing floor area in combination with technical policy to ameliorate the impact of outdoor temperature on buildings’ energy demand and thus bring about the necessary decoupling.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

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