Modelling energy-efficient renovation adoption and diffusion process for households: A review and a way forward

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ABSTRACT

The residential sector is one of the major sources of energy consumption, with a high energy conservation potential. Energy consumption reduction could be achieved through Energy-Efficient Renovation (EER). This paper presents a systematic review of EER adoption influences and EER diffusion modelling. The review starts with an overview of EER adoption drivers, barriers, and policies, then introduces the adoption influences, including socio-demographics, housing factors, social influences, and environmental attitudes. The significances of these influences vary across different studies, and studies focussing on influences cannot provide insights on the number of resources and efforts needed to overcome the barriers. EER modelling of adoption decision-making and energy efficiency diffusion was introduced, focusing on Agent-Based Modelling (ABM). The most investigated technology diffusion is Photo-Voltaic (PV) panels. Most ABM models were developed based on behaviour theories. These models are used for evaluating policy effectiveness. Most policies analyses amongst the reviewed papers are limited, neglecting the influences of housing situations and building codes and standards. Besides, few models are developed based on real-world data. It is concluded that agent-based models in EER are needed to include a broad range of technologies or incorporate existing empirical EER studies or empirical adoption data for reliable simulation results.

1. Introduction

Building-related carbon emissions have increased significantly since 2010. In 2019, CO₂ emission from buildings was 10 Gt (Gigatons), accounting for about 28% of the total CO₂ emission (IEA, 2020b). The carbon emission reached an all-time high in 2019. Meanwhile, it is predicted that global energy demand for buildings could increase up to threefold from 2010 to 2100 (Levesque et al., 2018). There is significant potential in the building sector for energy consumption and carbon emission reduction. It is suggested that housing technical properties, such as the type of heating technology, are the main determinant of energy use intensity (Risch & Salmon, 2017). Another study describes that retrofits and technical improvement could explain about 50% of the heating energy consumption reduction (Galvin & Sunikka-Blank, 2014). In the meantime, energy-efficient technologies contribute to the sustainable development of society (IEA, 2019a), improving living comfort (IEA, 2019b), and bringing health benefits (Long, Young, Webber, Gouldson & Harwatt, 2015).

However, there has been a slowdown in energy efficiency adoption (IEA, 2019a). The diffusion of energy-efficient technology falls behind expectations in the building sector (Byrka, Jedrzejewski, Szajd-Weron & Weron, 2016). IEA (2020a) found that the building energy intensity has decreased continuously by about only 1% per year in the EU and North America since 2010, and building energy intensity increased in China between 2010 and 2019 due to economic growth. There is found to be a gap between the techno-economic potential of energy-efficient renovation and actual market behaviour (Camarasa, Nägeli, Ostermeyer, Klippel & Botzler, 2019).

Numerous policies were launched to encourage the adoption of building energy efficiency. These policies can be categorized into regulatory measures, financial and fiscal incentives, information campaigns, and market-based instruments (Economidou et al., 2020). According to IEA (2020b), energy-efficient policy coverage had a growth rate of 2–3% in recent years. Note that the increase in policy coverage does not necessarily indicate policy stringency. One example is the lack of updated lighting policies, which fail to phase out inefficient lighting in many countries (IEA, 2020b). Hence, energy efficiency policy evaluation attracts increasing attention to find answers to policy inefficacies.
There are several characteristics affecting the efficiency of policies for diffusion of EER. Study of these characteristics can be traced back to the innovation diffusion theory by Rogers (1962), in which the diffusion of the innovation is studied from a macro-level. More recent studies analyse diffusion by assessing the uptake of the EER at the household-level considering the heterogeneity amongst households. Several studies aim to identify factors affecting the adoption of EER. For example, Schleich (2019) found that detached house owners are more likely to adopt energy-efficient retrofits in EU countries. Achtihnicht and Madlener (2014) studied technology features affecting the adoption of EER, while Trotta (2018) focused on socio-demographics, dwelling, and attitudes. Some of these characteristics can also act as barriers to the adoption process.

Factors affecting EER adoption has been extensively utilized to simulate the energy efficiency policies. Agent-based modelling is one of the bottom-up modelling methods used for diffusion simulations. It could address the heterogeneous nature of households (Moglia, Cook & McGregor, 2017). For example, Huang et al. (2019) used agent-based modelling (ABM) to simulate the upscaling process of energy-efficient technology amongst different households. Literature in this field studied the impact of policy interventions. Different policies are introduced, such as subsidies, tax reductions, and product bans (Chappin & Afman, 2013).

Several review papers helped construct the general framework of households’ decision-making process, energy-efficient renovation policies, and agent-based policy evaluation. These reviews contribute to summarizing energy efficiency policies (Economidou et al., 2020), exploring the advantages of agent-based modelling (Moglia et al., 2017), and connecting energy efficiency policies and adoption barriers (Hesselink & Chappin, 2019). This review focuses on connecting and comparing papers in two research fields: the adoption decision-making process and policy evaluation using agent-based modelling.

This study reviews the current literature concerning EER, including the EER adoption decision-making process and agent-based modelling policy analysis. Research methods and results for households’ energy efficiency adoption behaviour and energy efficiency policy analysis are discussed and evaluated. This study aims to find the connections and the gaps between the EER adoption and EER policy evaluation as two distinct study areas and discuss their application and limitations to identify possible research opportunities. The main contribution of this study is providing suggestions for ABM application in EER diffusion studies.

This study is structured as follows. Section 2 describes the process and criteria for literature selection. Section 3 gives a general introduction of the motivators and barriers for energy efficiency adoption. Section 4 and Section 5 introduce the research status quo. Section 6 and Section 7 discuss the applications and limitations of the selected literature. Finally, research opportunities and suggestions based on the discussions are presented.

2. Method

A systematic literature review is conducted to analyse studies concerning the EER adoption decision-making process and agent-based EER diffusion modelling. In the following paragraphs steps included in review process have been presented. The definition of EER in this study is presented firstly. Household EER is the adoption of housing-related energy-efficient technologies, renewable energy technologies, and insulation-improving retrofits. More specifically, energy-efficient technologies and renewable energy technologies include energy-efficient heating, boiler, appliances, and PV panels. Insulation improving retrofit is considered here as the process of increasing roof, wall, and floor insulation levels. On the contrary, energy-saving behaviour (such as setting lower heating temperatures) and electric vehicle usage are not in the scope of household EER for this research.

This literature review includes the EER adoption decision-making process and agent-based EER policy evaluation. Accordingly, the literature search includes two parts. The search was done on the 30th September 2020, using the advanced search option of the Scopus Scientific Library. The search queries used is shown as follows:

- ("energy efficiency" OR "energy-efficient" OR "energy technology" OR "energy-saving") AND ("renovation" OR "retrofit" OR "renovate") AND ("housing" OR "household" OR "residential" OR "domestic") AND ("adoption" OR "diffusion")
- ("agent-based modelling" OR "agent-based modelling" OR "agent-based model") AND ("household" OR "residential" OR "consumer" OR "domestic") AND ("energy") AND ("adoption" OR "diffusion") OR ("renovation" OR "renovate" OR "retrofit")

Besides the shown queries, there were three more search limitations for both queries: language was limited to English, articles and conference papers were the only types of documents considered, and papers with publication year before 2010 were excluded. The queries were designed to allow for broader searches, the shown queries are the final version after the corrections. The search of the first and the second queries led to 75 and 90 studies, respectively. After the search, titles and abstracts of the papers were scanned and handpicked to check their relevance. Literature evaluating building physical performance or different retrofit strategies was excluded from the first query results. The second query results excluded papers that do not involve agent-based modelling, residential building, and EER technology. The selection process produced the final paper selections of 23 and 33 papers without overlap between the two study fields. Afterward, a thorough review of the selected paper was conducted.

3. Overview of adoption drivers and barriers and policies

3.1. Adoption drivers and barriers

There are numerous drivers presented in the literature which improve the adoptability of EER. The drivers include housing comfort improvements, energy-saving and cost-saving on energy bills, reducing environmental impact, protecting the environment, needing renovation, and increasing housing value (Achtihnicht & Madlener, 2014; Ebrahimigharebaghi, Qian, Meijer & Visscher, 2019; Long et al., 2015; Mlecnik, 2010). Lowering energy bills and increasing housing comfort are two of the most frequently mentioned drivers for EER adoption. However, only a small proportion of households in the market adopted EER due to the lower energy bill (Petittor, Wilson & Chryssochoidis, 2015), and as Mlecnik (2010) suggests, a lower energy bill might be linked to an increase in property value rather than EER adoption. Pelenur (2018) found the financial benefits and environmental awareness are major drivers for EER adoption while saving money or environmental awareness alone is not enough to spur housing EER adoption.

Compared with the drivers, barriers attract more attention when researchers aim to find solutions for accelerating the diffusion of EER. The energy efficiency adoption barriers can be assigned to different categories. (Ebrahimigharebaghi et al., 2019) categorized barriers into two groups: intrinsic and extrinsic. Intrinsic barriers exist within the households, such as preferences. In contrast, extrinsic barriers are regulations, policies, and the costs of EER, which are determined outside the household’s environment. Hesselink and Chappin (2019) and Long et al. (2015) categorised the barriers into four groups: structural, economic, behavioural, and social barriers. Structural barriers are outside the sphere of households, including a lack of incentives, codes, and standards. Economics refers to households’ limited capital access. Behavioural barriers include other priorities and do-not-want-disruption, while social barriers originate from households’ social peers and mass media.

After reviewing the literature, a need for a more comprehensive and understandable categorizing of barriers was found. In this categorization...
scheme, four types of barriers are identified: limited access, attitudinal and behavioural barriers, dwelling factors, and institutional barriers. Limited access is caused by limited resources, including both financial and informational. Financial barriers are presented in different ways, such as expensive costs (Kuhe & Bisu, 2019; Pelenur & Cruickshank, 2012; Qiu, Colson & Grebitus, 2014), do-not-want-more-debt (Priest, Greenhalgh, Neil & Young, 2015), and lack of financial saving (Broers, Vasseur, Kemp, Abujidi & Vroonac, 2019). One of the information access barriers is the difficulty of finding reliable information and professionals (Ebrahimigharebaghi et al., 2019; Ebrahimigharebaghi, Qian, Meijer & Visscher, 2020; Priest et al., 2015). Limited information can also be described as uncertainty about the energy-saving or payback period (Achtnicht & Madlener, 2014; Qiu et al., 2014). The second barrier category is attitudinal or behavioural barriers. Households with apathy about energy consumption or low interest in technology are not likely to adopt EER. They also might view the adoption of EER as an inconvenience or a disruption, and they believe that their house does not need EER (Broers et al., 2019; Long et al., 2015; Pelenur, 2018). Physical dwelling barriers include institutional and technical restrictions in the house (Broers et al., 2019; Long et al., 2015; Pelenur & Cruickshank, 2012). Institutional barriers are caused by governments and energy companies, such as governments providing little or no incentives or having an unsuitable policy target (Ebrahimigharebaghi et al., 2019). A barrier caused by energy companies is the lack of willingness to promote energy efficiency (Pelenur & Cruickshank, 2012). Given the diversity and complexity of these barriers, it is challenging to accurately identify the decision-making process, let alone design and issue policies that successfully tackle these barriers. Examples of both successful and unsuccessful policies are elaborated in the following section.

3.2. Policies

The study conducted by Economidou et al. (2020) suggests that a single policy measure cannot achieve an immense transformation of EER adoption. Governments also often use various measures for promoting EER in practice. These policies could be classified into four categories: financial and fiscal, information and training, codes and standard, and market-based instruments. Policy types and technical examples are given in Table 1 (based on MURE (Mesures d’Utilisation Rationnelle de l’Energie) 2020 and Economidou et al., 2020).

Some of the measures are proven to have significant positive impacts on EER undertakings. For example, Slovenia’s Eco Fund subsidy programme successfully promoted EER adoption between 2012 and 2014 (Dolišak, Hrovat & Zorić, 2020). This policy covered the construction of building insulation, window replacement, and energy-efficient technologies. It was first introduced in 2009 and was ineffective before 2012 as few households were encouraged to adopt an EER by the policy. The study suggests that the effectiveness difference in two time periods is because of the time needed for the policy to be widely known and the time necessary for planning EER. In contrast, two studies focusing on evaluating the Green Deal in Britain present surprising results (Pettifor et al., 2015; Pettifor & Chryssochoidis, 2018) are developed based on Rogers’s five-stage innovation decision-making process. A similar decision-making process model is presented in Ebrahimigharebaghi et al. (2019), and further developed in Ebrahimigharebaghi et al. (2020). A decision-making model adapted from the aforementioned papers is developed and shown in Fig. 1.

Stage 0, ‘not considering’, represents that households do not enter the EER decision-making process. These households may not know about EER or do not have EER adoption intentions. The ‘getting interested’ stage (stage 1) means that households are aware of EER and consider the EER as an alternative. Next, in the ‘gaining knowledge’ stage (stage 2), households learn knowledge about EER, such as information about options, costs, and functioning, which is often provided by professionals (Ebrahimigharebaghi et al., 2020). In this stage, inadequate knowledge and information have negative influences on households’ EER adoption. In contrast, a tailored face-to-face EER audit can help overcome this barrier (Broers et al., 2019). The next stage is planning (stage 3). Households need to get detailed information, find professionals and get permission in some cases (Ebrahimigharebaghi et al., 2020; Pettifor et al., 2015). In this stage, limited finance and high EER costs can play a negative role. After the planning stage, households decide whether they will adopt EER in the decision stage (stage 4). In stages 2, 3, and 4, gaining information and finding professionals are two major transaction costs and hinder the adoption of EER. After the decision, households can implement and experience the EER. This stage is not included in the decision-making process; however, it is a part of the EER adoption process. During the implementing stage, architects’ and contractors’ difficulty in adopting EER can cause negative attitudes of households toward EER. Households would not recommend the uncomfortable experience to others which can affect the diffusion of EER (Mięcik, 2010).

4.2. Adoption influences

It can be summarized from studies focusing on EER decision-making process that adoption drivers and barriers are often linked with households’ characteristics, dwellings situations, and social environments. For example, a low-income household may be encouraged to adopt EER for lowering energy bills, while a negative attitude towards energy efficiency can hinder the adoption. These characteristics and situations are viewed as influences of EER adoption. Households that are more open toward EER can be identified through studying these influences. Suggestions regarding possible policy options and their target household groups can be provided. Investigating and comparing adopters and non-adopters is commonly used for studying influences. Choice experiments reveal different households’ preferences in EER adoption (Achtnicht & Madlener, 2014; Rouvinen & Matero, 2013). These influences can be

| Policy types | Measures |
|--------------|----------|
| Financial & Fiscal | Subsidies, grants, free energy audits, tax deduction, low and zero-interest loan, retrofit pilot scheme, structural funds |
| Information & training | Information campaigns, information centers, smart metering and billing |
| Codes & standards | Energy labelling, mandatory standards and regulations, building codes, minimum thermal standard |
| Market-based instruments | Trading scheme, covenant energy savings rent sector, white goods exchange |

Table 1: Policy types and examples.
divided into four categories: socio-demographics, housing factors, social influences, and environmental attitudes, which are presented in the following paragraphs.

4.2.1. Socio-demographic influences

Table 2 demonstrates significant socio-demographic influences in selected studies and how these influences affect the adoption of EER. Table 2 also demonstrates similar results found amongst different studies, especially for those frequently analysed influences such as age and income.

Studies find that socio-demographic influences, including income, age, household size, and education, are not significantly different between adopting and non-adopting households (Pelenur & Cruickshank, 2014; Pettifor et al., 2015). Moreover, in Hamilton et al. (2016), the influence of neighbourhood rurality is not significant, opposite to Qiu et al. (2014).

There are also diverging results concerning the impact of influences. One of the most obvious examples is the influence of income. As described in Table 2, most studies suggest that higher-income households are more likely to have the financial ability to conduct EER. However, Gamtessa (2013) and Hamilton et al. (2016) found that high-income households are less likely to undertake EER. Studies suggested that a possible reason is that energy expenditure accounts for a smaller proportion amongst these households, and they may not care much about the energy bill and do not have the motivation to decrease the energy bill through EER. Pelenur and Cruickshank (2012) suggest no significant connection between income and EER adoption.

Two studies in Britain show contradictory results as Hamilton et al. (2016) suggest less EER adoption in high-income households while Trotta (2018) indicates the opposite. In Germany, Achtlicht and Madlener (2014) suggests that low-income households are much more likely to adopt EER, while Schleich, Gassmann, Meissner and Faure (2019) does not find income as an influence with major impact. Studies from the same country at different times suggested different results. Possible reasons can be the change of peoples’ attitudes toward energy efficiency and the influence of policies.

4.2.2. Housing factors

The influence of house type and building age is similar across studies despite the time and country differences. Flats (Trotta, 2018), row-houses (Gamtessa, 2013) are significantly less likely to adopt EER, and semi-detached or detached houses are significantly more likely to adopt EER in most countries (Schleich, 2019). For example, households in detached dwellings are 1.8 times more likely to adopt EER compared with households in apartments in the Netherlands (Ebrahimigharehbaghi et al., 2020). The suggested reason for this phenomenon is that flats or apartments usually have more restrictions than semi-detached or detached dwellings. The influence of building age is universal amongst the reviewed papers. Households living in the old buildings are more likely to adopt EER than their counterparts in newer buildings (Achtlicht & Madlener, 2014; Dolsak et al., 2020; Ebrahimigharehbaghi et al., 2019; Hamilton et al., 2016; Pettifor et al., 2015; Schleich, 2019).

It is suggested that most homeowners will consider renovation or replacement when the building component is approaching the end of its functional life (Achtlicht & Madlener, 2014). The suggested reason is that building standards regarding energy efficiency become stricter over time, and the newer housings are usually equipped with energy-efficient technologies and good insulation. Hence, they are less likely to have the necessity of any form of renovation in general.

Dolsak et al. (2020) suggest that in Slovenia, households with higher electricity costs are more likely to adopt EER, Gamtesa (2013) suggests that in Canada home size affects EER adoption; they found that a larger floor area implies a higher likelihood of EER adoption. It was also discovered that households with individual electricity meters are more likely to adopt EER (Schleich et al., 2019). According to Hamilton et al. (2016), the owners of 3-bedroom detached dwellings are more likely to have energy-efficient measures than others. Gamtesa (2013) suggests that the number of floors and building shape can significantly impact households’ EER adoption decision, as multi-floor homes and homes with more than six corners appear less likely to be retrofitted in Canada. Reasons for dwelling layouts’ influence on EER adoption are not discussed in these papers. The existence of past retrofit activity has a significant negative influence on EER adoption (Dolsak et al., 2020). A suggested explanation is that households do not need another retrofit or may not have enough funds after a recent EER. A low level of comfort and the humidity problem of the housing are significant drivers for EER.

| Table 2 | Socio-demographics and its influence on EER adoption. |
|---------|------------------------------------------------------|
| Socio-demographic influences | Literature proved its significance | Detailed result description |
| Age | Ebrahimigharehbaghi et al. (2019), Qiu et al. (2014), Schleich (2019) and Trotta (2018) | Elderly households are more likely to adopt energy-efficient retrofit measures |
| Education | Ebrahimigharehbaghi et al. (2020) | Households with higher professional education are more likely to adopt EER |
| Marital status | Trotta (2018) | Married households are more likely to adopt EER |
| Household size | Gamtessa (2013) | Larger households have a lower likelihood of adopting EER |
| Income/financial status | Dolsak et al. (2020), Ebrahimigharehbaghi et al., 2020, Schleich (2019), and Trotta (2018) | Households with higher income are more likely to invest in EER |
| Years of residence | Qiu et al. (2014) | The longer the year of residence in the house, the more likely to adopt EER |
| Likely to move | Ebrahimigharehbaghi et al. (2020) and Schleich et al. (2019) | Possibility of moving decrease the probability of adopting EER |
| Housing location | Qiu et al. (2014) | Urban and suburban households are less likely to conduct EER |
| | Dolsak et al. (2020) and Hamilton et al. (2016) | Households in different government regions of the country have different possibilities for EER investment |
| Ownership of the house | Hamilton et al. (2016) and Schleich et al. (2019) | Tenants are less likely to adopt EER |
| Employment | Long et al. (2015) | Unemployed people are more likely to adopt EER for increasing housing comfort and housing value |

Fig. 1. EER adoption decision-making process.
an opportunity for EER adoption (Achtnicht & Madlener, 2014). Examples of these opportunities are the necessity of replacing the heating system and building envelope renovation. A study in Portugal concludes that EER usually stems from renovation necessity (Abreu, Oliveira & Lopes, 2019).

4.2.3. Social influences

According to Bale, McCullen, Foxon, Rucklidge and Gale (2013), social influences for EER adoption diffusion range from online to face-to-face interactions amongst households. Social influences on households’ adoption can be described as ‘peer effects’. One example is that peer effects positively impact households’ PV adoption after introducing the Solar Community Organizations in the US (Noll, Dawes & Rai, 2014). This effect is common in residential PV diffusion due to PV panels’ visibility (Mundaca & Samahita, 2020). Social networks are essential for spreading EER information, and as described in Rogers (1962), innovation diffusion is a communication process. Favourable attitudes from family or friends can encourage EER adoption (Schleich et al., 2019), while negative experiences of EER adoption in their social network can be a barrier, according to Broers et al. (2019). The difficulty of modelling real-world social networks regarding EER makes it impossible to predict actual diffusion. However, it is possible to get insights into the social influences such as diffusions in different social network scenarios and interventions’ effectiveness (Bale et al., 2013).

4.2.4. Environmental attitudes

Higher environmental awareness is associated with a higher EER adoption rate (Schleich, 2019). Occasionally, environmental awareness is specified as climate knowledge, which is a crucial influence according to Achtnicht and Madlener (2014). However, another study suggests no apparent correlation between pro-environmental attitude and EER adoption amongst British households (Trotta, 2018). EER adopters always have positive energy and environmental attitudes. However, as described previously, positive environmental values and intentions do not always lead to actual EER adoption behaviour. This phenomenon is described as the “knowledge-action gap” and “value-action gap” (Pelennur, 2018).

4.2.5. Other factors

Besides the four major categories of influences shown previously, other influences are also investigated. The first kind is the homeowners’ risk preferences, loss aversion, and time preferences (present bias). Studies suggest that risk-averse, loss-averse households and households with a lower time discount are less likely to adopt EER (Qiu et al., 2014; Schleich et al., 2019). The results of these two studies are similar to Heutel (2019), which investigated the presence of Prospect Theory in the context of energy efficiency. Results demonstrate that households asymmetrically weigh their losses and gains when facing energy efficiency uncertainties. These influences are considered underlying factors of implicit discount rates for households, which are the key parameters in model-based policy evaluations in Schleich, Gasmann, Faure and Meissner (2016). Households’ pro-environment behaviour of volunteering with a conservation group strongly connects with the consumption of energy-efficient appliances (Trotta, 2018). Features of the renovations, such as cost, payback period, and the guarantee period, also play important roles in the adoption decision-making processes, according to Achtnicht and Madlener (2014). Two types of costs for EER, capital investment and operating cost, both have significant impacts on EER adoption according to choice experiment results (Rouvinen & Matero, 2013).

Governments often play crucial roles since they can intervene in the adoption and diffusion. The intervention can directly or indirectly influence households’ adoptions. Some policies have little impact, while others are more effective, as described in Section 3.2. The presence of policy measures such as energy audit and financial support positively influences EER adoption, and some adopters even identified ‘free of charge’ as one of the primary drivers of EER adoption (Dolsak et al., 2020; Gamtessa, 2013; Long et al., 2015).

4.2.6. Analysis methods

Most of the papers adopted statistical analysis for analysing the influences except for (Bale et al., 2013) and (Kuhle & Bisu, 2019). Logit and probit models are the most common methods for the empirical analysis amongst the decision-making paper selection. They are applied to estimate the magnitude of the influences (Ebrahimigharebaghi et al., 2020; Gamtessa, 2013; Hamilton et al., 2016; Pelenur & Cruickshank, 2012; Schleich, 2019; Schleich et al., 2019; Trotta, 2018; Wilson et al., 2018). The discrete choice experiment is used for analysing the influences of technology features on adoption decisions (Achtnicht & Madlener, 2014; Rouvinen & Matero, 2013). Other options for investigating the influences and analysing the EER adoption include linear regression analysis (Dolsak et al., 2020), factor analysis (Priest et al., 2015), and chi-square test (Long et al., 2015; Pelenur & Cruickshank, 2012). There are some differences amongst these methods. For example, logit and probit models are regression analysis, while factor analysis searches for unobserved latent variables. Nevertheless, these differences do not affect analysing the significance of influences.

Overall, it is also found that research results show both similarities and differences, and the adoption of energy efficiency is not determined by a single factor but influenced by various factors. Most differences are shown in the socio-demographic influences, which do not influence the EER adoption directly. For example, the reason for a higher EER adoption rate of the elderly is that they spend more time in the house than the younger people and will benefit more from EER. The links between the socio-demographics and underlying drivers or barriers largely depend on contextual factors such as culture, general awareness of the environmental impacts in the society, and policies. Influences of factors including housing situation and attitudes show more consistency than socio-demographics. The similarities are also presented in a general way that EER adopters are always those who are motivated to adopt a renovation and who have the resources and access.

5. Energy efficiency diffusion agent-based models

Agent-Based Models (ABMs) can be used for exploring the patterns of groups by simulating individuals’ decision-making processes and interactions (Goldstone & Janssen, 2005). In contrast, equation-based diffusion modelling has limitations, including incapability of modelling high-level aggregation of heterogeneous preferences, describing communication and interaction, and simulating the variety and complexity of the decision-making process. These limitations can be addressed by ABM (Moglia et al., 2017). ABMs are widely used to model the diffusion process of energy-efficient technology for scenario analysis and diffusion prediction (Hesselin & Chappin, 2019; Zhang, Vorobyechik, Letchford & Lakkaraju, 2014). Agent-based diffusion models share four basic components: heterogeneous agents, network structure, interpersonal communications, and adoption decision rules (Zhang, Lu & Chen, 2018). The Overview, Design concepts, and Details (ODD) protocol is widely adopted when describing the ABM (Haryadi, Ali Imron, Indrawan & Triani, 2019; Mittal, Krejci & Dorneich, 2019; Moglia, Podkalicka & McGregor, 2018) as it helps to standardize the description by providing the structure and dynamics of the model in a logical and readable manner (Grimm et al., 2020). Most of the papers focus on scenario analysis. Only a few aim to find a better model configuration (Iachini, Borghesi, & Milano, 2015) or feature EER adoption success prediction (Robinson & Rai, 2015). Besides, it is common that only one specific type of product, such as PV panel, is studied when using ABM.

ABM is a bottom-up modelling method. Hence, the EER diffusion modelling process always starts with determining the agents’ features and decision-making rules. Other necessary procedures include defining the interaction rules amongst agents and introducing intervention
measures. Introducing these basics into the model is the initialization, which is the foundation of agents’ autonomy. These basics are described respectively in the following sub-sections. After that, this section introduces the most common methods and theories used for policy analysis in the EER field.

5.1. Decision theory and decision influences

It is common to have several modules or sub-models when developing the adoption behavioural component in ABMs. For example, Nunez-Jimenez, Knoeri, Hopmann & Hoffmann (2020) adopted three modules in the model, including policy adjustment, adoption decision-making, and technology learning. These models often include components such as attitude, financial ability, and social influence. The utility function is often used to quantify and describe non-numeric components such as attitude. However, the theoretical backgrounds and methods of structuring and elaborating these models vary.

The Theory of Planned Behaviour (TPB) framework (Ajzen, 1991) is widely used for formulating behavioural decision-making models. Behaviour depends on intentions and perceived behavioural control, which refers to individuals’ motivations and abilities separately in TPB. Attitudes, subjective norms, and perceived behavioural control are accounted for in predicting actions (Ajzen, 1991). These factors can be categorized into the attitude and control components (Rai & Robinson, 2015; Robinson & Rai, 2015). Schiera, Minuto, Bottacciol, Borchelli and Lanzini (2019) and Caprioli, Bottero and De Angelis (2020) adapted TPB and added a new component of actual control for describing PV adoption behaviour. (Caprioli et al., 2020; Hesselink & Chappin, 2019) suggest that TPB is frequently adopted because of its flexibility, easy application, and usefulness for studying innovation diffusion. Roger’s (1962) Innovation Diffusion Theory was also adopted for calculating the probability for energy-efficient technology adoption (Mohandes, Sanfilippo & Fakhri, 2018, 2019).

The Consumat theory (Jager, 2000) is a theoretical basis for grouping agents, and each group has a different decision strategy. This theory is applied in two studies (Moglia et al., 2018; Sopha, KLÖCKNER & HERTWICH, 2011) and proposes four decision strategies based on peoples’ level of need satisfaction (LNS) and Uncertainty (U), as shown in Table 3. Repetition decision strategy refers to consumers repeating previous behaviours. Individuals of deliberation type will update relative information, evaluate all possible alternatives, and optimise the choice. Imitation behaviour relates to social learning theory. It refers to choosing the most popular product in their neighbourhood or social network. The social comparison is a mixed decision strategy. Consumers might adopt other people’s behaviour or repeat previous behaviours, depending on which choice can satisfy higher needs.

Several studies introduced different ways of categorizing agents’ decision strategies. Sachs, Meng, Girola and Hawkes (2019) described five investment strategies for different agent groups, including focusing on the immediate expense, net present value, reducing energy consumption, reducing CO2 emission, and comfort. Households’ decision strategy can be single-objective or multi-objective. A similar method of identifying six types of agents was present in lighting technology adoption (Flicks & Theirs, 2014).

Attitude is one of the major influences in the adoption decision framework. Peoples’ attitudes continually change and evolve, influenced by information received from counterparts or society. Relative Agreement (RA) is often adopted to simulate the dynamic attitude or opinion formation process (Caprioli et al., 2020; Rai & Robinson, 2015; Robinson & Rai, 2015; Schiera et al., 2019). According to RA rules, each agent is characterized by its opinion and a degree of uncertainty to the opinion. The evolution of the opinion and its uncertainty are consequences of individuals’ interactions (Defuant, Neau, Amblard & Weisbuch, 2001). Most of the attitude components are based on assumptions. In these models, influences such as education level, income, households’ location, energy consumption, and roof area do not directly impact the decision. They cause differences in attitudes, abilities, and aims for agents, working as thresholds or deciding their strategies.

5.2. Social networks

Social influences are included in almost every energy-efficient technology diffusion study using ABMs. The social influence can be described as the subjective norm (in TPB), the peer pressure (Huang et al., 2019), or the neighbourhood effect (Mohandes et al., 2018). The social influence originates from physical social interaction or online interaction (Boumaiza, Abbar, Mohandes & Sanfilippo, 2018; Huang, Dorneich, Kreji & Passe, 2017). The physical social influence can be divided into three different levels. The micro-level influence is the imitation of connected friends; meso-level and macro-level influences originate from social comparison with a group of friends and at the community level, respectively (Moglia et al., 2018). The influence also comes from a more general level, such as advertisements (Zhao, Mazhari, Son & Cellik, 2011). The component of studying social influence in ABM is the social network, which contains three elements: the structure, the density, and the weight of the links on the network (Bale et al., 2013).

The two most adopted network topologies in the paper selection are the small-world network and the scale-free network. The small-world network was adopted by Cao, Choi and Zhao (2017); Caprioli et al. (2020); Huang et al. (2017); Mittal et al. (2019); Rai and Robinson (2015); Robinson and Rai (2015); Schiera et al. (2019), and Sopha et al. (2011). The scale-free network was adopted by Boumaiza et al. (2018), Guo and Yin (2013), Hagheveis, Askin and Armbruster (2016), Huang et al. (2017, 2019), Kiravu, Oladiran and Yanev (2014), and Wang, Zhang, Li and Li (2018). The small-world network is between the regular network and the random network. It is generated from a regular network, and then a degree of the disorder increases randomness (Schiera et al., 2019). The scale-free network starts with the random network, and preferential attachments are incorporated (Huang et al., 2019). Communications on the internet are often regarded as a scale-free network (Wang et al., 2018).

The diffusions of EER in different networks are compared and evaluated. Moglia et al. (2018) compared the diffusion of energy efficiency in four different network topologies, small-world, random, scale-free, and spatially based network, and the results indicate that the difference is relatively small. However, Sopha et al. (2011) found that the diffusion of heating systems in the small-world network is faster than in spatial proximity and the random networks. Huang et al. (2017) introduced a small-world network as the network topology for the physical social network and a scale-free network for the online social network. Iachini, Borghesi, & Milano, (2015) developed an extended version of the rank-based model for modelling social networks. Some studies adopted more arbitrary methods to generate social networks by assigning several fixed connections (Pearce & Slade, 2018) or grouping agents into agent sets (Mittal & Kreji, 2017). All these methods are acceptable as long as social network modelling aims at scenario analysis instead of diffusion prediction (Bale et al., 2015; Wang et al., 2018).

5.3. Evaluated interventions

Scenario simulations in the reviewed papers have different focuses. These scenarios include different technology features (Guo, Zhang,
Dong, Shen & Yin, 2014), social influences (Huang et al., 2019; Khansari & Hewitt, 2020), and policy scenarios. This section elaborates on the policy scenarios of these papers. The most discussed policies are financial incentives and soft interventions.

One of the most simulated policy scenarios is the subsidy, which is a type of financial incentives. There are two types of subsidies. The first type is dedicated to purchasing the technology or the product (Hicks, Theis & Zeliner, 2015; Moglia et al., 2018), typical for energy-saving technologies. The second type provides subsidies for energy-generating technologies such as PV (Wang et al., 2018). Faber, Valente and Janssen (2010) focus explicitly on comparing the effectiveness of subsidy policies targeting purchase and usage and suggests subsidy scheme for usage can achieve a fast market penetration. Some subsidies are social network-based, providing purchase discounts to residents if at least one adopter is in their network (Caprioli et al., 2020; Moglia et al., 2018). The second kind of subsidy works similarly to Feed-in Tariffs (FIT), one of the most common renewable energy incentives. Households that installed renewable energy technology can receive a subsidy or payback tariff based on renewable energy production (Snape, Boait & Rylatt, 2016). RHI (Renewable Heat Incentive) is a typical tariff-based policy adopted in the UK. RHI was used for promoting heat pumps and new installations were lower than expected (Snape, Boait & Rylatt, 2015). Its performance is compared with the FIT scheme, another similar policy in the UK, to find reasons for the former’s failure while success for the latter. The tariff can be provided to electricity generated (GT) or electricity exported (ET) to the grid. These two kinds of tariffs are compared by Pearce and Slade (2018). In some scenarios, subsidies and electricity tariffs are applied simultaneously, and the subsidy is an extra incentive for adopting renewable energy technology (Mohandes et al., 2018). Financial policies also include the investment tax credit, allowing renewable energy technology adopters to deduct part of the capital cost from tax. This policy ultimately reduces investment in renewable energy. A proper combination of FIT and investment tax credit can cost fewer government funds for achieving the same development target (Zhao et al., 2011). The carbon tax is also a financial measure. It increases the cost of electricity from conventional fuel, thus lowering renewable energy costs (Mohandes et al., 2018). Free insurance that covers the damage cost of renewable technology has been shown to be effective (at least by Wang et al., 2018).

Soft interventions such as information or energy-saving campaigns often involve the provision of information, education, and training. These aim to influence households’ attitudes and perceptions (Sopha et al., 2011). Cao et al. (2017) suggest that energy-saving campaigns cause the fade out of incandescent. Wang et al. (2018) suggest that information campaigns can achieve the same results as subsidies in specific conditions. The influences of information campaigns depend on the main topic of the campaign. The information campaigns on environmental issues did not efficiently boost PV panels’ adoption, while increasing technology awareness is suitable for the same purpose (Caprioli et al., 2020). Information screening is also efficient and promotes households’ PV uptake by preventing the diffusion of harmful rumours (Wang et al., 2018).

Regulations and market-based policies were less investigated policies. The incandescent lamp ban is simulated in light technology and can cause a sharp change (Cao et al., 2017). Energy efficiency leasing allows households to use energy-efficient products and renewable energy generation products without purchasing (US Department of Energy, n.d.). It is considered one of the promising options for reducing capital investment. However, this type of intervention is only included in one research (Zhang et al., 2014) amongst the selected papers, and its effectiveness is not evaluated.

6. Discussion

In this paper, the EER adoption Decision-Making (DM) process and usage of ABMs for energy-efficient technology diffusion were discussed. Some DM papers focus on identifying adoption influences in different decision stages (Broers et al., 2019); others examine the significance of different influences. Socio-demographic factors, housing factors, social influences, and environmental attitudes are the four types of most studied influences.

Both similarities and differences are found in studies regarding the significance of these influences, which implies that there is common decision logic behind the adoption while situations in specific contexts are different. After the analyses, most studies provided policy implications based on the evaluation results of influences. The policies are proposed to either tackle the barriers or encourage the drivers. However, no quantitative guide for formulating policy can be attained. For example, if the high cost of EER is a major barrier, then maybe financial incentives can be used for this situation. But there is no implication about how much subsidy or tax reduction is needed. Overall, these analyses results can provide information about which problem should be solved. However, implications about needed efforts and resources cannot be obtained.

Most literature focused on DM considers EER as a technology package amongst these papers, the EER often does not refer to a specific technology but a wider range of renovations adopted by households to achieve energy efficiency. In contrast, most reviewed agent-based modelling papers have a narrower scope. They tend to focus on one type of product, such as PV panels or lighting products. In the selected papers, the adoption of PV and solar thermal systems received the most attention. 21 papers cover solar energy generation technology, three focus on lighting technologies and two on heating technology. Only three papers analyse the adoption and diffusion of housing renovation, including more than just a single technology (Huang et al., 2017, 2019; Khansari & Hewitt, 2020). One of the possible reasons for the popularity of PV adoption simulation is the data availability. Six of the PV adoption agent-based models used real-world adoption data in the US (Rai & Robinson, 2015; Robinson & Rai, 2015; Zhang et al., 2014), UK (Pearce & Slade, 2018; Snape et al., 2016), and Italy (Caprioli et al., 2020), which does not appear in papers studying lighting and housing renovation. Real-world data is not essential for developing ABMs. However, they can be used to improve the precision of the model through validation. Another possible reason can be the observability of PV panels. According to Rogers (1995), visibility can stimulate communications about the technology and accelerate diffusion. PV panels are highly observable compared to the improvement of insulation or the adoption of energy appliances, making them more suitable for studying spatial cluster effect and social influences for technology diffusion.

Comparing the influences covered by DM studies and ABM studies, there are several universally crucial impacts, including attitudes, social influences, and perceived information. However, there are also obvious differences between these two research fields. The first difference is that most of the ABM papers only focus on solar energy. The models developed in these papers do not need to cover some of the influences for EER. For example, renovation necessity and building situations are critical when households decide the renovation adoption, but they may not influence the installation of PV panels. These influences are not covered even by ABM papers focusing on general housing renovation. Besides, policy scenarios such as smart metering and building codes and standards are not covered because most ABM papers are single technology-oriented and focus on solar energy or lighting.

The second difference is that in DM papers, socio-demographic factors (besides economic situation) are directly connected with adoption behaviour. In contrast, in the ABM paper selection, these factors are basic inputs of the household agent and do not directly influence the adoption decision. In this case, the models are acceptable when studying the diffusion trend or general policies. The applicability of this type of model is limited when the diffusion situations of different age groups are compared or when simulating policies targets specific groups of households or buildings.

The third difference is that all DM papers studied the adoption...
decision based on real-world data, whether from a database or survey. In contrast, only six of the ABM papers used real-world data to validate the model. When the model is developed based on behaviour theories and no real-world data are used, the model’s accuracy cannot be guaranteed. The reason is that these behaviour theories may not be suitable. The example in UK confirms the doubt about the applicability of behaviour theories in EER adoption (Pettifor et al., 2015). The Green Deal policy in the UK was designed to address the behavioural barriers based on TPB. However, research suggests no obvious increase in EER adoption after the Green Deal was launched (Pettifor et al., 2015). This case does not imply that the theory is wrong. The dependability of the theory was tested since it was proposed in 1991, and it is agreed in research that the theory describes the logic for making EER decisions. However, it suggests that the real-world situation is complicated, and adjustments may be needed to apply the behaviour theories in specific situations. The agent-based models will be more convincing if they are supported by real-world data, whether the data is used for model development or calibration.

Overall, the DM and ABM papers meet their objectives. However, there are limitations for both categories of papers. The DM papers provide information regarding the area in which efforts are needed to encourage EER adoption. However, they failed to explain what is the most effective way and how much effort is required. The ABM papers focus on policy evaluation; however, they have a limited technology scope, and the reliability of the simulation results is not confirmed in most cases. Most data used for ABM calibration are from government projects, government databases, or data from utility companies. The data in empirical studies are rarely used for developing ABM, even though they contain information about real-world EER adoption behaviour. Currently, the two fields are not connected according to our findings. The research absence between the two categories of papers is implied after the paper search procedure, as there is no overlap between the two groups of papers. Even though the two categories of papers can overcome the limitations of each other, this has not been achieved in most cases.

7. Conclusions

This paper reviewed studies regarding the decision-making process of energy efficiency adoption and energy efficiency diffusion simulation using ABM. The decision-making process for EER adoption was presented. The decision process is composed of three stages, getting interested, gaining knowledge, and planning. The major influences of the EER adoption were identified: socio-demographics factors, housing factors, social influences, and environmental attitudes. These influences have different impacts on the adoption decision, dependent on the context of the studies. Agent-based models for simulating energy efficiency diffusion are described and compared. These models include possible different impacts of the influence on the adoption and effort. It is suggested to incorporate empirical data in the model according to the analysis result of this study. Reasons for this suggestion include possible different impacts of the influence on the adoption and the applicability of behaviour theories in a specific context. Besides, the simulation results can only explain the diffusion differences amongst scenarios but not diffusion possibilities in reality, especially when unrealistic assumptions were made. Hence, there is a need for developing or calibrating ABMs based on substantial real-world data, allowing for realistic and reliable simulations. Such a model can be used for not only reliable policy scenario analysis but also future predictions. Another suggestion is that policymakers must consider the time factor of implementing a policy. Information about the policy requires time to be conveyed to households, and planning for EER adoption is a time-consuming process considering the abundance of resources needed. Overall, a longer period is necessary for the policies to be broadly known and take effect. The diffusion of the policy information also needs to be considered in ABMs for more realistic simulations.

Declaration of Competing Interest

We have no conflicts of interest to disclose.

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