Modelling Photovoltaic System Adoption for Households: A Systematic Literature Review

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Modelling Photovoltaic System Adoption for Households: A Systematic Literature Review

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Abstract: Despite the decrease in the cost of photovoltaic (PV) systems, its transition processes have encountered various challenges due to the low adoption rate. Therefore, as policymakers worldwide attempt to speed up the PV system's uptake, it is necessary to understand the decision-making process in the household sector. This study aims to review the modeling approach and factors influencing the PV adoption decision-making. A Systematic Literature Review (SLR) was conducted using the Preferred Reporting Items used for Systematic Reviews and Meta-Analyzes (PRISMA) framework. The results showed that Equation-Based Modeling (EBM) is the most widely used approach. However, the Agent-Based Modelling (ABM) recently received more attention because it captures household heterogeneity, detail adoption decision-making processes, and the interactions among the decision makers, which overcome the limitations of the EBM. Furthermore, the financial aspects and social interactions have been much discussed in the PV adoption modeling. However, environmental awareness and support from local solar companies need to be incorporated in the PV adoption modeling for better understanding, thereby obtaining effective interventions to support the PV system's uptake.

Keywords: Agent-Based Modelling; Equation-Based Modelling; photovoltaic system; influential factors, household heterogeneity

1. Introduction

Energy supply is paramount for the survival of any country, and it is currently dependent on conventional energy generated from burning fossil fuel resources, such as coal, oil, and gas[1]. Several issues, including increased demand, natural resource depletion, and climate change problems, led to the transition from low-carbon to a sustainable energy source. It is important to consider energy security in order to overcome issues that tend to affect economic growth, environmental conservation, and resource depletion[2]. Therefore, it is essential to build a society independent of fossil fuels to have a stable economic and social environment[3].

The building sector is responsible for a third of greenhouse gas emissions[4]. Therefore, its reduction is realized through energy-efficient designs[5][6] and the use of renewable energy sources[7]. Photovoltaic (PV) systems are one of the promising options that enhance renewable energy sources' deployment in the building sector. The development of its technology has resulted in a cheaper PV system, which is attractively installed in households. In addition, a rooftop PV System does not only enable households to consume energy from the grid, but also allows these households to generate it and thus are known as prosumers[8]. The presence of prosumer has been proven to be a solution for sustainable energy[9,10].

However, the uptake of the PV through an adoption process is strongly influenced by the acceptance of its technology at the household level[11]. These households as decision-makers consider various aspects during the adoption process and play a unique role in the transition to renewable energy[12]. Therefore, during the implementation of effective policies, it is important to understand solar PV systems' adoption mechanism by evaluating consumers' heterogeneity and their social-environmental interactions[13]. Furthermore, there is a need to understand the decision-making process and the associated influential attributes of households in order to explore potential policy interventions to facilitate the uptake of PV systems[13].

Therefore, this study aims to review the modeling approach used for PV adoption decision-making and identify the influential factors underlying the PV adoption. A Systematic Literature Review (SLR) was carried out using the Preferred Reporting Items for Systematic Reviews and Meta-Analyzes (PRISMA) framework. This analysis was based on 67 peer-reviewed publications on

PV.

Over the past few decades, there have been rapid developments in technological adoption and diffusion. Rogers was the first to introduce the concept of innovation diffusion,[14] and further reported that it is communicated in a social system. Rogers stated that the communication aspect is an essential part of the processes involved in technology adoption. Computationally, the uptake of innovation is modeled to follow an S-curve[13]. Common equations-based explanations for this curve are a logistics regression[15] or the Bass diffusion models[16]. Equation-Based Modelling (EBM) often adopts these two approaches to model technology adoption. Besides, EBM is based on equations compiled from system-level observations by ensuring decision-makers are categorized into groups (populations) which omit heterogeneous individual preferences[13].

Unfortunately, various individuals have different preferences, which influence the criteria involved in decision making concerning technology adoption[13]. In addition, decision-making is also influenced by other factors such as information, communication, social norms, behaviors, and 'social pressure to adopt'[13][17]. However, EBM has certain limitations in modeling individual-level preferences. In EBM, diffusion trends are averaged, it fails to reflect the specific decisions made by individuals. Therefore, the dramatic changes encountered in adoption are inappropriately explained. Although equation-based diffusion models are able to predict aggregate adoption behavior in a population, these are limited when evaluating complex policies and targeted interventions to increase technology uptake[13]. Therefore, Agent-Based Modelling (ABM) was deployed to overcome the limitations of Equation-Based Modelling (EBM)[13,18,19]. The ABM models the agents (i.e., decision makers), their interactions and interdependence of individual agents to understand emerging behaviors. This approach was widely used to explore policies or interventions in a system to achieve certain goals[20][21]. ABM has the ability to analyze various complex problems that requires computation at different scales, both in interrelated and interdependent environments[22].

Consequently, by reviewing the existing literature on PV adoption, this study provides insight concerning the modeling approach used for PV adoption and diffusion and the influential factors included in the model. Besides, having proper knowledge of these fundamental factors and applying the appropriate modeling approach is essential to understand the entire PV system as well as aids in designing an effective energy policy facilitating the uptake of the PV system in households.

This research is organized into five sections. The first section highlights the complexity of technology adoption, followed by the state of arts of the existing modeling approach in Section Two. Section Three describes the methodology for the systematic literature review. Additionally, the results and discussions are reported in Sections Four and Five. Section Six is the concluding aspect, which creates avenues for future research.

2. Modeling Approach of Technology Adoption and Diffusion

Technology or innovation diffusion refers to the spread and adoption of technology in human populations[13]. Rogers initially introduced this concept in accordance with the Diffusion of Innovation (DoI) model, which was adopted to explain the strategies used to convey innovation through certain communication channels to a group of social system members over time[14]. This adoption occurs when some people are more inclined to embrace a particular innovation before others[14]. Meanwhile, people tend to learn about innovation from others through the diffusion process during social interactions. Based on the decision strategy used and the technology or products' level of acceptance, there are five types of adopters. They include innovators, early adopters, early majority, late majority, and laggards[14]. The uptake of innovation is assumed to follow an S-curve where it starts slowly and gradually speeds up, and as greater saturation rates are reached, it slows down again[13].

Equation-Based modeling (EBM) and Agent-Based modeling (ABM) are widely-used modeling approach[18]. Moreover, both approaches recognize that the world encompasses two types of entities, namely the individual and the observable, each with a temporal aspect[19]. Individuals identified as being different from one another. They possess behaviors and "do things" over time. Observables are measurable characteristics of interest that are either associated with individuals or groups as a whole. It takes an articulate relationship to predict the behavior of this system over time. ABM and EBM have fundamental differences associated with the relationship between entities and the focus of modelling[19].

EBM starts with a set of equations that express the relationships among observables. The evaluation of these equations results in the evolution of the observables over time. The equation applied aims to capture the variability or the dynamics of time and space. The modeling of renewable energy adoption with the EBM approach is classified into three classes[18].

First, EBM deploys regression equation. The studies developed a predictive model for the diffusion of renewable energies by illustrating the regression between the evolution of large-scale energy systems (across the country) and economic trends such as commodity prices, gross domestic product (GDP), and energy consumption.

Second, EBM applies diffusion theory. This group incorporates a social perspective into the adoption modeling while focusing on the diffusion of technology in society and the effect of its application to the expansion of decentralization. Bass models, Rogers concept, Theory Planned Behavior (TPB), Technology Acceptance Model (TAM), and Theory of Reasoned Action (TRA) are widely used in this group. In accordance with adoption problems, logistic regression and Bass models are often used to describe the adoption pattern over time (S – curve).

Third, the EBM approach utilizes a socio-dynamic procedure that investigates renewable energy adoption patterns by classifying individuals into sub-populations based on certain characteristics. Although these equations are derived from individuals' interrelated behaviors, EBM is unable to explicitly represent these behaviors[13,23].

On the contrary, ABM describes individuals as unique, autonomous, and adaptive entities[17]. They are unique because they possess different characteristics, autonomous because each individual acts independently to pursue their respective goals. Conversely, individuals interact locally with their neighbors - in the same geographical space. They are regarded as adaptive because their behaviors are adjusted to the current state, other agents, and environment[17].

Some interesting observables tend to be defined only at the system level. On the contrary, others are expressed either at the individual level or as an aggregate [19]. In other words, the evolution of system-level observables emerges from an agent-based model. However, the modeler does not explicitly use these observables to drive the model's dynamics as in equation-based modeling.

ABM examines individual-level interactions and uses it to describe complex social behaviors. This approach requires highly detailed agent data, which is difficult to obtain for a greater level of analysis[18]. On the contrary, EBM with diffusion and regression theory equations has certain limitations in describing individuals' heterogeneity in detail. To overcome these weaknesses, an equation-based approach was developed using the socio-dynamic framework [24]. This divides the social system individuals into smaller subpopulations based on their thematic characteristics and further defines observables that change over time according to a series of input parameters[24]. In accordance with a socio-dynamic framework, technology adoption patterns are simulated using techno-economic data that are accessed without sacrificing important social dynamics such as the formation of public opinion on technology[18].

It is worthy to note that technology adoption modeling has a trade-off between the covered complexity of social behavior and the ease of accessing data[18]. Based on Figure 1. the data collection for EBM with the regression equation was easy to acquire, however, it was unable to cover the complexity of social behavior. Although EBM with the diffusion theory equations considers the experience of innovation in society, it is unable to describe individual heterogeneity in detail. The socio-dynamic approach seeks to simulate adoption patterns at a macro scale, utilizing easily accessible data by compromising important social dynamics[18]. Conversely, ABM accurately describes social behavior's complexity, irrespective of the difficulties encountered during data collection.

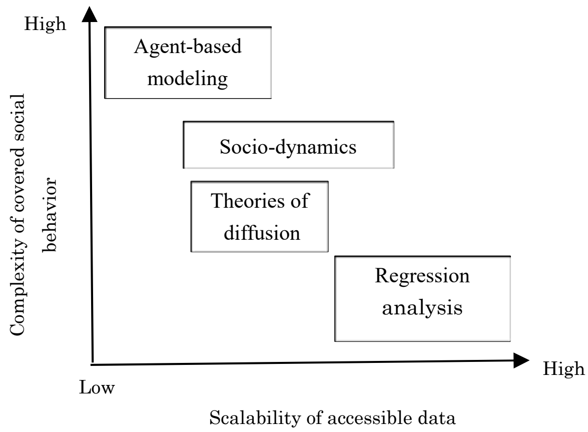

Fig. 1: Approaches to model PV adoption patterns [18]

3. Methodology

SLR was conducted based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyzes (PRISMA) framework, as shown in Figure 2. The literatures used were published from 1992 to 2019.

PRISMA is an evidence-based minimum set of items used for reporting systematic reviews and meta-analyzes. This method focuses on the reporting of reviews based on evaluated randomized trials. However, it also serves as a basis for reporting systematic reviews in other types of studies[25]. This framework encompasses four stages, including identification, screening, eligibility, and inclusion[25]. In addition, each stage involves a checklist of items deemed important for transparently reporting a systematic review.

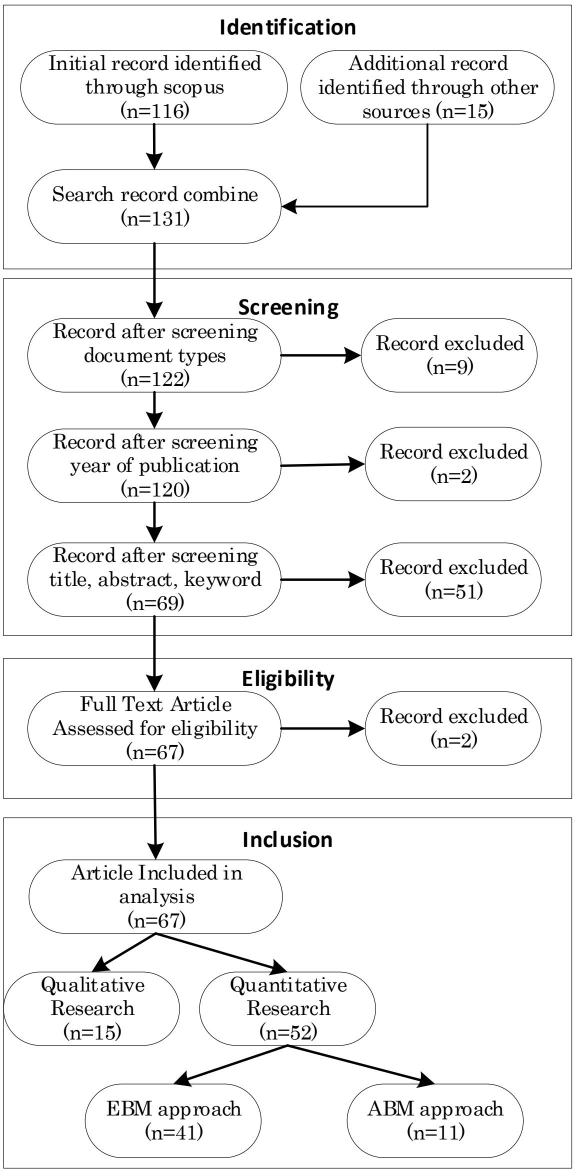

Fig. 2: PRISMA flowchart for the study selection process (adapted from [25)])

Identification is carried out by tracing the Scopus database, using a combination of keywords consisting of "solar," "photovoltaic," "adoption," and "behavior." The initial search produced 116 papers. Further literature searches were performed using a snowball approach by tracing references and citations from the data obtained. This led to an additional 15 journals, resulting in a total of 131 articles. Subsequently, screening was conducted by excluding 6 review papers and 3 article-in-press papers. In total, 122 articles were obtained.

The PV research initially carried out in 1992 discussed the home-power transition from traditional electricity to photovoltaic systems in the United States[26)]. Afterward, there were no PV literatures till 2006. Therefore, due to its non-existence from 1993 to 2005, the literatures published in 1992 were removed, thereby culminating in 120 articles. This analysis was based on articles published from 2006 to 2019.

Based on the fact that this study focuses on the adoption of PV systems in the household sector, further screening was performed by filtering paper title, keywords, and abstracts. The articles not associated with the study scope are the application of PV systems in public facilities (2 articles), industry (1 article), and broader energy topics (9 articles) were discarded. The papers concerning the use of solar PV in electric vehicles (5 articles), water heaters (7 articles), and heating systems (6 articles) were not included. Furthermore, discussions of Solar PV systems in the context of technology (12 articles), economics (6 articles), risk assessment, and feasibility studies (3 articles) were not evaluated. After these provisions, 69 papers were obtained and included in the subsequent stage.

The third stage involves checking the paper's eligibility by examining the availability of the entire article. Unfortunately, 2 articles failed this criterion, thereby leaving only 67 journals for the final analysis.

In accordance with the classification described in Figure 1, the articles were grouped. Those associated with the modeled PV adoption behavior and introduced interactive rules that guide the individual level to describe the complex social behavior were grouped in ABM. Meanwhile, the adoption models initiated based on a set of equations were grouped in the EBM. The articles in this group are further divided based on the equations used in modeling. Models with DoI-based equations, Bass's diffusion, and other adoption theories were grouped into EBM with a theory of diffusion. Subsequently, models that investigate the relationship of specific factors with PV system adoption rates using regression equations were grouped in EBM with regression analysis. Articles that simulate adoption patterns at a macro scale by dividing the actors of a social system into smaller sub-populations regarding their thematic characteristics were further grouped in the socio-dynamics approach.

4. Results

The number of PV studies has increased over the years, as shown in Figure 3. It seems that the future trend is also likely to increase.

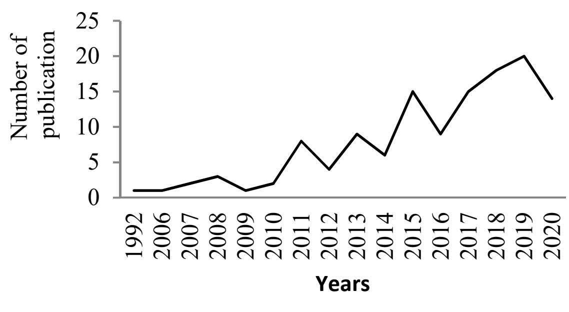

Fig. 3: PV system publication over the years

However, out of the 67 articles included in the analysis, 28 (42%) discussed the PV system adoption in Europe, while 21 (31%) applied in the United States. These findings are consistent with the studies carried out on the rapid development of a PV system in countries with four seasons, sufficient sunlight, and moderate temperatures, which are assumed to be the optimal condition for its utility. Meanwhile, the 13 articles from Asia were dominated by Japan and China. A total of 4 articles discussed applying PV systems in Australia, and only 1 analyzed its application in Africa.

However, not all articles on the PV system utilized a quantitative model. Table 1 shows that from the 67 articles, 15 focused on qualitative research where surveys, reviews, and interviews were used to explore various motivators, barriers, and related customer behavior in adopting a PV system. Moreover, the qualitative research provided a list of matters that are considered important when formulating environmental and energy policies [27].

Table1: Qualitative research

Method	Author(s)	Aspect: Motivators	Aspect: Barriers	Aspect: Behaviors	Number of Articles
Survey	[28]	√	√		8
	[29], [30]		√		
	[31], [12], [32]			√	
	[33], [34]	√			
Interview	[35]	√	√		3
	[36], [37]			√	
Review	[38], [39]	√			4
	[40]		√		
	[41]			√	

An in-depth review was conducted on 52 quantitative papers, which modeled the adoption of PV. Table 2 shows that EBM is a widely used approach compared to ABM with 11 articles.

Table 2: Distribution of quantitative research

Method		Authors	Total
Equation-Based Modelling	Socio-dynamics	[18], [42], [43], [44], [45]	5
	Theories of Diffusion	[46], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63]	18
	Regression Analysis	[64], [65], [66], [67], [68], [69], [70], [71], [72], [73], [74], [75], [76], [77], [78], [79], [80], [81]	18
Agent Based Modelling		[11], [82], [83], [84], [85], [86], [87], [88], [89], [90], [91]	11

Consequently, out of the 41 EBM articles, 18 implemented the theory of diffusion approach. A similar number of articles adopted the regression analysis approach. However, only five utilize the socio-dynamic approach. This is consistent with previous studies stating that the Bass diffusion model and regression analysis are the two most widely-used EBM approaches. Meanwhile, the socio-dynamic approach is few because it is relatively new in modeling studies of the PV adoption, and so is the ABM.

4.1. PV System Adoption and Diffusion Models

EBM with the theory of diffusion and regression analysis approaches has been dominating over the years, as shown in Figure 4. PV system adoption modeling using ABM started in 2011 and has developed in recent years. The socio-dynamics approach to enhance the ability of EBM to facilitate population heterogeneity was introduced in 2015, and its use is still limited to date.

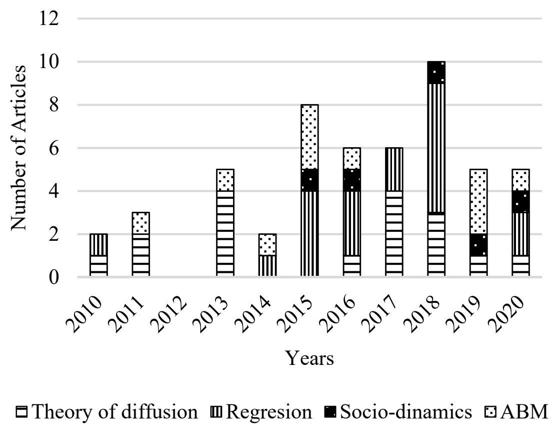

Fig. 4: PV system adoption Modelling over the years

It was discovered that various diffusion theories such as the Bass model, Theory Planned Behavior (TPB), Technology Acceptance Model (TAM), and Theory of Reasoned Action (TRA) are used for modeling the adoption of PV using the EBM. The Bass model generally serves as a framework for analyzing and estimating government incentives' effect on a broad-country level PV adoption patterns[53,59]. It is a known fact that incentives help facilitate the further application of the PV system.

The relationship between psychological, social, and economic aspects concerning the intention to use the PV system was investigated with equations from various other diffusion theories. An application of the extended TAM model was proposed to estimate and explain the public acceptance of PV systems in Taiwan. Furthermore, consumer intentions and purchasing behavior were explored based on certain perceptions, namely ease of use, usability, and attitude[62]. The TRA approach was adopted to evaluate American homeowners' attitudes, awareness, and normative conscious and unconscious beliefs using PV systems[57].

Based on TPB, PV adoption modeling was carried out by exploring the purchase intention motive, while subjective norms were assessed in accordance with peer behavior and expectations. Furthermore, attitudes towards PV systems are based on aspirations for social status, autarchy, financial benefits, costs, effort, and associated risks[60]. Some other studies used the TPB framework to assess people's knowledge of energy sources and environmental impacts, which are the main motivations for switching to green energy[63]. TPB was also used to investigate the effect of socio-psychological factors (environmental attitudes, Perceived Behavioral Control (PBC), subjective and descriptive norms, including knowledge of renewable energy) on individual intentions to adopt renewable energy policies[58].

Another theoretical framework used to investigate the psychological and social determinants of residential solar interest was drawn from three theories that explained the decision to pursue this procedure. This includes DoI, TPB, and Value-Belief-Norm theories[55]. The parameters of environmental attitudes and knowledge of PV applicability are analyzed to identify which aspect of demand determines the further development of this environmental technology[52]. Some previous studies developed a framework based on Roger's Diffusion of innovation theory in order to examine household adoption of solar power[46,48–51].

Other equation-based PV system adoption models were performed using various regression models to analyze the relationship between financial and non-financial aspects as well as the intention to adopt. These approaches were based on statistical data analysis, which tends to evaluate the relationship between predictors and adoption decisions. Linear regression analysis of structured questionnaires was used to estimate purchase intentions in accordance with independent variables, such as income, ownership of household, external support, the value of use, and relative benefits [70]. Meanwhile, other studies adopted linear regression with environmental factors and intention as the independent and dependent variables, respectively[79].

The proposed hypothesis stated that the influence of the factors is not always linear. Besides, some research is being carried out concerning non-linear regression equations to investigate the influence of an investment's Net Present Value (NPV) with interest in PV system adoption[80]. A similar method is adopted to investigate the influence of non-financial aspects such as engagement, environmental value, and knowledge[77]. Logistic regression is the most widely used equation to explore the influence of various aspects, such as economicv[64,71,76], social demography[68,74], psychology[64,68], recommendations[64] and policies[65,73] towards the intention to use the PV system. Examining the literature concerning the willingness to either make payment or accept this system, a regression meta-analysis was used to investigate the major determinants of PV acceptance, including the demand and supply aspects[75].

However, only a few literatures concerning the adoption of PV applied a socio-dynamic framework. Based on this framework, a socioeconomic model was used to analyze the PV system's expansion at the household level in Germany and Italy[18]. A retrospective dynamic analysis was conducted to identify the importance of profitability factors and public opinion on the adoption of this system. The model was projected to investigate the feed-in tariff policy to achieve an expansion target[18].

Considering that spatial and socioeconomic factors often mediate the diffusion of new technologies, detailed data on PV installations in Connecticut were used to identify the spatial patterns of diffusion that indicate considerable clustering of adoptions[42]. This clustering does not simply follow the spatial distribution of income or population, rather, it is dependent on the number of nearby previously installed systems as well as developed environmental and policy variables[42]. Spatiotemporal technology adoption model was used to predict residential photovoltaic (PV) modules' behavior and its effect on the incentive structure[43]. Another research concerning the use of epidemic diffusion models was carried out to describe the spatial diffusion of rooftop household photovoltaic installations in Germany[45]. The results showed that the adoption behavior of imitation is highly localized, and it is an important factor for the diffusion of household photovoltaic systems.

The ABM approach was used to explore the way and manner individuals interact with each other during the decision-making process. It was used to investigate individual adoption behavior as a model image on a broader scale. In accordance with the ABM approach, the effectiveness of investment credit and tax policies on rooftop PV adoption is simulated[86]. A two-level simulation model was utilized, taking into account the payback period, revenue, advertising, and environmental-based peer effects. Subsequently, lower-level models were used to calculate the payback period for acceptance by various household classes. At this level, the hourly energy transition between PV system generation, local electricity grid, and household demand was adopted with the dynamic systems. The model imitated hourly electrical consumption. The high-level modeling framework simulated customer acceptance behavior in residential areas. Furthermore, their decisions are influenced by the four factors mentioned earlier, and the number of advertisements served as a dynamic factor over time.

Logistic regression integration with predictive models divided into a multi-agent simulation platform was carried out in the prediction of solar rooftop adoption in San Diego, United States of America, by analyzing the agent's training mechanism[87]. The results showed the involvement of NPV, peer effect, and house characteristics variables as a basis for forecasting the amount of electricity to be generated. Conversely, rooftop PV diffusion in Italy[82] was simulated by ABM with the adoption category as suggested by Roger[14]. This involves the considerations of financial aspects through the payback period and is assessed according to the Italian family's socioeconomic classification "sinus-milieus." The obtained model was used to predict the number of PV system adopters with incentive intervention from the government, thereby reducing investment costs[82)]. ABM integration with optimization is used to determine the diffusion rate of green technology under uncertainties. Integer programming model was adopted to determine the most optimal combination of green roof systems and solar panels in terms of the payback period. Furthermore, the adoption model was analyzed with the ABM by considering the weather uncertainty[85)].

The ABM model was also developed to analyze the efficiency and effectiveness of financial policies toward the acceptance of solar PV systems in Indonesia[88)]. This effectiveness is measured by the number of adopting agents due to the applied financial policies, while efficiency is measured by the amount of funds spent by the government on policy implementation. This study was conducted to evaluate the effect of the Feed-in Tariff (FiT) policy, net measurement, and grant programs. The study has focused on financial feasibility, without considering the influence of interactions during decision making[88)].

The integration of ABM with TPB and GIS was used to examine the influence of attitudes or opinions on PV systems while the strength of interactions in social network structures is based on patterns to provide a spatial picture of adoption in Texas[90)]. The behavior and interactions of agents in a system are modeled by implementing a set of rules developed based on the research subjects that utilized psychological approaches and social theories such as TPB and DoI. Further, ABM is integrated with GIS to observe agents' social network patterns[92)] while TPB is the theoretical basis for decision making[91)].

The ABM model using TPB[91)] is empirically grounded on local utility company policy concerning rebates, longitudinal household surveys, and available public data. It is also in accordance with house and land value and site-specific conditions related to PV system effectiveness. The agent was initialized based on city survey data, which considers the payback period's attributes household income, attitudes toward PV, and social influence. Furthermore, the distance between households and social effects regarding small-world networks structure is considered when building networks.

In addition to behavioral factors, the learning aspects' effects were also examined at the PV system adoption level by analyzing similar attitudes in basic behavior [11)]. On the contrary, four influencing factors were identified, namely perceptions of the benefits of technology, the complexity of innovation, social influence, and knowledge related to government incentives and costs that show the degree of similarity between adopters and non-adopters[11)].

4.2. Influential Factors underlying the Adoption of PV System

In addition, understanding the underlying factors that influence the adoption of PV systems is essential in the determination of appropriate energy policies. Table 3 indicates influencing factors underlying the adoption of PV System.

Qualitative research was carried out through surveys, interviews, case studies, and literature reviews to identify the motivations and obstacles needed to predict the PV system adoption. Furthermore, reviews in 28 countries acknowledged high initial investment cost as the main barriers[40)] while the motivators are the users, the government, and the local PV industry[34)]. The increase in electricity price, due to policy measures, has caused potential adopters to be less dependent on its supply. Moreover, such desire is often complemented with environmental awareness, peer effects, and financial stability. The local solar company is identified to be an important factor for adoptions. A high level of communication between local solar companies and adopters is a key factor in minimizing the perceived complexity and facilitating the decisions made by the adopters[34)].

Table 3: Influencing Factors underlying the Adoption of PV System

Aspect	Total	Factor	Author(s)	Number of articles
Socio-demographic	10	Age & Education	11,82)	2
		Income	11,82,85,86,88,91)	6
		Electricity consumption	85)	1
		Number of family members	85,87)	2
		Home location	87,88,90)	3
		Homeownership	11,88,89)	2
		House characteristics	11,82,86,87,90,91)	6
		Household class	11,82,84)	3
Technical	5	Efficiency Capacity factor	85,86,88)	3
		Solar irradiation	86,91)	2
		Installation fee	82,86,88)	3
		Operation & Maintenance fee	82,88)	2

		The results of PV electricity	82,86)	2
		PV electricity prices	82,88,91)	3
Financial	10	Capital cost	88,89)	2
		Revenue Requirement	88)	1
		Payback Period	82,84,86,90,91)	5
		Net Present Value.	11,85,87)	3
Information & interactions	10	Social network	11,82,85,87,90)	5
		Advertisement	85,86)	2
		Neighbors	11,82–84,86,87,89,91)	7
		Seminar / exhibition	11)	1
Psychology	3	Attitude	11,85,91)	3
		Behavioral Control	11,85,91)	3
		Subjective norms	11,85,91)	3
Environment	2	CO_2 emissions	82,88)	2
		Construction material	82,88)	2

Furthermore, 22 PV users were interviewed regarding their opinion on the Feed-in Tariff policy, and it was discovered that they responded differently [12)]. However, age, income, knowledge, and finance were the most used criteria to predict the social dimension. The results showed the existence of a significant relationship between individual traits and adoption behavior

Finance is a significant factor that needs to be considered due to the PV system's initial high costs. The environmental aspect is also extensively adopted as a predictor, although pro-environmental attitudes, consumers' understanding, and belief in the importance of its use do not guarantee renewable energy adoption behavior. This shows a wavering outcome in terms of behavioral change after promoting pro-environment knowledge and attitudes. It is interesting to note that it does not guarantee acceptance when the financial savings benefits exceed the investment costs.

Households regarded as decision-makers in PV system adoption often evaluate technology based on communication and trusted information sources such as friends and not on personal criteria. In addition, societal norms and 'social pressure to adopt' strongly influence others' behavior. These respective households have different preference profiles that eventually guide the criteria while making purchases.

The adoption modeling with ABM varies in the utilized theoretical basis and involves complex aspects, with diverse predictors in several studies. The socio-demography, finance, information, and interaction are three aspects widely included in modeling PV adoption with ABM. Besides, various predictors from the socio-demographic aspect were used to describe the household heterogeneity. Factors related to the financial aspects and social interaction between agents were discussed using different aforementioned parameters and considered significant influences on adoption decisions.

The high investment cost of a PV system, asides from the savings it offers, raises the question associated with the investment payback period. Therefore, this period is widely used as a predictor of the PV system adoption model's financial aspects. Some studies reported that psychological aspects are regarded as an effort to develop ABM modeling based on diffusion theory, namely TPB and DoI. The environmental aspects were involved in this research to explore the relationship between environmental sustainability perceptions and willingness to use PV systems.

5. Discussion

The number of studies related to PV adoption increased over the years, in line with the PV system's growing utility. These studies or analyses are usually carried out in developed countries. The policies related to environmentally friendly products are properly implemented in these countries because they have a greater concern for global environmental problems[93)]. It is necessary to investigate the differences between developed and developing countries, especially regarding PV adoption, to determine the appropriate policies.

Environment awareness was discovered to be the main motivator, while initial investment costs are a major barrier to PV technology adoption. However, the decision to adopt renewable energy sources is often irrational. A reduction in investment costs does not guarantee that households are willing to adopt a PV system because people have different attitudes and preferences. Apparently, household evaluation is not only based on the financial criteria, rather, it is also dependent on communication and information obtained from friends. In addition, social norms and pressure greatly influences the behavior of others. The common strategies such as economic incentives or information campaigns are not sufficient, rather more refined measures such as feedback, improvement of consumer efficacy, activation of social norms are needed[94)]. Therefore, PV adoption modelling requires the ability to accommodate these factors.

EBM is used to recognize the correlation between interrelated individual behaviors, however, it is unable to describe household heterogeneity. On the contrary, ABM is an alternative approach used to overcome the deficiencies of equation-based diffusion modeling because it has the ability to describe the heterogeneity of household preferences, communication, and social influence in the decision-making process. Besides, due to its high flexibility, ABM is also used to explore the effects of various policy interventions on the adoption rates. In addition, the use of parameters from calibrated and validated empirical data produces similar accuracy as equation-based modeling. Amid the dominance of EBM, the ABM approach was used to develop the PV system adoption modeling.

Factors influencing the PV adoption including socio-demographic, technical, financial, information and interaction, psychological and environmental factors should be incorporated in the PV adoption model. Socio-demographics, finance, information and interactions factors can be used as household attributes to represent household heterogeneity. Financial aspects and social interactions between agents were found to have significant influences on adoption decisions. The economic aspect was considered due to the high initial investment cost of PV systems. Moreover, social interactions are also relevant due to the close relationship with adoption behavior. When it comes to adoption decision making, the model can use of a theoretical framework such as DoI and TPB which have been widely applied.

It is important to note that the technical aspect has not been extensively investigated. Meanwhile, technological visibility is currently one of the considerations by potential adopters. In accordance with the fact that the PV system is a new technology, its application requires special knowledge. Therefore, there is a crucial need to obtain information, make purchases, as well as to conduct maintenance and repair services. Moreover, the distributor is a downstream part of the PV industry where consumers are known to deal directly with the service providers. However, this facility's absence in some countries was recognized as one of the obstacles of PV system diffusion, especially in rural areas[34)]. The influence of distributor availability factors serves as a guarantor supply of security, and part of the technical aspects needs to be addressed in future research. Furthermore, the PV adoption model should also evaluate the environmental impact of the overall PV system to provide insight on the overall system performance for better policy interventions.

6. Conclusion

The studies carried out on the adoption of PV systems have increased significantly in the past few years. This indicates that the research area is still progressing and is likely to develop continuously. Developed countries mostly dominate these studies. This indicates the necessity for similar studies to be carried out in developing countries. The present study reviewed the literatures on PV adoption published within the period of 2006 to 2019 using the Systematic Literature Review using Preferred Reporting Items for Systematic Reviews and Meta-Analyzes (PRISMA) framework.

These results show that EBM is the most widely used modeling approach for PV adoption, particularly those with a diffusion theory. Although, due to the incapability of EBM to explicitly model household heterogeneity and adoption mechanisms, the ABM overcomes the limitation and is likely to receive more attention in the future as a result of its capability to model household heterogeneity and detail adoption decision making of the PV system.

Furthermore, various factors have been analyzed to determine the effect of financial and non-financial aspects on adoption behavior. The payback period, net present value, capital cost, and revenue requirements are some of the factors used to investigate the influence of the financial aspect. Income, house characteristics, location, homeownership, number of family members, age, education, electricity consumption are factors related to the socio-demographic aspects, which are also used to describe household heterogeneity. The influence of information and the interaction aspects are examined with several factors such as social networks, advertisements, seminars, or exhibitions, including the influence of neighbors. Several studies that involve the psychological aspects examined the influence of intention, subjective norms, and behavior on the adoption of PV. Subsequently, these studies also involved the environmental aspects taking into account the causes of CO_2 emission and the PV system's construction materials. Based on the technical aspect, the discussion is limited to techno-economic factors such as PV efficiency, capacity factor, operation, maintenance and installation costs, PV electricity prices and yield, and solar radiation, whereas the supporting system such as maintenance and repair services has not been discussed in the literature. On the other hand, building an ecosystem for the PV system has argued to be necessary to sustain the system in the long-term.

Relating to factors underlying PV adoption, the high investment cost is a major barrier. Meanwhile, increasing electricity price, environmental awareness, peer effects, financial stability, and support from local solar companies is an important motivator for PV adoptions. The financial aspects and social interactions have been discussed in the literatures. On the contrary, environmental awareness and support from local solar companies have not really been addressed. This implies that future research on PV adoption modeling needs to incorporate those factors for better understanding and effective interventions to support this system's uptake and to sustain its adoption.

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