Article

Academic Topics Related to Household Energy Consumption Using the Future Sign Detection Technique

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Abstract: With the emergence of new technologies and policies to transition to clean energy, the household energy consumption sector is also changing. In response to policy, environmental, and technical changes, researchers need to find out what significant issues are related to household energy consumption, and comprehensively analyze which issues are likely to attract attention in the future to contribute to research in the household sector. Based on the abstracts of academic papers published between 2011 and 2020, this study uses probabilistic topic modeling to increase understanding of academic issues in the household energy consumption sector and statistically reviews changes in issues over time. As a result of the analysis, topics related to digitalization and renewable energy, such as microgrid system, smart home, residential solar power generation systems, and non-intrusive load monitoring (NILM), belonging to Strong signals, are being actively studied. Weak Signals, which can attract attention in the future, are included in discussions on coal energy consumption, air pollutant emissions, energy poverty, and energy performance evaluation. The analysis results show that carbon neutrality, such as decarbonization and fossil energy consumption reduction, is expanding to research in the household energy consumption sector.

Keywords: household energy consumption; structural topic modeling; weak signal; future sign

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1. Introduction

Household energy consumption accounts for a large portion of total energy consumption. Household energy consumption accounts for approximately a third of the world's primary energy demand and significantly impacts the environment [1]. It is estimated that rapid development and income growth will increase energy demand in the household sector and lead to more greenhouse gas (GHG) emissions [2]. The household energy consumption sector is changing due to the emergence of the Internet of Things (IoT) and artificial intelligence (AI) technology to manage household energy demand, the promotion of energy efficiency policies to transition to clean energy, and the increase in single-person households. In response to policy, environmental, and technical changes, researchers are trying to find ways to reduce household energy consumption by improving energy efficiency and predicting energy consumption through new technologies.

For researchers to contribute to the household energy consumption sector in the future, a comprehensive analysis is needed on what significant issues related to household energy consumption are increasing, what issues are decreasing, and which issues are likely to attract attention in the future. Through the analysis, researchers can find out what research is currently needed concerning household energy consumption and explore appropriate research topics for each sector, such as policy, environment, and technology. The main research questions in this study are as follows.

1. What are the research topics that academia is currently paying attention to regarding household energy consumption?
2. What are the research topics that have increased or decreased statistically between 2011 and 2020?

3. What research topics could attract attention in the future regarding household energy consumption?

This study aims to increase understanding of academic issues related to household energy consumption using probabilistic topic modeling and statistically examine changes in issues over time. In particular, it aims to contribute to researchers' discovery of research topics by exploring issues that may attract attention in the future.

The structure of this study is as follows. Section 1 is the introduction part. Section 2 reviews academic issues related to household energy consumption through a literature review. Section 3 describes the methods of this study. Section 4 deals with topics related to household energy consumption derived from the analysis of this study. Section 5 examines the meaning of the main topics in detail. Section 6 deals with conclusions such as contributions and limitations of this study.

2. Literature Review

As discussed earlier, energy consumption in the household sector is facing a change. Interest in improving household energy efficiency is increasing in various fields, such as policy, environment, and technology, and household energy consumption is being studied in various fields. Before comprehensively examining topics related to household energy consumption, it is necessary to investigate related issues through existing literature.

It was found that most of the comprehensive studies dealing with household energy consumption used bibliometric analysis. Han and Wei [1] looked at the latest research trends, research gaps, and prospects of household energy consumption through the bibliometric and network analysis of 1134 publications published from 1983 to 2018. Hu et al. [3] identified collaborative networks and the latest trends through bibliometric analysis of 2984 academic publications published from 2011 to 2018 on the subject of household energy consumption. Ma et al. [4] analyzed literature on household energy consumption sector published between 1970 and 2018 through bibliometric analysis to identify research stages, advanced research countries, and major research topics in this sector. According to studies using bibliometric analysis, there are many studies in the policy, environment, and technology sectors about household energy consumption.

The topics of the literature dealing with policy issues of household energy consumption include deriving implications through policy status analysis [5–7] and policy effectiveness analysis [8,9].

Research on deriving implications through policy status analysis includes a review of global energy policies, consumption status, and trends in the residential energy efficiency improvement sector [5], socio-economic cost analysis of residential energy efficiency improvement policy [6], and investigation of the establishment, implementation, and outcome of energy policies in the residential sector [7]. Sheng et al. [7] argued that it is crucial to establish a policy system that can reflect the interests of all relevant stakeholders to create policies to successfully achieve energy transitions in the residential energy sector.

In addition to deriving implications through policy status analysis, there are also studies on analyzing policies effects. Studies on the effectiveness of policies include analyzing the effect of policy goals and programs on energy efficiency [8] and analyzing the effect of residential energy efficiency policies on household energy consumption across Europe [9]. Adan and Fuerst [8] revealed that energy efficiency measures driven through Carbon Emission Reduction Target (CERT) and Community Energy Saving Program (CESP) reduced the total energy consumption of residences. In particular, when three measures, including cavity wall insulation, loft insulation, and new boiler, were taken in the same year, the total energy consumption of residential areas decreased 10.5% annually. Aydin and Brounen [9] pointed out that many countries have introduced regulations aimed at energy efficiency in the residential sector due to growing concerns over global climate change and energy dependence. However, it is still unclear whether such policies have been effective in reducing residential energy consumption. It also presented evidence that

the mandatory energy efficiency labels for home appliances and strengthened building laws reduce residential energy consumption.

Topics of the literature dealing with environmental issues of household energy consumption include carbon dioxide emission [10–12] and climate change [13–15].

Studies on carbon dioxide emissions include a proposal of a building design model to minimize the life cycle cost and carbon dioxide emissions of residential buildings [10], the effect of eco-refurbishment on energy demand and carbon dioxide emissions [11], and the effect of insulation in residential buildings on primary energy demand and carbon dioxide emissions [12]. Tettey et al. [12] noted that renewable raw materials greatly help reduce primary energy consumption and greenhouse gas emissions.

Research on the effects of climate change includes reviewing the impact of climate change on heating and cooling demand for residential spaces by region [13], and the impact of climate change on energy consumption in the household sector [14,15]. Shourav et al. [15] revealed that rising temperature could significantly impact residential energy consumption, especially peak energy consumption is very sensitive to temperature.

As the spread of information and communications technologies (ICT) in the energy field increases, the existing energy system is being digitalized [16]. In line with this, in the field of technical issues of household energy, many studies are being conducted mainly on energy management using digital technologies. The topics of the literature dealing with the technical issues of household energy consumption include the Home Energy Management System (HEMS) [17–19] and the improvement of the accuracy of predicting household energy consumption [20–26].

Studies on HEMS include proposals for a new home energy management system using wireless communication technology to reduce carbon emissions [17], proposals for optimized HEMS to promote the integration of renewable energy sources and energy storage systems [18], and analyzes the impact of HEMS on power consumption [19]. Tuomela et al. [19] indicated that HEMS reduced total power consumption in winter by up to 30%, according to their experiment.

Research on improving the accuracy of predicting household energy consumption includes improving the prediction accuracy using machine learning [20–24] and improving prediction accuracy using linear regression models [25,26]. Zhang et al. [27] noted that predicting energy consumption is helpful for power demand management, utility companies supply, and demand plans. Williams and Gomez [25] argued that accurate energy consumption forecasts significantly impact utility companies forecasting of power generation demand and prioritizing investment projects.

In addition to policy, environmental, and technical issues, many research topics identify factors affecting household energy consumption [28–30] and behavioral intervention [31–33].

Research on identifying factors influencing household energy consumption dealt with socio-economic factors such as energy price, consumer attitude, economic situation, and environmental factors, such as ultrafine dust concentration. Bhattacharjee and Reichard [28] indicated that in order to improve energy efficiency and mitigate the steady increase in household energy consumption, it is necessary to consider the fact that not only human behavior, but also non-human factors such as weather and energy prices affect energy consumption.

Research on behavioral intervention includes a review of the effect of behavioral intervention on household energy savings [31], review of the impact of the intervention, such as providing customized information and feedback, on changes in household energy consumption and energy-related behavior [32], and a study that examines what kind of feedback is most successful in reducing household power consumption [33]. Abrahamse et al. [32] indicated that households exposed to intervention saved more gas, power, and fuel than those who were not, and performed various energy-saving behaviors, such as setting up a thermostat.

As discussed earlier, comprehensive studies on household energy consumption mainly used bibliometric analysis. Major issues included deriving implications through policy status analysis, analyzing effects from policy introduction, carbon dioxide emissions, climate change, HEMS, energy consumption prediction, and behavioral intervention. Bibliometric analysis has the advantage of representing research fields, topics, and trends in a wide range of academic research fields, and summarizing a large amount of information. However, the bibliometric analysis relies on existing information such as the title, publication date, keyword, and citation information of the paper. It is challenging to understand latent topics and the overall flow of the paper, since it focuses mainly on countries, journals, and researchers for each paper. Therefore, in recent years, research has attempted to grasp the trends and details of topics using topic analysis to overcome the limitations of bibliometric analysis. In the energy sector, research is being conducted to comprehensively analyze energy-related issues using latent Dirichlet allocation (LDA)-based topic modeling or structural topic modeling (STM). Jiang et al. [34] examined the main topics of hydroelectric power generation research using LDA-based topic modeling. According to Jiang et al. [34], hydroelectric studies have shown that the main topics are related to environmental, ecological, and sustainability issues such as fish, type, climate, emissions, lakes, sediments, and Turkey, which is a major country striving to develop hydroelectric power. Na et al. [35] analyzed the research trends of smart grids using dynamic topic modeling to understand smart grid technology's progress and characteristics and find ways to innovate technology. Among the papers registered in Web of Science, 3723 papers were analyzed by designating 'smart grid' as a search word for papers published from 1997 to 2016. Overall research trends, such as research growth and research share, were identified. Bickel [36] collected the abstracts of 26,533 Scopus papers published from 1990 to 2016, and analyzed 300 topics using LDA-based topic modeling. As a result, topics such as energy storage, optical materials, nanomaterials, and biofuels were important topics in the renewable energy sector. Xu et al. [37] analyzed 29 topics using LDA-based topic modeling for 3743 papers published in the field of renewable energy in electrical and electronics from 1992 to 2018. As a result, the main topics were microgrids, smart grids, electric vehicles, network communication technology, and power system stability. Park and Kim [38] collected papers containing the word 'renewable energy' in the title, abstract, and keyword of academic papers published from 2010 to 2019 among academic papers registered at ScienceDirect, and analyzed them through STM. Through this analysis, Park and Kim [38] statistically reviewed the temporal changes of studies on renewable energy and examined topics that will draw attention in the future. As discussed earlier, studies using topic modeling have existed among energy-related issues to comprehensively analyze topics in the hydroelectric power generation, smart grids, and renewable energy sectors. However, it is difficult to find a study using topic modeling to comprehensively analyze academic issues in the household energy consumption sector.

3. Materials and Methods

This study entered keywords related to home energy consumption at ScienceDirect and collected academic paper abstracts. Keywords used when searching the academic abstracts included 'home energy consumption', 'residential energy consumption', 'household energy consumption', and 'house energy consumption'. The period was set for the last 10 years, from 2011 to 2020. As a result of the abstract collection, 5947 papers were collected, 2092 in the first half of the 2010s (2011–2015) and 3855 in the second half of the 2010s (2016–2020). ScienceDirect serves as a database of scientific publications by British publisher Elsevier, is evaluated as one of the academic search systems suitable for evidence synthesis in the form of systematic reviews, and can be used as a principal search system [39].

This study utilized 'stm', an R package for STM, to perform topic analysis based on the STM model. STM is a probabilistic topic model technique proposed by Robert [40] and can be seen as more advanced than the LDA model. For example, STM expanded

the existing topic model to specify a generalized linear model (GLM) framework that can analyze the metadata of documents. Through STM, observed covariates such as time of document release and document sources can affect the topic prevalence and topical content, which are components of the model. Topic prevalence refers to the ratio of documents focusing on a specific topic, and topical content refers to word rates used when discussing a topic. This series of processes can confirm whether topics related to household energy consumption have changed statistically significantly between 2016 and 2020, as compared to 2011 and 2015.

Strong signals used in this study refer to signals with a positively increasing rate of interest. Weak signals, first used by Ansoff [41], opposite concepts to Strong signals, are signals about which topics are still of low interest but have the potential to develop in the future. Yoon [42] analyzed the growth rate of words, documents, and frequencies using text mining, and extracted Strong signals and Weak signals. Previous studies that explored future signals using text mining extracted future signals using a keyword emergence map based on term frequency (TF) and a keyword issue map based on document frequency (DF) [43–45]. However, this method had a limitation in that signals that were not included in both the keyword emergence map and the keyword issue map were not included in the future sign in conclusion. Another limitation is that it is difficult to interpret the meaning of signals extracted by future signs since they have the form of words. To overcome this limitation, Park and Cho [46] proposed a method of extracting documents similar to each keyword, making it easier to interpret the meaning of keywords selected as future signs.

In this study, to overcome the limitations of the existing method, a topic proportion is used instead of the frequency of keywords and documents based on the method used by Park and Kim [38]. As shown in Figure 1, instead of the average TF and the average DF, the topic proportion extracted through STM is placed on the x-axis. In addition, instead of the increasing rate based on TF and DF, the increasing rate of the topic proportion is placed on the y-axis. Through this method, the problem of omitting some keywords is solved, and the interpretation of future signs is simplified because one topic consists of several keywords.

Figure 1. New process identifying future signs by using STM [38].

4. Results

This study identified indices such as held-out likelihood [47], residuals [48], semantic coherence, and lower bound to determine the appropriate number of topics to be analyzed using the 'stm' package. Residual check is an overdispersion test for the variance of multi-

nomial within the STM data management process. If too much residual is dispersed, more topics may be required to absorb further dispersions. Semantic coherence is maximized when words most relevant to a given topic are frequently gathered. The higher the held-out likelihood and semantic coherence, and the lower the residuals and lower bound, the more suitable the model is. As shown in Figure 2 below, this study first extracted 160 topics. As a result of the analysis, the growth rate of held-out likelihood slowed down in about 100 topics, and the lowest value of residuals appeared in about 120 topics. However, when looking at semantic coherence and lower bound, the consistency of the model decreased as the number of topics increased. Therefore, a trade-off exists between held-out likelihood & residuals and semantic coherence and lower bound. Considering the earlier results and that the more topics derived through STM increase, the more detailed the research topics are, this study decided to extract and analyze 100 topics.

Figure 2. Diagnostic values by the number of topics.

In Figure 3 below, a total of 100 topics extracted through STM are arranged in a quadrant. The first quadrant refers to Strong signals, and the second quadrant to Weak signals. The dividing line drawn by the dotted line on the x-axis means the average value of the overall average topic proportion. The dotted line drawn on the y-axis is based on zero. If the increasing rate is greater than 0, the topic proportion increased in the second half of the 2010s compared to the first half of 2010s, and if it is less than 0, the topic proportion decreased. In order to present the research results more meaningfully, the result and discussion sections present the analysis results by dividing them into Strong signals and Weak signals.

Figure 3. Placement of topics in the quadrant.

4.1. Strong Signals

As shown in Table 1, 31 out of 100 topics belonged to Strong signals, and in the second half of the 2010s, there were eight topics showing p -values that were the same or less than the significance level of 0.05. Among the topics selected for the Strong signals, the topics with p -values of 0.05 or less are as follows.

Table 1. Topics selected as Strong signals.

Topics	Keywords	Mean	Inc.	Estimate	Std. Error	t -Value	Pr ($> t $) ¹
3	pcm, storag, phase, temperatur, refriger, condens, chang, perform, evapor, consumpt, ...	0.010	0.004	0.000	0.002	0.004	0.997
8	system, integr, propos, convent, base, compar, perform, hybrid, result, feasibl, ...	0.012	0.029	0.000	0.001	0.462	0.644
9	polici, tax, impact, model, economi, subsidi, target, trade, govern, general, ...	0.011	0.024	0.000	0.002	0.127	0.899
19	climat, chang, increas, zone, weather, futur, impact, condit, warm, global, ...	0.010	0.026	0.000	0.001	0.204	0.838
22	applianc, consumpt, load, propos, approach, monitor, data, algorithm, disaggreg, detect ...	0.012	0.361	0.004	0.002	2.205	0.028 **
28	urban, citi, area, densiti, spatial, neighborhood, land, local, plan, residenti, ...	0.011	0.109	0.001	0.001	0.779	0.436
29	network, iot, devic, data, node, applic, wireless, communic, propos, monitor, ...	0.011	0.371	0.003	0.002	1.701	0.089 *

Table 1. Cont.

Topics	Keywords	Mean	Inc.	Estimate	Std. Error	t-Value	Pr (> t) ¹
37	technolog, chang, polici, challeng, review, identifi, focus, transit, framework, explor, . . .	0.017	0.165	0.003	0.002	1.381	0.167
41	user, manag, base, propos, time, end, autom, present, applic, environ, . . .	0.010	0.035	0.000	0.001	0.267	0.790
43	data, consumpt, statist, pattern, cluster, sampl, analysi, group, collect, spatial, . . .	0.013	0.308	0.003	0.001	2.336	0.020 **
49	grid, storag, charg, distribut, batteri, generat, load, oper, vehicl, voltag, . . .	0.011	0.380	0.003	0.002	1.959	0.050 **
51	consumpt, growth, elast, econom, panel, estim, countri, incom, residenti, relationship, . . .	0.011	0.138	0.001	0.002	0.717	0.474
53	household, incom, expenditur, level, consumpt, survey, suggest, increas, higher, educ, . . .	0.015	0.006	0.000	0.001	0.038	0.969
58	propos, flexibl, schedul, manag, program, problem, model, microgrid, consid, distribut, . . .	0.013	1.018	0.009	0.002	4.048	0.000 ***
59	model, predict, simul, forecast, data, develop, approach, valid, consumpt, paramet, . . .	0.019	0.250	0.004	0.002	2.519	0.012 **
62	effect, polici, rebound, direct, estim, indirect, increas, model, consumpt, subsidi, . . .	0.012	0.018	0.000	0.002	0.128	0.898
67	electr, consumpt, residenti, increas, generat, result, determin, major, decreas, reduc behavior, consum, adopt, . . .	0.011	0.102	0.001	0.001	1.346	0.179
69	energy-sav, prefer, environment, awar, polici, resid, attitud, . . .	0.013	0.282	0.003	0.002	1.699	0.089 *
71	emiss, carbon, dioxid, footprint, reduct, direct, mitig, low-carbon, indirect, account, . . .	0.012	0.100	0.001	0.002	0.695	0.487
74	self-consumpt, storag, photovolta, batteri, econom, profit, invest, increas, instal, residenti, . . .	0.015	0.922	0.010	0.003	3.690	0.000 ***
77	smart, meter, data, custom, grid, util, manag, inform, enabl, consumpt, . . .	0.011	0.341	0.003	0.002	1.942	0.052 *
78	occup, behaviour, behavior, consumpt, monitor, result, influenc, understand, impact, survey, . . .	0.010	0.023	0.000	0.001	0.161	0.872
85	profil, load, hour, data, time, consumpt, daili, resolut, individu, tempor, . . .	0.011	0.162	0.002	0.002	0.994	0.320
87	batteri, hybrid, wind, storag, load, system, size, kwh, turbin, result, . . .	0.011	0.109	0.001	0.002	0.588	0.557

Table 1. Cont.

Topics	Keywords	Mean	Inc.	Estimate	Std. Error	t-Value	Pr (> t) ¹
88	demand, peak, load, residenti, shift, reduc, side, potenti, reduct, time, ...	0.010	0.082	0.001	0.001	0.777	0.437
89	optim, minim, solut, object, algorithm, propos, function, consid, combin, obtain, ...	0.012	0.311	0.003	0.001	2.395	0.017 **
91	control, strategi, manag, oper, algorithm, hem, propos, reduc, intellig, develop, ...	0.010	0.321	0.003	0.001	1.959	0.050 **
92	temperatur, artificialintellig, condit, room, consumpt, thermostat, time, condition, set, oper, ...	0.010	0.216	0.002	0.001	1.451	0.147
94	price, tariff, consum, respons, market, increas, chang, custom, retail, tou, ...	0.010	0.263	0.002	0.002	1.585	0.113
96	factor, consumpt, characterist, variabl, influenc, size, regress, relationship, differ, signific, ...	0.017	0.040	0.001	0.002	0.418	0.676
97	thermal, heat, experiment, temperatur, numer, simul, test, effect, result, perform, ...	0.012	0.013	0.000	0.002	0.073	0.942

¹,* Significance level: 0.1, ** significance level: 0.05, *** significance level: 0.01. The reason why statistical values and keywords are displayed together is to comprehensively understand the meaning of the topic and each statistical value. Keywords corresponding to 100 topics are in Table A1 of Appendix A.

As shown in Table 2 below, topic 22 discusses analyzing power usage patterns, predicting loads, and detecting abnormalities through non-intrusive load monitoring (NILM). Topic 43 deals with identifying household power consumption patterns and analyzing household power consumption characteristics through clustering methods. Topic 49 deals with household energy demand management using smart charging of electric vehicles. Topic 58 is dominated by studies on energy management of household microgrid systems. Topic 59 deals with predicting energy consumption such as power and gas in residential buildings. Topic 74 discusses the economic and profitability analysis of the residential solar power generation system. Finally, Topic 89 deals with energy-efficient residential building design through optimization. Finally, Topic 91 deals with the home energy management system (HEMS).

Table 2. Relevant documents with Strong signal topics ¹.

Topics	Keywords	Authors (Year)	Titles
22	applianc, consumpt, load, propos, approach, monitor, data, algorithm, disaggreg, detect ...	Houidi et al. (2020)	Multivariate event detection methods for non-intrusive load monitoring in smart homes and residential buildings
		Rashid et al. (2019)	Can non-intrusive load monitoring be used for identifying an appliance's anomalous behaviour?
		Dinesh et al. (2017)	Non-intrusive load monitoring under residential solar power influx
29	network, iot, devic, data, node, applic, wireless, communic, propos, monitor, ...	Iqbal et al. (2018)	A generic internet of things architecture for controlling electrical energy consumption in smart homes
		Collotta and Pau (2015)	Bluetooth for Internet of Things: A fuzzy approach to improve power management in smart homes
		Geraldo Filho et al. (2019)	Energy-efficient smart home systems: Infrastructure and decision-making process

Table 2. Cont.

Topics	Keywords	Authors (Year)	Titles
43	data, consumpt, statist, pattern, cluster, sampl, analysi, group, collect, spatial, ...	Zhou et al. (2017)	Household monthly electricity consumption pattern mining: A fuzzy clustering-based model and a case study
		Filippín et al. (2013)	Evaluation of heating energy consumption patterns in the residential building sector using stepwise selection and multivariate analysis
		Mamchych and Wallin (2014)	Looking for Patterns in Residential Electricity Consumption
49	grid, storag, charg, distribut, batteri, generat, load, oper, vehicl, voltag, ...	Khemakhem et al. (2020)	A collaborative energy management among plug-in electric vehicle, smart homes and neighbors' interaction for residential power load profile smoothing
		Mesarić and Krajcar (2015)	Home demand side management integrated with electric vehicles and renewable energy sources
		Golshannavaz (2018)	Cooperation of electric vehicle and energy storage in reactive power compensation: An optimal home energy management system considering PV presence
58	propos, flexibl, schedul, manag, program, problem, model, microgrid, consid, distribut, ...	Zakariazadeh et al. (2014)	Smart microgrid energy and reserve scheduling with demand response using stochastic optimization
		Morsali et al. (2020)	A relaxed constrained decentralised demand side management system of a community-based residential microgrid with realistic appliance models
		Da Silva et al. (2020)	A preference-based demand response mechanism for energy management in a microgrid
59	model, predict, simul, forecast, data, develop, approach, valid, consumpt, paramet, ...	Liu et al. (2020)	A hybrid prediction model for residential electricity consumption using holt-winters and extreme learning machine
		Potočník et al. (2019)	A comparison of models for forecasting the residential natural gas demand of an urban area
		Dong et al. (2016)	A hybrid model approach for forecasting future residential electricity consumption
69	behavior, consum, adopt, energy-sav, prefer, environment, awar, polici, resid, attitud, ...	Spandagos et al. (2020)	"Triple Target" policy framework to influence household energy behavior: Satisfy, strengthen, include
		Zhang et al. (2018)	Impact factors of household energy-saving behavior: An empirical study of Shandong Province in China
		Zhang et al. (2020)	Willingness to pay a price premium for energy-saving appliances: Role of perceived value and energy efficiency labeling
74	self-consumpt, storag, photovolta, batteri, econom, profit, invest, increas, instal, residenti, ...	Ellabban and Alassi (2019)	Integrated Economic Adoption Model for residential grid-connected photovoltaic systems: An Australian case study
		Rodrigues et al. (2017)	Economic analysis of photovoltaic systems for the residential market under China's new regulation
		Cristea et al. (2020)	Economic assessment of grid-connected residential solar photovoltaic systems introduced under Romania's new regulation
77	smart, meter, data, custom, grid, util, manag, inform, enabl, consumpt, ...	Yildiz et al. (2017)	Recent advances in the analysis of residential electricity consumption and applications of smart meter data
		Zhou et al. (2017)	Discovering residential electricity consumption patterns through smart-meter data mining: A case study from China
		Oh et al. (2020)	Analysis methods for characterizing energy saving opportunities from home automation devices using smart meter data
89	optim, minim, solut, object, algorithm, propos, function, consid, combin, obtain, ...	Fesanghary et al. (2012)	Design of low-emission and energy-efficient residential buildings using a multi-objective optimization algorithm
		Sghiouri et al. (2018)	Shading devices optimization to enhance thermal comfort and energy performance of a residential building in Morocco
		Hamdy et al. (2011)	Applying a multi-objective optimization approach for Design of low-emission cost-effective dwellings

Table 2. Cont.

Topics	Keywords	Authors (Year)	Titles
91	control, strategi, manag, oper, algorithm, hem, propos, reduc, intellig, develop,	Kim et al. (2012)	Implementing home energy management system with UPnP and mobile applications
		Shakeri et al. (2018)	Implementation of a novel home energy management system (HEMS) architecture with solar photovoltaic system as supplementary source
		Shakeri et al. (2017)	An intelligent system architecture in home energy management systems (HEMS) for efficient demand response in smart grid

¹ Only relevant documents for topics with a *p*-value of 0.1 or less are presented.

Research topics in Topic 58 include proposing an energy scheduling method for microgrids considering the introduction of demand response programs [49], an energy management strategy for home microgrid systems [50], and a demand response (DR) optimization model based on real-time power prices for energy management of microgrids [51]. Microgrids are considered an alternative to the current centralized energy generation system since they can benefit from various aspects, such as the economy and environment [52]. In Topic 58, DR has been mentioned in that it can improve the systematic flexibility of microgrids. Zakariazadeh et al. [49] revealed that introducing a demand response program reduces the total operating cost of microgrids and enables more efficient use of energy resources. da Silva et al. [51] argued that the demand response optimization model presented through experiments could effectively minimize the energy consumption cost of microgrids and reduce environmental pollution.

Topic 58 also includes research on energy optimization and energy management of smart homes [53–57]. As the spread of ICT in the energy field has recently expanded, efforts for smart home research are being emphasized more.

The main research topics in Topic 74 include economic analysis of residential solar power generation systems [58–60] and evaluation of household self-consumption solar power generation systems profitability [61]. Ellabban and Alassi [58] cited the high initial costs of solar power systems as one of the major obstacles to the faster supply of solar power systems in the household sector. Therefore, Ellabban and Alassi [58] argued that it is crucial to determine whether an investment in household solar power generation systems is economically reasonable. Cristea et al. [60] noted that household solar power generation systems are economically feasible when subsidies are provided, especially for small systems with small energy production capabilities.

Topic 74 deals with household batteries in addition to research on household solar power generation systems. Primary research on household batteries includes the optimization of photovoltaic power generation to improve the profitability of residential batteries [62], evaluation of advantages of distributed household batteries [63], and improvement of the economic efficiency of household battery technology by combining them with energy storage applications [64].

Research topics in Topic 22 include identifying the operation schedule of home appliances using NILM [65], detecting a malfunction or abnormality in home appliances [66], detecting individual loads [67], identifying solar heat inflow in houses with household solar power generation facilities [68], and measuring the power consumption of home air conditioners and refrigerators [69]. NILM is a technology that predicts energy consumption by home appliances by analyzing the pattern of power supplied to the home [70,71]. It is possible to check whether home appliances are operating normally by monitoring of power consumption of various home appliances by using the technology. Gopinath and Kumar [72] revealed that NILM had become a popular and new approach to monitoring events and energy consumption of electronic devices in recent years. Dinesh et al. [68] used NILM to obtain reliable estimates of solar power generation for 400 households and used the analysis results over the past four days to predict the total load for the next day.

Among the topics selected for Strong signals, topics with *p*-values above 0.05 and below 0.1 are as follows. Topic 29 discusses energy consumption management of the smart

home. Topic 69 mainly focuses on research on household energy-saving behavior. Topic 77 discusses household energy consumption analysis using smart meter data.

4.2. Weak Signals

As shown in Table 3, 18 out of 100 topics were assigned to Weak signals, and in the second half of the 2010s, there was one topic that showed *p*-values that were the same or less than the significance level of 0.05. Topic 7 discusses coal energy consumption in households, as shown in Table 4 below.

Table 3. Topics selected as Weak signals.

Topics	Keywords	Mean	Inc.	Estimate	Std. Error	<i>t</i> -Value	Pr ($> t $) ¹
2	treatment, calv, feed, intak, restrict, period, fed, age, protein, libitum	0.004	0.177	0.001	0.001	0.490	0.624
7	pollut, coal, artificialintellig, emiss, sourc, combust, china, burn, control, industri	0.007	0.572	0.003	0.001	2.253	0.024 **
11	cool, roof, summer, winter, reduc, high, radiat, condit, season, load	0.009	0.005	0.000	0.001	0.039	0.969
17	oil, concentr, increas, extract, boiler, decreas, facil, instal, degrad, capac, ...	0.005	0.083	0.000	0.001	0.290	0.772
24	metabol, expenditur, cell, group, mice, oxygen, consumpt, stress, glucos, addit, ...	0.004	0.237	0.001	0.001	0.665	0.506
25	product, process, industri, manufactur, technolog, produc, develop, case, analysi, requir, ...	0.008	0.200	0.001	0.001	1.613	0.107
42	health, risk, increas, spend, effect, exposur, benefit, impact, need, chang, ...	0.006	0.236	0.001	0.001	0.947	0.344
44	cost, econom, lower, pressur, annual, capit, result, depend, show, motor, ...	0.007	0.021	0.000	0.001	0.195	0.846
46	wast, recycl, manag, recoveri, scenario, potenti, municip, generat, resourc, landfil, ...	0.006	0.322	0.002	0.001	1.225	0.221
48	materi, properti, consumpt, effect, good, moistur, high, amount, addit, composit, ...	0.006	0.015	0.000	0.001	0.076	0.939
55	construct, concret, structur, steel, frame, materi, composit, block, embodi, aggreg, ...	0.007	0.158	0.001	0.002	0.689	0.491
61	poverti, fuel, countri, vulner, access, inequ, women, poor, polici, bangladesh, ...	0.007	0.465	0.003	0.002	1.646	0.100 *
65	process, result, metal, machin, high, fabric, compar, consumpt, layer, properti, ...	0.007	0.260	0.002	0.002	0.936	0.349
72	design, architectur, integr, solut, select, altern, base, present, develop, concept, ...	0.009	0.008	0.000	0.001	0.109	0.913
73	thermal, comfort, hvac, indoor, condit, environ, improv, adapt, occup, maintain, ...	0.009	0.312	0.003	0.001	1.909	0.056 *

Table 3. Cont.

Topics	Keywords	Mean	Inc.	Estimate	Std. Error	t-Value	Pr (> t) ¹
81	rate, degree, differ, three, consumpt, total, help, limit, comparison, threshold, ...	0.005	0.298	0.001	0.001	1.800	0.072 *
86	home, famili, avail, consumpt, include, year, deliveri, test, need, high, ...	0.005	0.058	0.000	0.001	0.389	0.698
90	food, product, consumpt, footprint, chain, global, suppli, resourc, consum, transport, ...	0.007	0.139	0.001	0.002	0.581	0.561

¹ * Significance level: 0.1, ** significance level: 0.05. The reason why statistical values and keywords are displayed together is to comprehensively understand the meaning of the topic and each statistical value. Keywords corresponding to 100 topics are in Table A1 of Appendix A.

Table 4. Relevant documents with Weak signal topics ¹.

Topics	Keywords	Authors (Year)	Titles
7	pollut, coal, artificialintellig, emiss, sourc, combust, china, burn, control, industri, ...	Pyka and Wierchowski (2016)	Estimated mercury emissions from coal combustion in the household sector in Poland
		Peng et al. (2019)	Underreported coal in statistics: A survey-based solid fuel consumption and emission inventory for the rural residential sector in China
		Kerimray et al. (2017)	Coal use for residential heating: Patterns, health implications and lessons learned
61	poverti, fuel, countri, vulner, access, inequ, women, poor, polici, bangladesh, ...	Middlemiss and Gillard (2015)	Fuel poverty from the bottom-up: Characterising household energy vulnerability through the lived experience of the fuel poor
		Belaïd (2018)	Exposure and risk to fuel poverty in France: Examining the extent of the fuel precariousness and its salient determinants
		Karpinska and Śmiech (2020)	Invisible energy poverty? Analysing housing costs in Central and Eastern Europe
73	thermal, comfort, hvac, indoor, condit, environ, improv, adapt, occup, maintain, ...	Chai et al. (2020)	Using machine learning algorithms to predict occupants' thermal comfort in naturally ventilated residential buildings
		Attia and Carlucci (2015)	Impact of different thermal comfort models on zero energy residential buildings in hot climate
		Sghouri et al. (2018)	Shading devices optimization to enhance thermal comfort and energy performance of a residential building in Morocco
81	rate, degree, differ, three, consumpt, total, help, limit, comparison, threshold, ...	Fernandes et al. (2020)	The contribution of ventilation on the energy performance of small residential buildings in the Mediterranean region
		Guillén-Mena and Quesada (2019)	Assessment model of energy performance in housing of Cuenca, Ecuador
		Cozza et al. (2020)	Measuring the thermal energy performance gap of labelled residential buildings in Switzerland

¹ Only relevant documents for topics with a *p*-value of 0.1 or less are presented.

The main research topics in Topic 7 include estimating mercury emissions from coal combustion at home [73], the relationship between coal consumption and pollutant emissions in the rural housing sector [74], reviewing coal consumption patterns for residential heating [75], and analyzing the gap in household coal consumption in urban and rural areas [76]. Kerimray et al. [75] indicated that although residential coal consumption has declined significantly since 1990 in most developed and developing countries, there are countries still have a high proportion of coal-using households for heating purposes. In some cases, the trend of coal consumption is increasing. Kerimray et al. [75] also argued

that relatively low coal prices and high supply levels are important barriers to the transition to clean energy.

In addition to a study on coal energy consumption at home, Topic 7 deals with the effect of household energy consumption on air pollutant emissions [77,78]. Chen et al. [77] claimed that household power consumption for cooling increased with climate warming; in contrast, household fuel consumption for heating decreased, resulting in a net increase in CO₂ emissions and a net decrease in black carbon, polycyclic aromatic hydrocarbons, and particulate matter less than 2.5 µm (PM_{2.5}). With major developed countries announcing greenhouse gas reduction targets and raising the targets, topics on air pollutant emissions will continue to draw attention in the future.

In addition to a study on coal energy consumption in households and the effect of household energy consumption on air pollutant emissions, Topic 7 deals with the relationship between energy use in household and indoor air quality [79] and the effect of the type of heating fuel in rural houses on indoor air quality [80]. Zhang et al. [80] revealed that fuel combustion efficiency greatly affects the indoor air quality of rural houses.

Among the topics selected for Weak signals, topics with *p*-values above 0.05 and below 0.1 are as follows. Topic 61 has several studies on energy poverty. Topic 73 discusses the prediction and improvement of thermal comfort of residential buildings. Finally, Topic 81 deals with the evaluation of the energy performance of residential buildings.

The main topics in Topic 61 include identifying tasks to solve the energy vulnerability of the fuel poor household [81], investigating key characteristics of fuel poor households [82], proposing indicators and methods to estimate energy poverty [83–85], and identifying socio-economic determinants of household energy poverty [86]. Middlemiss and Gillard [81] indicated that tasks to solve energy vulnerabilities include quality of housing, energy cost and supply problems, stability of household income, lease relationships, social relationships inside and outside the home, and solving health problems. Lin and Wang [85] proposed that the target household group be different depending on power consumption and income level when implementing energy efficiency improvement policies to effectively deal with energy poverty. Sharma et al. [86] argued that energy poverty mainly depends on household consumption and expenditure, and an increase in housing size for low-income households increases electricity costs and energy poverty.

The main topics in Topic 73 include predicting the thermal comfort of residents in naturally ventilated residential buildings [87], the effect of various thermal comfort models on energy consumption and thermal comfort of zero-energy residential buildings [88], optimization of shading devices to improve the thermal comfort and energy performance of residential buildings [89], thermal comfort management of modern high-rise residential buildings [90], and the effect of air conditioning system upgrade on thermal comfort of low-income houses [91]. Mudge and Saman [91] indicated that energy consumption decreased by an average of 16% for houses with replaced cooling systems.

The main topics in Topic 81 include the impact of ventilation strategies on the energy performance of small residential buildings [92], the proposal of a household energy performance evaluation model [93], and the measurement of the thermal energy performance gap in residential buildings [94]. Cozza et al. [94] argued that a successful energy policy requires estimating the building's energy-saving potential. To estimate the building's energy-saving potential, Cozza et al. [94] measured the thermal energy performance gap, defined as the difference between the theoretical and actual energy consumption of residential buildings.

5. Discussion

5.1. Strong Signals

As shown in Figure 3 and Table 1, Topic 58 is the most notable among Strong signals, since the increasing rate is the highest, and topic proportion is also relatively high. Topic 58 had many studies on the energy management of microgrid systems. Microgrids can support generating and storing electricity by individuals, so it can be expected that research on the availability of energy storage systems will also become active. In addition, the movement

to participate in the use of smart grids is increasing not at the national level, but at the regional level. Virtual power plant (VPP) based on smart grid technology integrate and manage various distributed resources, thus research on VPP can be expected to become active in the future with microgrids.

Topic 74 has the second-highest increasing rate and occupies a relatively high topic proportion, and is mainly focused on the economic and profitability analysis of solar power generation systems for the household. Solar power generation for the household is increasing in that it can be used for various purposes and reduce costs. Accordingly, research on the economic and profitability analysis of solar power generation systems for the household is being actively conducted. In addition, the initial investment cost for facility installation, inconsistency between energy supply through solar power generation, and demand at household are obstacles to be resolved to spread the supply of household photovoltaic systems. Therefore, research on this issue is expected to be actively conducted in the future.

Topic 22 has a relatively high topic proportion and has many studies on NILM as a statistically significant topic. With the spread of IoT in the energy sector, there is an increasing demand for technology development that analyzes energy consumption history and patterns at home using NILM and efficiently manages energy by learning through AI technology. In line with this, research on NILM's technology improvement is being actively conducted. In the future, it can be expected that research on improving the accuracy of consumption history and pattern analysis and providing personalized services through NILM will be actively conducted.

In addition to NILM, Topic 22 also discussed extracting data on the individual power consumption of each home appliance through energy disaggregation [95–97]. As a similar study to this one, there is a study that analyzed the energy digitalization sector. Park et al. [98] analyzed academic papers from 2016 to 2018, and referred to disaggregation as segmentation of power use in the household sector. Interestingly, in the study by park et al. [98], disaggregation was found to belong to Weak signals. However, in this study, which uses relatively recent data, disaggregation was found to belong to Strong signals. Therefore, the topic of disaggregation is currently expanding from Weak signals to Strong signals.

Among the topics selected for the Strong signals, topics with p -values equal to or greater than 0.05 or less than 0.1 discussed the smart home energy consumption management (Topic 29), management of household energy demand by utilizing smart charging of electric vehicles (Topic 49), household energy-saving behavior (Topic 69), analysis of household energy consumption using smart meter data (Topic 77), and HEMS (Topic 91). In the future, the number of electric vehicles will increase, and the battery of electric vehicles will be regarded as an energy storage system. They will serve as an energy source for smart charging. Accordingly, research on the smart charging of electric vehicles is receiving significant attention. In addition, many studies are being conducted on energy-saving behavior in households, such as energy-efficient labels attached to home appliances, willingness to pay premium prices for energy-saving home appliances, and rebate programs for energy-efficient home appliances.

In summary, according to the deployment and utilization of renewable energy, energy management of microgrid systems, economic and profitability analysis of household solar power generation systems, and research on household batteries are attracting attention as Strong signals. In addition, with the spread of ICT in the energy sector, research on energy optimization of smart home is also being actively conducted. Finally, studies on energy measurement and prediction, such as NILM and energy disaggregation, were also selected as Strong Signals.

5.2. Weak Signals

As shown in Figure 3 and Table 3, topic 7 has the highest increasing rate among Weak signals. Topic 7 mainly focuses on research on coal energy consumption in households.

Coal energy-related issues are rapidly increasing as interest in coal demand management grows to transition to clean energy. Major developed countries are announcing energy transition policies aimed at achieving carbon neutrality. In addition, it can be expected that coal demand will decrease in the future due to modernization of houses such as changes in housing type and heating method, preference for clean fuel, and increase in national income. In the future, research on predicting the demand and supply of coal energy and support policies for replacement with clean fuels will draw attention.

Topic 61 also shows a high increasing rate compared to other topics. Topic 61 includes many studies on energy poverty. Despite social and economic development, some countries have difficulty accessing energy. Some households cannot afford to spend an appropriate level of energy cost, and efforts to reduce the number of energy-poor households continue. It can be predicted that research on new standards and indicators for the energy-poor as time changes and various energy welfare policies for the energy-poor will receive attention.

Topic 73 also shows a relatively high increasing rate. Topic 73 discusses the prediction and improvement of thermal comfort of residential buildings. Thermal comfort is a topic that is receiving much attention in energy research in the building sector. In the household energy sector, passive houses to improve thermal comfort can attract attention in the future. Passive houses using heat generated in buildings can reduce energy consumption and carbon dioxide emissions. Research on the performance enhancement of insulation and windows of passive houses, shading effects, and ventilation devices can be expected to draw attention in the future.

The last topic to look at in detail in Weak signals is Topic 81. Topic 81 deals with the evaluation of the energy performance of residential buildings. Major developed countries have established their standards to evaluate and certify the energy performance of buildings. Accurately grasping and evaluating the energy performance of residential buildings can lead to improvement in residential energy efficiency. In addition to interest in the transition to clean energy and remodeling old houses, the revision of household energy performance evaluation standards and the development of a household energy performance certification system are some of the research topics that can be noted in the future.

In summary, regarding Weak signals, discussions on the impact of coal energy consumption and household energy consumption on air pollutant emissions show relatively high increasing rates. Next, interest in the relationship between energy use in houses and indoor air quality also shows a high rate of increase. In addition, the issue of energy poverty is emerging, and discussions on predicting and improving the thermal comfort of residential buildings and evaluating energy performance were selected as Weak signals.

5.3. Comprehensive Discussion and Future Research

This study divided academic interest related to household energy consumption into Strong signals and Weak signals, and examined which topics are emerging. Herein, this study tries to understand the academic interest more comprehensively in household energy consumption by briefly reviewing the contents of Strong signals and Weak signals and comparing them with one another.

Figure 4 below shows the trend of increasing interest over time and related keywords to understand the two signals more intuitively. In Strong signals, topics related to energy technology innovation such as microgrids, smart home, solar power, and batteries are predominant. Although these keywords are closely related to policy, economy, and environmental issues rather than merely implying technological issues, distributed resources, as well as flexible and intelligent energy grid technologies are essentially at the center of the discussion. In other words, over the past 10 years, research topics related to household energy consumption have mainly focused on expanding the use of smart and clean energy technologies in the household sector and discussing whether the benefits provided by the technologies can be enjoyed.

Figure 4. Keywords and flow of Strong signals and Weak signals.

The Weak signals mainly include issues other than technological innovation, such as carbon neutrality, coal, air quality, and energy poverty. In the era of carbon neutrality, energy welfare issues for the low-income class, energy transitions for ordinary households, reduction of fossil fuel use, and air quality improvement issues are being emphasized. Recently, as awareness of the seriousness of the climate crisis has increased and each country's carbon neutrality policies have been promoted, it is considered that carbon neutrality-related issues are being actively discussed in the household energy sector. These changes highlight the growing awareness of the importance of policies and institutions that promote safe, clean, and affordable energy use beyond the challenges of increasing the adoption of clean energy technologies and increasing energy consumption efficiency in the household sector.

Through the results of this study, it is possible to grasp the current trend and understand the recent changes. However, it is not easy to determine which changes will continue in the future. Even if it can be assumed that the current trend continues, it remains an assumption. In order to more validly judge the change of future academic interest, additional analysis of the dynamics of future signs is required. Over time, some signals may be changed to other signals [98]. For example, in this study, energy disaggregation has belonged to Strong signals, but in past studies similar to this study, it had belonged to Weak signals. Existing studies that have explored future signals through text mining techniques have emphasized the need to explore the change of signals over time [46,99,100]. Park et al. [98] argued that it is necessary to examine when Weak signals change to Strong signals, and explore how long the Strong signals will remain as such in future signals. Since this study did not analyze the process of changing from Weak signals to Strong signals separately, it is necessary to explore the timing and process of future signs changing.

In addition, AI technology used to predict, optimize, and detect anomalies in the energy sector did not belong to both of Strong signals and Weak signals. However, it is noteworthy that it is a meaningful study when combined with the topics analyzed through this study. For example, NILM and energy disaggregation, which belong to Strong signals and are currently actively researched, can improve prediction accuracy through the learning of AI. Research on predicting the thermal comfort of residential buildings belonging to Weak signals can also be seen as a research topic that can attract more attention in the future with the spread of AI technology. Currently, research is being conducted on improving thermal comfort by maintaining the comfort temperature of the building through real-time control and minimizing the energy load of the air conditioning system through detection of residents' activities by using AI technology [101,102].

6. Conclusions

Through this study, changes in academic issues related to household energy consumption were statistically reviewed. In particular, this study reviewed which topics were the most interested and which were still less interested but could receive attention in the future.

As a result of the topic analysis, Strong signals included microgrid system and smart home due to energy digitalization, such as the spread of IoT, solar power generation systems, and batteries for the household. In addition, topics related to energy measurement and prediction, such as NILM and energy disaggregation, were selected. These topics are mainly related to digitalization and the spread of renewable energy supply, which are currently being actively studied.

In Weak signals, results that interestingly reflect the current situation aimed at carbon neutrality were found. Discussions on coal energy consumption and air pollutant emissions in the household energy consumption sector were also selected as research topics that could draw attention in the future, as the transition policies to clean energy such as policies to reduce fossil energy consumption are being widely promoted. In addition, discussions on energy poverty and performance evaluation, which have not previously received much attention, are rising to the surface as they expand to the house energy consumption sector.

In short, topics related to energy technology innovation appeared as major issues in Strong signals. In the past decade, studies related to household energy consumption have mainly discussed the benefits of these technologies along with the spread of smart and clean renewable energy technologies in the household sector. On the other hand, as a result of reviewing Weak signals, it was found that issues related to the promotion of carbon-neutral policies, energy welfare, and quality of life are emerging as major interests beyond technical issues. A comprehensive review by Strong signals and Weak signals confirmed that improving energy efficiency in the household sector through technological innovation and awareness and the importance of energy consumption policies and systems that can achieve carbon neutrality are emphasized.

Through the results of this study, researchers need to pay attention to studies belonging to Weak signals that are still less involved but can attract attention in the future. In particular, attention needs to be paid to predicting coal energy demand and supply, air pollutants from household energy consumption, new standards and indicators for the energy poor, and energy consumption savings through passive houses.

Researchers need to pay attention to policies to reduce coal energy consumption, including support policies for clean fuels, referring to the fact that coal consumption at households belongs to Weak signals. It should also be considered that discussions on energy welfare policies for the energy poor are likely to expand in the future. In addition, it is necessary to make efforts on institutionalization such as revising household energy performance evaluation standards and developing a household energy performance certification system about household energy performance evaluation.

The areas requiring further research are as follows. First, in this study, the median of the average topic proportion, which is the basis for classifying signals, was used as the dividing line of the x-axis, and the median value depends on the number of samples. Further research is needed to determine the number of topics and dividing lines more objectively and convincingly. Second, the current trend was identified through this study, and the recent changes could be understood. However, to predict what changes will continue in the future and clearly understand changes in future academic interests, it is required to explore the timing and process of future signs changing. Finally, it is necessary to expand research combined with AI in the household energy consumption sector. It should be noted that AI technology did not belong to both Strong signals and Weak signals but is currently being used in various energy research. Along with the spread of AI technology, research topics belonging to Weak Signals, such as research on predicting the thermal comfort of residential buildings, can attract more attention in the future. In addition, NILM and energy disaggregation, which belong to Strong Signals, are

expected to be studied in the future. It is possible to improve prediction accuracy through the learning of AI.

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Appendix A

Table A1 contains keywords of 100 topics, including Strong signals and Weak signals.

Table A1. Topics and keywords.

Topics	Keywords
1	effici, improv, consumpt, reduc, increas, import, label, order, standard, focus, ...
2	treatment, calv, feed, intak, restrict, period, fed, age, protein, libitum, ...
3	pcm, storag, phase, temperatur, refriger, condens, chang, perform, evapor, consumpt, ...
4	residenti, build, technolog, develop, review, polici, energi, applic, current, code, ...
5	weight, driven, feed, transmiss, diet, product, administr, anim, increas, consumpt, ...
6	vehicl, transport, travel, charg, car, mobil, public, station, infrastructur, mode, ...
7	pollut, coal, artificialintellig, emiss, sourc, combust, china, burn, control, industri, ...
8	system, integr, propos, convent, base, compar, perform, hybrid, result, feasibl, ...
9	polici, tax, impact, model, economi, subsidi, target, trade, govern, general, ...
10	project, green, compani, base, various, oper, scope, uae, ship, mine, ...
11	cool, roof, summer, winter, reduc, high, radiat, condit, season, load, ...
12	build, renov, zero, achiev, refurbish, target, nzeb, near, implement, strategi, ...
13	emiss, greenhous, fuel, ghg, reduct, fossil, gas, consumpt, increas, transport, ...
14	region, develop, consumpt, countri, differ, central, nation, area, resourc, northern, ...
15	light, led, replac, illumin, lamp, adopt, differ, technolog, energy-effici, bulb, ...
16	invest, financi, barrier, incent, owner, homeown, polici, benefit, market, measur, ...
17	oil, concentr, increas, extract, boiler, decreas, facil, instal, degrad, capac, ...
18	food, consum, dietari, nutrient, consumpt, nutrit, meal, children, group, adult, ...
19	climat, chang, increas, zone, weather, futur, impact, condit, warm, global, ...
20	water, hot, heater, domest, consumpt, suppli, rainwat, total, resourc, integr, ...
21	activ, peopl, live, age, associ, time, pattern, higher, popul, generat, ...
22	applianc, consumpt, load, propos, approach, monitor, data, algorithm, disaggreg, detect ...
23	heat, pump, sourc, perform, ground, artificialintellig, recoveri, result, instal, gshp, ...
24	metabol, expenditur, cell, group, mice, oxygen, consumpt, stress, glucos, addit, ...
25	product, process, industri, manufactur, technolog, produc, develop, case, analysi, requir, ...
26	consumpt, china, intens, structur, increas, chang, urban, rural, residenti, popul, ...
27	rural, low, servic, improv, hospit, program, institut, initi, medic, older, ...
28	urban, citi, area, densiti, spatial, neighborhood, land, local, plan, residenti, ...
29	network, iot, devic, data, node, applic, wireless, communic, propos, monitor, ...
30	environment, impact, life, cycl, assess, result, lca, phase, stage, analysi, ...
31	oper, unit, thermal, plant, primari, cogener, combin, chp, storag, residenti, ...
32	food, school, veget, children, consumpt, fruit, eat, snack, parent, adolesc, ...
33	practic, social, consumpt, way, context, live, relat, societi, aspect, cultur, ...
34	window, shade, orient, glaze, perform, daylight, facad, consumpt, simul, differ, ...
35	renew, sourc, generat, technolog, resourc, suppli, potenti, wind, fossil, possibl, ...
36	ventil, indoor, artificialintellig, humid, qualiti, natur, outdoor, mechan, concentr, fan, ...

Table A1. Cont.

Topics	Keywords
37	technolog, chang, polici, challeng, review, identifi, focus, transit, framework, explor, ...
38	build, residenti, consumpt, type, apart, total, offic, commerci, locat, larg, ...
39	run, line, week, mass, bodi, increas, physic, activ, wheel, durat, ...
40	associ, dietari, ssb, age, drink, risk, consumpt, obes, women, year, ...
41	user, manag, base, propos, time, end, autom, present, applic, environ, ...
42	health, risk, increas, spend, effect, exposur, benefit, impact, need, chang, ...
43	data, consumpt, statist, pattern, cluster, sampl, analysi, group, collect, spatial, ...
44	cost, econom, lower, pressur, annual, capit, result, depend, show, motor, ...
45	sustain, develop, communiti, local, access, resourc, toward, suppli, framework, achiev, ...
46	wast, recycl, manag, recoveri, scenario, potenti, municip, generat, resourc, landfil, ...
47	hous, passiv, new, consumpt, singl, detach, single-famili, famili, monitor, standard, ...
48	materi, properti, consumpt, effect, good, moistur, high, amount, addit, composit, ...
49	grid, storag, charg, distribut, batteri, generat, load, oper, vehicl, voltag, ...
50	cold, winter, china, rural, heat, mode, area, indoor, resid, summer, ...
51	consumpt, growth, elast, econom, panel, estim, countri, incom, residenti, relationship, ...
52	usa, annual, estim, averag, year, util, state, consumpt, residenti, kwh, ...
53	household, incom, expenditur, level, consumpt, survey, suggest, increas, higher, educ, ...
54	perform, evalu, tool, assess, methodolog, analysi, differ, case, result, simul, ...
55	construct, concret, structur, steel, frame, materi, composit, block, embodi, aggreg, ...
56	feedback, inform, consumpt, household, effect, particip, intervent, group, chang, reduc, ...
57	retrofit, stock, measur, canadian, canada, saudi, reduc, approach, feasibl, payback, ...
58	propos, flexibl, schedul, manag, program, problem, model, microgrid, consid, distribut, ...
59	model, predict, simul, forecast, data, develop, approach, valid, consumpt, paramet, ...
60	fuel, cell, hydrogen, effici, membran, exergi, cycl, applic, high, perform, ...
61	poverti, fuel, countri, vulner, access, inequ, women, poor, polici, bangladesh, ...
62	effect, polici, rebound, direct, estim, indirect, increas, model, consumpt, subsidi, ...
63	tank, hot, dhw, storag, water, collector, temperatur, thermal, flow, domest, ...
64	ecolog, tree, speci, greater, forag, rang, cattl, anim, valu, time, ...
65	process, result, metal, machin, high, fabric, compar, consumpt, layer, properti, ...
66	rural, fuel, cook, stove, firewood, lpg, consumpt, fuelwood, villag, area, ...
67	electr, consumpt, residenti, increas, generat, result, determin, major, decreas, reduc, ...
68	bioga, agricultur, farm, product, crop, plant, digest, wastewat, treatment, irrig, ...
69	behavior, consum, adopt, energy-sav, prefer, environment, awar, polici, resid, attitud, ...
70	articl, european, present, europ, match, spain, union, facil, competit, sever, ...
71	emiss, carbon, dioxid, footprint, reduct, direct, mitig, low-carbon, indirect, account, ...
72	design, architectur, integr, solut, select, altern, base, present, develop, concept, ...
73	thermal, comfort, hvac, indoor, condit, environ, improv, adapt, occup, maintain, ...
74	self-consumpt, storag, photovolta, batteri, econom, profit, invest, increas, instal, residenti, ...
75	gas, natur, consumpt, turkey, import, possibl, residenti, industri, suppli, high, ...
76	dwell, regul, construct, standard, stock, typolog, requir, built, consumpt, kwhm, ...
77	smart, meter, data, custom, grid, util, manag, inform, enabl, consumpt, ...
78	occup, behaviour, behavior, consumpt, monitor, result, influenc, understand, impact, survey, ...
79	heat, space, district, domest, suppli, scenario, network, central, floor, distribut, ...
80	save, potenti, conserv, reduct, achiev, consumpt, strategi, program, result, resid, ...
81	rate, degre, differ, three, consumpt, total, help, limit, comparison, threshold, ...
82	power, generat, suppli, plant, loss, consum, increas, small, new, amount, ...
83	insul, wall, envelop, thermal, extern, thick, heat, high, differ, simul, ...
84	method, measur, calcul, estim, consumpt, base, actual, differ, valu, compar, ...
85	profil, load, hour, data, time, consumpt, daili, resolut, individu, tempor, ...
86	home, famili, avail, consumpt, include, year, deliveri, test, need, high, ...
87	batteri, hybrid, wind, storag, load, system, size, kwh, turbin, result, ...
88	demand, peak, load, residenti, shift, reduc, side, potenti, reduct, time, ...
89	optim, minim, solut, object, algorithm, propos, function, consid, combin, obtain, ...
90	food, product, consumpt, footprint, chain, global, suppli, resourc, consum, transport, ...
91	control, strategi, manag, oper, algorithm, hem, propos, reduc, intellig, develop, ...
92	temperatur, artificialintellig, condit, room, consumpt, thermostat, time, condition, set, oper, ...

Table A1. Cont.

Topics	Keywords
93	biomass, wood, forest, product, fuel, consumpt, countri, avail, bioenergi, biofuel, ...
94	price, tariff, consum, respons, market, increas, chang, custom, retail, tou, ...
95	solar, panel, photovolta, instal, thermal, radiat, collector, period, locat, year, ...
96	factor, consumpt, characterist, variabl, influenc, size, regress, relationship, differ, signific, ...
97	thermal, heat, experiment, temperatur, numer, simul, test, effect, result, perform, ...
98	refriger, experiment, consumpt, perform, expans, cycl, test, wash, evapor, flow, ...
99	sector, countri, residenti, scenario, world, total, final, global, commerci, industri, ...
100	ssbs, consumpt, associ, consum, contribut, food, group, tax, Beverag, survey, ...

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