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Global, regional, and local acceptance of solar power

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ABSTRACT

This study aims to analyse solar power acceptance by different methods in various knowledge domains to gain a holistic view of global, regional, and local acceptance. This includes considering different related aspects of solar energy, including the overall concept, solar panel, the device converting sunlight into electricity, and photovoltaics, the technology. This multidisciplinary approach is possible through the advancement of artificial intelligence technology. Technology acceptance and sentiment, the emotion, are different concepts with slightly different influences on technology deployment. Acceptance can be granted as a social license and can be affected by how the media discusses the technologies. The acceptance further influences investment decisions and wider technology adoption. Sentiment can be obtained by machine or human-made analysis, in which the polarity (positive, negative, or neutral) is defined while the acceptance levels are indicative. This study applies opinion mining, chat generative pre-trained transformer, and generalised aggregated lexical tables methods to analyse the acceptance and sentiment of solar power at different levels. The findings and the original contribution involve highlighting the potential of artificial intelligence to study general acceptance. Artificial intelligence appears capable of providing a fast indication of both media sentiment and the level of acceptance of solar power. Traditional opinion mining seems to be more capable of acknowledging trends. This supports understanding the market environment and factors affecting technology development and deployment. Decision-making can benefit from a fast indication.

1. Introduction

In industrial product development and market deployment contexts, the energy industry product development can take a long time while requiring significant investments, making investors and companies keen to understand the market environment and factors affecting technology development and deployment [1]. Different factors affect the commercialisation of technologies, including regulatory (complexity of policies, or lack of them), market (market uncertainty), business model (unclear profit logic), economic (high investments needed), financing (inadequate funding), and technical barriers [2]. Environmental concerns and environmental regulations also play a role in energy technology commercialisation [3]. Also, emission trading schemes may affect certain technologies [4]. In addition, general acceptance by the public can significantly affect energy technology market deployment potentially via political decision-making and legal and regulatory frameworks [5]. The acceptance by the public has significance as the opposition may cause costly delays in energy technology deployment [6]. Hence, general acceptance by the public can affect the viability of the technology and the technology development and market deployment.

The type of approach adopted in this study implies more techno-economic context than a purely social science-based view with causal acceptance models. The discussion between sciences is still ongoing on the methods and results from data analysis. For example, AI-based technology frameworks utilising fuzzy neural networks [7], relate to the more traditional field of acceptance studies. The current view is that AI-based methods are complementary rather than replacing traditional, accepted causal models from social sciences [8]. However, the consensus seems to be that they may give fast indicative directions for managerial decisions. This is manifested via positioning technology acceptance fast on different analysis levels and stakeholder groups.

Manifold examples of the significance of public acceptance of technology exist, including the skepticism linked to waste-to-energy plants

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Abbreviations

AI	artificial intelligence
CA-GALT	generalised aggregated lexical tables
ChatGPT	chat generative pre-trained transformer
PV	photovoltaics

in terms of environmental and health risks [9], geological storage of carbon dioxide and carbon capture and storage technologies due to the fear of leakages [10], nuclear power due to safety concerns [11], wind power due to concerns over aesthetics [12], or offshore plants affecting marine ecosystems [13], or noise and risk to animals [14]. Similarly, the public acceptance of nanotechnologies is affected by the perceived risks of developing diseases, allergies, and technology creating pollution and waste [15]. The public acceptance of gene technologies is affected by concerns over their impact on health [16]. Also, the future success of hydrogen energy technology is one example of the potential impact of public acceptance [17]. These examples highlight the potential of having effective means to understand the level of general acceptance of technologies and further underline the potential benefits of understanding the possible impact on decision-making and the benefit of any measures to influence the acceptance levels.

The public acceptance of energy technologies has been studied using machine learning and opinion-mining for carbon capture and storage [4,18,19]; biomass power [20]; solar power [21,22]; wind power [23–25]; coal power [26]; and nuclear power [27,28]. Studies also exist for renewable energy and energy production in general [5,29], and social network analyses [30]. Various other acceptance studies that employ a variety of other means do exist, including error-prone and limited manual text analysis.

The energy innovation system entails complexity as public acceptance, energy cost, capacity, and collaborations all play a role aside from any technological complexity [31]. The attitudes and opinions of the public seem to count in renewable energy development and investments [32]. The acceptance is seen to impact any energy policy implementations [33]. Acceptance has also been linked to cooperation mechanisms that relate to solar power [34] and is found to affect the willingness to pay [35]. Hence, understanding the community benefits is seen to increase the acceptance of solar power [36]. Therefore, it is evident that acceptance has significance for solar power technologies from various perspectives.

This study focuses on the general acceptance of solar power by applying three methodologies. These include previously studied opinion mining, generalised aggregated lexical tables (CA-GALT) analysis, and a new artificial intelligence tool, namely chat generative pre-trained transformer (ChatGPT) to assess its applicability for such an analysis. Understanding how solar power acceptance appears at global, regional, and local levels is sought. The findings are compared to those gained by analysing the media sentiment in both editorial and social media by using a proven methodology for media monitoring. Additionally, this study aims to classify solar power status on the stairs of acceptance concept [37], in which the stair height relates to the resistance towards implementation, implying negative acceptance and communication needs.

The novel contribution of this study involves applying opinion mining, ChatGPT, and CA-GALT methods to analyse the acceptance and sentiment of solar energy at the global and regional levels. This involves focusing on different related aspects of solar energy. Specifically, the application of ChatGPT to study the general acceptance of solar power technology provides a novel contribution, showing potential for providing a fast indication of both media sentiment, and the level of acceptance. This can be complementary to traditional opinion mining and media monitoring that can better acknowledge trends. CA-GALT analysis provides additional value by providing a means to point to data points requiring further attention. The contribution also involves indicating positive acceptance of solar power at different levels, excluding any temporary regional country or product/project level fluctuations in acceptance. The understanding of acceptance-related chains of reasoning is enhanced in the solar power context.

2. Levels of acceptance, global, regional, and local

Global, regional, and local technology acceptance are interconnected and refer to the levels of technology adoption and integration. Global acceptance relates to the widespread adoption, whilst regional and local levels refine and adapt technologies to fit specific cultural, economic, and contextual needs. The levels influence each other in a complex way that is not fully understood. Understanding acceptance at different levels and the related various factors are of value.

Global acceptance and technology are interconnected via technology serving as a unifying force on a global scale, widespread adoption and advancements drive global acceptance by breaking down barriers of distance and fostering connectivity among diverse populations. The model of technological diffusion allows viewing the advancement of technology across the globe through the stages of innovators, early adopters, early majority, late majority, and laggards [38]. The acceptance and integration of technology globally can be seen to depend on these stages of diffusion, influenced by factors like cultural norms, economic capacity, and technological literacy. Global acceptance of energy technologies is linked to issues such as global climate negotiations [21] and the resulting agreements, public opinion, which is traditionally measured via questionnaires [39], technology reputation [40], political acceptance [5], and stakeholder acceptance [41].

Regional Acceptance is connected, in addition to regional policies, to technological infrastructure and it plays a pivotal role in regional development. Regions with robust technological infrastructure tend to attract investments, businesses, and skilled labour, contributing to their acceptance and growth within their respective geographical boundaries. Modernization theory [42] posits that regions with advanced technological infrastructure tend to progress more rapidly, enabling them to meet the needs of their inhabitants effectively. The level of technological infrastructure in a region influences its acceptance by residents and neighbouring areas. Regional acceptance of energy technologies links to country-level acceptance [43], country-level reputation [40], country-level political acceptance [41], regulations [3,44], subsidies [45], and stakeholder acceptance [41].

Local acceptance and technology are interlinked, the most known phenomenon being the not in my back yard effect [46]. The infrastructure connection includes community engagement, while successful implementation of technology infrastructure at the local level hinges on community involvement, considering the specific needs, preferences, and capacities of the local population. The technology acceptance model [47] focuses on perceived ease of use and perceived usefulness as critical factors in determining the acceptance and adoption of technology. When applied to local contexts, it becomes essential to tailor technological infrastructure to match the community's technological readiness and perceived benefits. Studies such as applying a methodology based on an analytic hierarchy process have been used to assess potential locations of solar power projects in Colombia, including technical-economic, social, and environmental risk criteria [48]. Recent studies introduce a stage model, which assumes adoption as a process of transition along three stages: no interest, under consideration, and installation [49]. Local acceptance of energy technologies links to local public acceptance [21,22], local project implementation [50], site-related issues [51], local political acceptance, and stakeholder acceptance [41].

The acceptance of technologies, in general, is affected by numerous factors, including knowledge, perceived risk, awareness, trust, policy, social influence, self-efficacy, demographics, and perceived usefulness. Knowledge refers to the experience with the technology and the possession of related information [45]. Perceived risk refers to risks perceived to link to safety or their probability [17]. Awareness relates to the related understanding or awareness of consequences and problems related to the technology [45]. Trust relates to the confidence in actors responsible for the technology [52]. The policy relates to regulations guiding decisions [44]. Social influence links to the individual beliefs of others and the weight of their importance [45]. Self-efficacy relates to the beliefs about the ability to use technology [52]. Demographics relate to variables such as age, gender, and education [53]. Perceived usefulness refers to the applicability of the technology for the intended use [54]. An understanding of these factors and any other additional ones that potentially affect technology acceptance is necessary for analysing the technology acceptance and assessing the related impact [55]. This as technology can have a reputation, similarly as a company may have a reputation or image among the public. Reputation and image are related but have a difference in perspective. Reputation refers to the "stories" that are being told about something [40], about solar power, for example, or a company, or a product. The collective perception of this something is based on past experiences [56]. Reputation is built over past behaviour, values, and performance and relates to trust and credibility [57]. The image relates to external appearance and communication [58]. Image is shaped by external aspects, such as media coverage [59], opinion by the public, and even social media [60]. The reputation and image link to the buyer's perspective toward company technology [61]. Hence, technology reputation is linked to acceptance and media sentiment, yet the mechanisms may not necessarily be clear.

Fig. 1 illustrates the levels of acceptance and provides a hypothesis of the chain from acceptance to market deployment in extreme cases, with large positive and large negative reputations and good and poor acceptance. The basis for the hypothesis grounds on the theoretical lens, whilst global, regional, and local technology acceptance present different interlinked scopes at which communities and societies adopt and integrate technology.

The levels of acceptance combine features from global technology acceptance, manifested via global agreements, and regional level, manifested via country-level policies and subsidies, while the local project implementation level includes issues related to stakeholder acceptance when implementing a project. The link between reputation, acceptance, and sentiment is not so straightforward. Generally, it can be said that even things with good reputations are not necessarily accepted by some stakeholder groups, while acceptance requires the granting of a "social license".

2.1. Stairs of acceptance

The stairs of acceptance concept [37] implies that technology-supported communication and other actions should start from the global level when advancing toward project implementation. This is as the resistance increases towards the implementation phase. The more accepted technology, the less need for communication efforts. The lower the individual steps are by height, the easier the implementation is. The stair height increases for the party implementing a project if the acceptance is low. This increase takes place in each stage while moving towards project implementation, which further adds to the possible local resistance issues (Fig. 2). The main assumption is that solar power is accepted at all levels (global, regional, and local) and that the steps are low.

The stairs of acceptance concept relate to global-level issues such as global public opinion, which can be currently measured via questionnaires [39] to form the basis for the first stair height at the beginning of an energy technology deployment project. If the global perception is highly negative or positive, it can impact the following steps in project implementation. At the country level, local policies and regulations can either speed up or slow down the technology implementation, thus affecting the stair height [37]. Countries such as Germany can be used as an example of country-level policy and regulation implementation effect. German parliament backed support policies for renewables-sourced electricity against often reluctantly approached nuclear and coal interests [62]. This can be seen to have expedited the renewable power deployment and lowered the country-level stair height. Also, the nuclear policy differences in Finland (positive) and Sweden (negative) are an additional example of regional country-level differences, where neighbouring countries have measurably different public sentiments, manifested via the implementation of local nuclear projects [63]. At the local

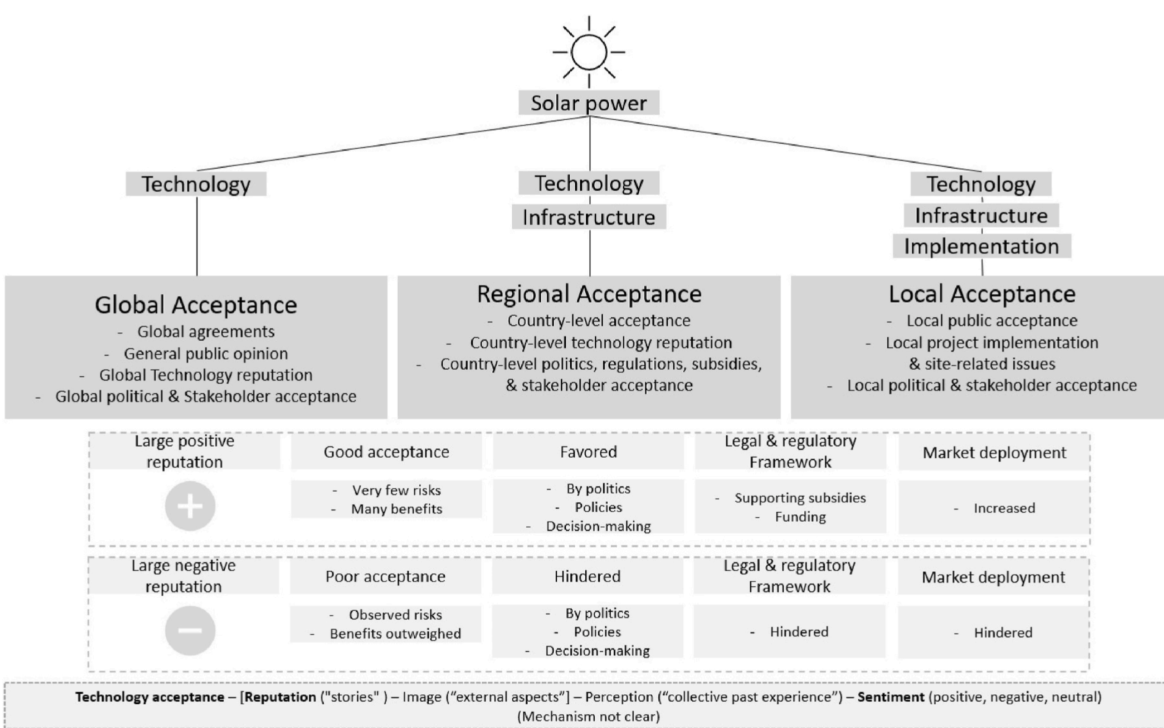

Fig. 1. Levels of acceptance and hypothesis of the chain from acceptance to market deployment.

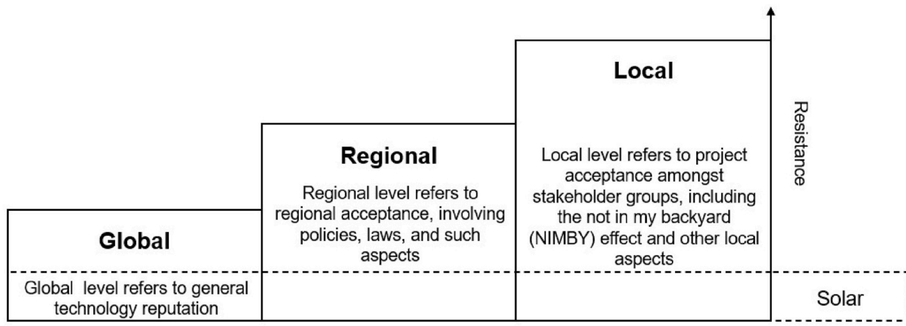

Fig. 2. Stairs of acceptance: From global level to project delivery (reproduced from Ref. [37] under the creative commons attribution license).

project implementation level, the most known concept describing local resistance is the not in my backyard yard effect [64], however, used just as an example of stakeholder issues at a local project level.

Both the hypothesis illustrated in Fig. 1 and the stairs of acceptance concept [37] in Fig. 2 still have a limited connection to existing more sociological theoretical frameworks such as the eight applied principles for the practice of energy [65]. Features presented by Ref. [65], include availability, affordability, due process, transparency and accountability, sustainability, intra-, and intergenerational equity, and responsibility, which are in this case more applicable to global-level system thinking. However, these features can be present in all analysis levels from global public opinion to country-level regulations and actual project implementation.

3. Methods and their application

The research approach combines different methods for different knowledge domains to gain a holistic, but reliable view of solar power acceptance. The measurement is generally challenging because methods such as opinion mining [66] measure acceptance only very indicatively with several error possibilities. To gain further methodological rigour, ChatGPT [67] was added to the palette. These types of studies are needed as they can complement purely social science-based views with causal acceptance models [8] and can provide a techno-economic context. The indicative nature of the findings signifies increased probability, whereas not all aspects are directly comparable to social science-based studies. Table 1 presents the main methods applied in the different levels of the study.

While opinion mining [66] and CA-GALTanalysis [71,72] are well-known and tested methods, this study is believed to be the first one applying ChatGPT [67] to study the general acceptance of solar power technology. The ability of ChatGPT to mine public opinion by mining sentiments in the text is tested. This relates to the natural language processing capabilities. Similarly, the ability to assess acceptance is tested. Fig. 3 illustrates the research process and methodology when combining ChatGPT with existing research frameworks. The following sections describe the details of the used methodologies. Different queries are used to visualise the differences and the main reasonings used by ChatGPT.

3.1. ChatGPT

An artificial intelligence chatbot developed by OpenAI, namely ChatGPT [67] has emerged as a significant new AI-based tool and is applied in this study to assess its applicability for analysing technology acceptance. Understanding is sought on how solar power acceptance appears at global, regional, and local levels when ChatGPT is applied for the analysis. The aim of understanding the applicability of the technology for research purposes is supported by earlier research calling for responsible and ethically sound means to use the technology to support professional work [73]. The potential of ChatGPT has been seen to include data analysis [70], which is exactly what is attempted in this research, to use ChatGPT to aid in analysing a vast amount of data. It is true, that AI has the potential to be used fraudulently to generate entire pieces of work [74], but this is not the intention. Instead, the intention is to experiment and find possibilities to embrace the opportunities [75]. It has been found that ChatGPT has not been capable of statistical analyses just yet, and it does advise about its limitations only if expressively requested [76]. Nevertheless, its demonstrated abilities in natural language processing [68,69] make it a potential candidate to be tested to analyse general acceptance. AI tools are stated to have the potential to provide meaningful insights and sentiment from large volumes of text [77]. ChatGPT may still have its deficiencies in reasoning [78], but it does not mean that it would be completely unusable. In fact [79], have seen the potential of ChatGPT for sentiment analysis, which can be applied to acceptance studies. Still, practical examples do not seem to exist for public acceptance or general acceptance. Only one clear example of using ChatGPT for sentiment analysis purposes can be found [80], but even this one does not directly link to studying acceptance.

The data ChatGPT has access to relies on a large corpus of data in text form and is based on a variety of sources, including news articles available through news outlets, books, academic papers, journals from various fields, online encyclopaedias, and web pages to generate the responses. The data includes billions of words, but the access is limited

Table 1
The main methods applied in the study.

Method	Short definition	Applied to	Measurement level
ChatGPT	Chat generative pre-trained transformer (ChatGPT) is an artificial intelligence tool that has demonstrated abilities in natural language processing [68,69] and potential for data analysis [70]. Previous experience of its use in assessing acceptance and sentiment is limited.	Acceptance, and sentiment indication; support for clarifying logic	Global, regional, and local
CA-GALT **analysis**	Correspondence analysis on generalised aggregated lexical tables (CA-GALT) is a statistical technique that extends traditional correspondence analysis to handle generalised aggregated lexical data, therefore providing a powerful tool for examining and visualising complex relationships within textual datasets [71,72].	Country clustering	Regional level
Opinion mining	Opinion mining is a natural language processing-based method to measure document sentiment, usually indicated as positive, negative, or neutral. The document sentiment is obtained by mathematical calculation of local document sentiments. Opinion mining can be used to gain an indication of acceptance [66].	Sentiment analysis	Regional level

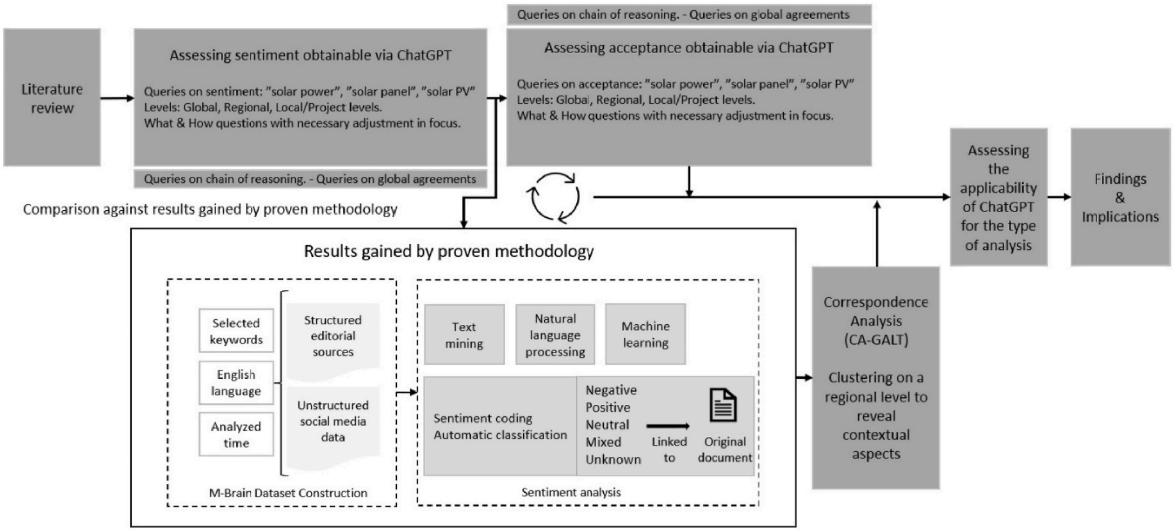

Fig. 3. Research process and methodology.

depending on the query and scope of the request. The data is pre-processed and used to train the machine learning model by ChatGPT so that the AI engine can understand the language and provide responses. The sources used may vary depending on the nature of the query. The version used to test the applicability of the technology for such analysis is GPT-4, March 14, 2023. No plugins or advanced data analytics options are applied. The accessible data had a cut-off point in the year 2021, which is a limitation. However, the limited access is not critical in this study as ChatGPT is utilised indicatively and the immediate output must always be critically considered.

3.2. Opinion mining via media monitoring

One set of results is gained by analysing the media sentiment [81] in both editorial and social media by using a proven methodology for media monitoring. This large dataset opinion mining entails machine learning-based media analysis by using a commercial tool intended for professional media monitoring. The analysis results in media sentiment gained via a systematic analysis of bafflingly wide data pioneered by Nuortimo [63,82]. This methodology is an AI-based method that intends to apply validated box methodology, where the challenge is not being able to analyse the algorithms protected by corporations, and not being able to have full visibility over the code itself. Still, it is possible to focus on the inputs and outputs, the main principles of the method, further compare the results and carry out manual validation [83]. Hence, the box becomes more validated, and one gains an understanding of what can be reached with the used algorithms. Further result validity can be gained by using a second software as a comparison. The analysis remains consistent as the logic of software-based analysis remains the same. The analysis can reach better consistency than human-based analysis, which is more prone to individual errors when the data series is large, involving hundreds of thousands or millions of data points. The analysed media sources include a global feed with over three million social media sources and 100,000 news outlets in 236 regions. The language is limited to English. Similar manual content analysis [84] is possible but would be limited possibly to some 100s or 1000s of sources due to the needed detailed reading of documents [63]. Media sentiment analysis is possible over extended periods, depending on the available computational power [85].

3.3. CA-GALT analysis

Correspondence analysis by generalised aggregated lexical tables (CA-GALT) on the solar power media dataset is applied to classify and cluster countries on a regional level based on the media hits. CA-GALT is a quantitative method that generalises classical correspondence analysis to the case of several variables in generalised aggregated lexical tables. The variables used in the research can be divided into two categories. In the context of textual data, the lexical table in the case of this study contains information about the frequency or occurrence of words or phrases across media monitoring texts or parts. 'Generalised aggregated' refers to a method of summarizing this information across different categories. The first category is obtained from media monitoring and involves counting hits among countries on twelve topical areas such as business and finance, energy, environment and nature, health and well-being, politics and society, science and research, and such. The second category of variables is obtained via ChatGPT and provides two ordinal-type variables: sentiment and acceptance.

The use of CA-GALT aims to establish a typology of the variables in the first category and a typology of the variables in the second category based on their mutual relationships. This approach involves untangling the influence of the second-category variables (external variables) on the first-category variables (lexical choices) by cancelling the associations among them and substituting them with their principal components to avoid instability from multicollinearity. Like basic correspondence analysis, CA-GALT can be understood as a visualization technique that distributes entities into two-dimensional planes according to their properties [71,72]. By applying CA-GALT to the distribution of hits among countries, it is possible to distribute countries onto a two-dimensional plane. This assists in identifying data points that require further examination.

4. Data-analysis results

The abilities of ChatGPT technology are tested at three levels, analysing at the global, regional, and local levels. The focus is on "solar power", "solar panel", and "solar PV" as they are related but refer to different aspects of solar energy, and the intention is to test the logic of ChatGPT to gain visibility over the differences at the three levels. Solar power is the overall concept, the solar panel is the device converting sunlight into electricity, and Solar PV, photovoltaics refers to the technology used in solar panels. The ability of the ChatGPT technology is assessed by trying to see the nature and quality of information possible to gain.

4.1. Global level

Sentiment and acceptance at a global level are addressed in Tables 2 and 3 by analysing the responses by ChatGPT when posing related questions. The questions include "what" and "how" questions as it is seen to affect the response slightly in some cases.

ChatGPT is also tested for its ability to perceive the chain of reasoning in the studied context. Question "What is the chain of reasoning from media sentiment to the global acceptance of "solar power"?" The same question was posed also for "solar panel", or "solar PV". Similar chains of reasonings are obtained, even when changing "media sentiment" to global sentiment". Fig. 4 illustrates the explained chain of reasoning.

The chains of reasoning are mostly the same for all three, yet a small difference is evident in the case of "solar PV". The media sentiment does refer correctly to the nature of media communication and the related tone, whether positive, neutral, or negative. The perception by the public is influenced by the media sentiment of "solar power", "solar panel", or "solar PV". The media coverage will influence the awareness of people. The positive sentiment and media coverage can increase awareness. Depending on the presentation, perception and awareness could also be presented together. The public perception and awareness can affect government policy towards solar power. Political support can lead to policies and incentives favouring solar power. Government policies will further lead to investments towards solar power and increase the deployment of solar technologies. The investments lead to increased adoption of technology, further contributing towards the acceptance. In the case of solar PV, the technology used in solar panels, market demand, and industry growth preceded the global acceptance. The logic is that government policies may positively affect market demand and will result in industry growth and economies of scale. The cost of technology decreases, and as the benefits are understood, acceptance increases. This result is generally comparable to previous studies describing similar chains of reasoning [5].

ChatGPT seems to be a proficient enough tool to gain an overview and indication of related global agreements in case hoping to understand, which global agreements might be relevant. Queries are made for all three, "solar power", "solar panel", and "solar PV" to list global agreements. For all three, the Paris agreement 2015 on climate change, the international solar alliance, and the United Nations framework convention on climate change are listed. Clean energy ministerial, United Nations sustainable development goals, and mission innovation are listed for solar power and solar PV. Kyoto protocol 1997, and renewable energy 100 for solar power, and the global solar council for solar PV. International renewable energy agency statute, World Trade Organization agreement on trade-related aspects of intellectual property rights, United Nations convention on the law of the Sea for solar panels.

Similarly, it is possible to gain an understanding of the general public opinion towards solar power in terms of the three "solar power", "solar panel", or "solar PV", indicating the general opinion towards them being positive. For solar power, some variation in global public opinion is indicated. Cultural and political context, level of awareness, and economic and aesthetic considerations are seen to have significance for public opinion. Similarly, the global technology reputation appears positive for all three. For solar power, the technology reputation is linked to the recognition by people.

In the same way, it is possible to see how the global political acceptance towards all three, "solar power", "solar panel", or "solar PV", is generally positive, but is indicated that there are still challenges to be addressed.

It is also possible to find out that the global stakeholder acceptance of all these is generally positive, including individuals, communities,

Table 3
What and how questions on global acceptance, solar power, solar panel, solar PV.

Question:	Reaction by ChatGPT:	Indication:	Notes by ChatGPT:	Factors stated by ChatGPT:
What is the global acceptance of "solar power"?	Generally accepted as a key renewable energy source.	Solar power is widely accepted globally.	Challenges for widespread adoption of solar power.	Emissions, energy security, economic growth.
How is the global acceptance of "solar power"?	No access to real-time information.	Widely accepted globally as a key technology.	Some challenges for widespread adoption.	–
What is the global acceptance of "solar panel"?	Generally accepted globally.	Widely accepted globally as a key technology.	Some challenges for widespread adoption of solar panels.	–
How is the global acceptance of "solar panel"?	Generally accepted globally.	Widely accepted globally as a key technology.	Some challenges for widespread adoption of solar panels.	–
What is the global acceptance of "solar PV"?	Generally accepted globally.	Generally accepted globally as a key technology.	Some challenges for widespread adoption of solar PV.	–
How is the global acceptance of "solar PV"?	Generally accepted globally.	Generally accepted globally as a key technology.	Some challenges for widespread adoption of solar PV.	–

Table 2
What and how questions on global sentiment, solar power, solar panel, solar PV.

Question:	Reaction by ChatGPT:	Indication:	Notes by ChatGPT:	Factors stated by ChatGPT:
What is the global sentiment for "solar power"?	No access to real-time information.	Generally positive sentiment.	Potentially also negative opinions due to reliability, ability to replace traditional energy sources, small vs. large scale.	Geography, politics, economic considerations.
How is the global sentiment for "solar power"?	Sentiment towards solar power is generally positive globally.	Sentiment is positive globally.	Key renewable energy source.	–
What is the global sentiment for "solar panel"?	No access to real-time information.	–	Indications by how sentiment analysis is carried out, and factors affecting it.	–
How is the global sentiment for "solar panel"?	No access to real-time information.	Sentiment towards solar panels seems to be positive.	–	Recognition of potential benefits of technology.
What is the global sentiment for "solar PV"?	The sentiment is generally positive.	Sentiment towards solar photovoltaics is generally positive.	Considered as a key technology for clean and renewable energy.	–
How is the global sentiment for "solar PV"?	No access to real-time information.	The global sentiment towards solar PV seems to be positive.	Tool to combat climate change, reduce emissions, and move towards sustainable energy system.	Cost, incentives, and awareness of benefits.

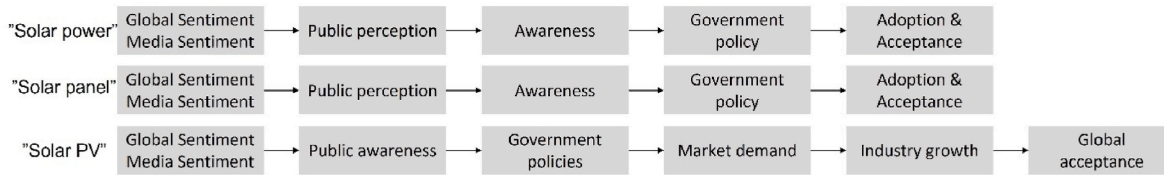

Fig. 4. Chain of reasoning from media sentiment to global acceptance ("solar power", "solar panel", "solar PV").

businesses, governments, non-governmental organisations, environmental groups, energy companies, the general public, and investors. Some concerns over solar panels and solar PV by some stakeholders are indicated.

In the following step, sentiment results by the proven media monitoring software are analysed on a global level for solar PV panels. In Table 4 distribution of global sentiment is displayed. A strong bias towards positive sentiment is detected (over 70 % of positive sentiment).

This result coincides with the opinion produced by ChatGPT which indicated the global acceptability of solar PV panels as a key technology.

4.2. Regional level

In this section, results of regional sentiment and acceptance of "solar PV" in European countries using media monitoring software are compared against ChatGPT results. Media monitoring software only provides the sentiment, whilst ChatGPT provides an indication of both, sentiment, and acceptance. In Table 5 one can observe a comparison among sentiment recognised by media monitoring software and ChatGPT sentiment in 27 European countries for which information in both sources is available. The acceptance indicated by ChatGPT is also indicated. ChatGPT is queried to obtain a scale of 0–100 for the sentiment and acceptance indication to see if numerical differences are possible to obtain. In the majority of countries (20 countries out of 27 observed or 74.07 %) sentiment of solar PV panels revealed by media monitoring software reflects sentiment results of ChatGPT. Media monitoring software sentiment is low in the Netherlands and Cyprus. In the latter low frequency of hits in media monitoring software is collected, but in the case of Netherlands media monitoring software indicates product reputation related reasons for lower positive sentiment. This additional information distinguishes the two methods, and the information can be used as the basis of further actions.

It appears that ChatGPT can provide a relatively good indication of the regional sentiment of "solar PV" when compared to findings obtainable via using professional software intended for media monitoring. In addition, ChatGPT can indicate regional acceptance, which is not obtainable directly via using the media monitoring software. It is noteworthy that acceptance is different from sentiment and that there are factors affecting the acceptance, including cost, initiatives, levels of sunlight, environmental factors, grid-related issues, regulatory issues, and the awareness by the public.

In general, there is a very high resemblance in sentiment between media monitoring software and ChatGPT, as shown in Table 5. However, there are slight differences observed in some East European countries, such as Croatia, Poland, and Romania. In all three of these countries, comments in M-Brain are classified as more positive compared to the sentiment identified by ChatGPT. The most significant discrepancy is observed in the Netherlands, where ChatGPT recognises positive sentiment and high acceptance, while the sentiment identified by media monitoring software is very low, with an indication of negative product reputation-related details.

Table 4
Global sentiment recognised by media monitoring software.

Sentiment	Frequency	Percentage
Positive	13807	70,95
Neutral	1290	6,63
Negative	2423	12,45
Mixed	1137	5,84
(unknown)	803	4,13
Total	19460	100,00

The result of the regional CA-GALT analysis is displayed in Fig. 5, where countries are placed separately in the two-dimensional space. The axes are acceptance and sentiment. The first dimension accounts for 88.89 % of the variance and is primarily influenced by sentiment, while the second dimension explains only 11.11 % of the variance and is mostly influenced by acceptance. Four clusters of countries are identified. No real clustering procedure is performed, rather countries are clustered as in classical correspondence analysis. In this context, themes that are linked together are more likely to occur for countries in similar positions in other two-dimensional presentations. For instance, in the first cluster, several countries are positioned (Germany, Finland, Spain, Austria, Portugal, Croatia, Malta, Lithuania, Czech Republic, Romania and Denmark). Countries in the first cluster share positive sentiment and positive acceptance. Countries from Northern Europe, such as the Netherlands, Luxembourg, Sweden, and the United Kingdom are positioned in the second cluster, which is characterised by negative sentiment and positive acceptance. In the third cluster, only Ireland and Slovenia are found, with both sentiment and acceptance being low. The last cluster includes France, Italy, Greece, Belgium, Poland, and Norway, with these countries sharing positive sentiment and negative acceptance.

4.3. Local level

The local level can be understood as local to a city, or local referring to a project. Queries are done on both city and project levels to gain a level of understanding of what information is obtainable.

Generally, it seems more challenging to gain local-level information by using ChatGPT as its access to data is somewhat limited. Also, the use of the English language only may affect the findings as the local language can be something other than English. Direct queries by cities seem to provide only limited information. Nevertheless, altering the questions slightly allows for some results. Table 6 illustrates the results on local sentiment for those European capital cities results are obtainable. The same is queried so that a scale of 0–100 was obtained. Additionally, Table 7 provides an indication of local acceptance obtained for a limited number of European capital cities.

It is worth noting that when a scale is given, the sentiment can be slightly different in the case of "solar power", "solar panel", and "solar PV" as these refer to different aspects of solar energy.

In the case of acceptance, it is worth noting that in general the levels of acceptance seem to be similar for all "solar power", "solar panel", and "solar PV" on a scale of positive, negative, neutral, even if these refer to different aspects of solar energy. When comparing the sentiment, and the acceptance, it is visible through the scale that the sentiment is less than the acceptance for Berlin, and London in the case of "solar power", Paris, Berlin, Rome, Madrid, Valletta, and London for "solar panel", and Berlin, Valletta, and London in case of "solar PV". These can be explained by "solar power", "solar panel", and "Solar PV" referring to different aspects of technology. Ljubljana, Slovenia is an interesting exception as no media sentiment is possible to gain, but acceptance is

Table 5
Regional sentiment compared between media analytics software and ChatGPT, and acceptance by ChatGPT.

Country	M-Brain % of positive sentiment	ChatGPT sentiment	ChatGPT sentiment 0-100	ChatGPT acceptance	ChatGPT acceptance 0-100
Austria	79,49	Positive	70	High	75
Belgium	81,44	Positive	80	High	80
Croatia	82,05	Mixed	60	Moderate	45
Czech Republic	85,37	Positive	75	High	70
Denmark	74,24	Positive	80	High	85
Finland	73,08	Positive	75	Moderate	60
France	75,25	Positive	80	High	75
Germany	84,90	Positive	85	High	90
Greece	83,33	Positive	75	High	70
Ireland	73,08	Positive	70	Moderate	60
Italy	79,31	Positive	75	Moderate	60
Latvia	100,00	Mixed	65	Moderate	45
Lithuania	82,50	Positive	70	Moderate	50
Luxembourg	82,22	Positive	75	Moderate	65
Malta	66,67	Mixed	65	Moderate	55
Netherlands	22,13	Positive	85	High	85
Norway	65,57	Positive	80	High	70
Poland	73,81	Mixed	65	Moderate	60
Portugal	78,38	Positive	75	Moderate	65
Romania	88,89	Mixed	60	Moderate	50
Slovenia	65,85	Positive	70	Moderate	60
Spain	83,33	Positive	75	High	80
Sweden	67,86	Positive	80	High	70
UK	72,75	Positive	80	High	80

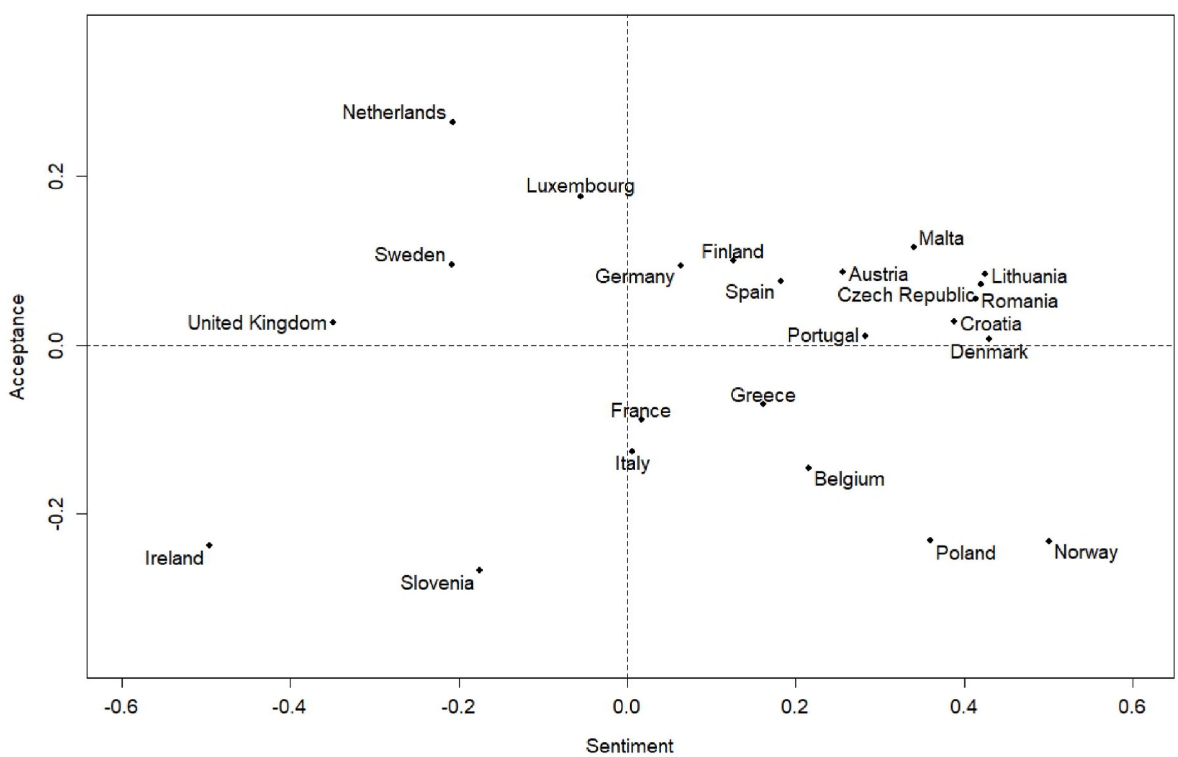

Fig. 5. Countries in two-dimensional space placed by CA-GALT analysis.

indicated. Interestingly an exact figure is provided for “solar power”, and “solar panel”. This might be explained by the limited availability of documents to ChatGPT in the English language. Similarly, no indications are provided for Helsinki, Finland in terms of media sentiment, but positive acceptance is indicated for “solar panel” only.

As the local acceptance can be seen to refer to project implementation, the local acceptance relating to projects is analysed. ChatGPT seems to find information better in the UK in this respect than elsewhere, potentially due to the wider use of the English language. Examples of local sentiments are presented in Table 8.

It appears that it is possible to obtain a level of indication for the media sentiment relating to solar power projects should ChatGPT have access to the necessary data. Qualitative indications are possible to obtain, the same as a numerical estimation on a scale of 0–100. The reliability of the estimation on a project level, however, can be linked to the availability of data. The way the issue is queried may also affect access to data.

Table 6
Local sentiment, solar power, solar panel, solar PV in European capitals.

[a] Sentiment "solar X″ Country – Capital	Sentiment "solar power" (Scale 0–100)	Sentiment "solar panel" (Scale 0–100)	Sentiment "solar PV" (Scale 0–100)
France – Paris	Positive (70–80)	Positive (60–70)	Positive (70–80)
Germany – Berlin	Positive (70–80)	Positive (60–70)	Positive (70–80)
Helsinki – Finland	-**	-**	-**
Italy – Rome	Positive (80–90)	Positive (70–80)	Positive (80–90)
Malta – Valletta	Positive (70–80)	Positive (60–70)	Positive (60–70)
Slovenia – Ljubljana	-**	-**	-**
Spain – Madrid	Positive (80–90)	Positive (70–80)	Positive (80–90)
United Kingdom – London	Neutral (50–60)	Neutral (50–60)	Neutral (60–70)

[a] ("What is the media sentiment for "solar x" in European capitals? Use scale positive, neutral, negative Please list alphabetically by country.") *(What is the media sentiment for "solar x" in European capitals? Use a scale of 0–100. Please list alphabetically by country.") ** Altered How questions.

Table 7
Local acceptance, solar power, solar panel, solar PV in European capitals.

[a]Acceptance "solar X″ Country – Capital	Acceptance "solar power" (Scale 0–100)	Acceptance "solar panel" (Scale 0–100)	Acceptance "solar PV" (Scale 0–100)
France – Paris	Positive (70–80)	Positive (70–80)	Positive (70–80)
Germany – Berlin	Positive (80–90)	Positive (80–90)	Positive (80–90)
Helsinki – Finland	–	Positive (80–90)	–
Italy – Rome	Positive (80–90)	Positive (80–90)	Positive (80–90)
Malta – Valletta	Positive (70–80)	Positive (70–80)	Positive (70–80)
Slovenia – Ljubljana	Positive (81) **	Positive (81) **	Positive (80–90) **
Spain – Madrid	Positive (80–90)	Positive (80–90)	Positive (80–90)
United Kingdom – London	Positive (70–80)	Positive (70–80)	Positive (70–80)

[a] (What is the local acceptance for "solar x" in European capitals? Use scale positive, neutral, negative. Please list alphabetically by country.") *(What is the local acceptance for "solar power" in European capitals? Use a scale of 0–100. Please list alphabetically by country."). ** Altered How questions.

5. Discussion

The general acceptance of a technology can significantly affect energy technology market deployment and the viability of the technology. This study provides value for those keen to understand the market environment and factors affecting technology development and deployment [1], including acceptance. Decision-making can benefit from a fast indication of both media sentiment, and the level of acceptance obtainable via ChatGPT as indicated in this study. Opinion mining is also beneficial by being able to better acknowledge trends. The acceptance has significance as resistance can cause costly delays in energy technology deployment [6]. The applicability of ChatGPT is assessed at three levels in this study, global, regional, and local. These levels are complementary and influence each other in a complex way. This study also classifies solar power status on the stairs of acceptance concept [37], which relates to the three levels of acceptance. The stair height relates to the resistance towards implementation, implying negative acceptance. The position of solar power in the global and regional stairs, and even local, based on solar power-related results by ChatGPT and the media monitoring software, seems to be very low, and stair-height practically non-existent. This can provide value for understanding acceptance and related resistance. The concept is nevertheless, not ruling out temporary regional country or product/project level fluctuations in product reputation and acceptance. This leads to viewing acceptance obstacles for solar power implementation as minor. This is also indicatively evident when observing the increase in solar power implementation statistics by IEA [86]. In global information flow contexts, global acceptance is a starting point for technology deployment. This view highlights the necessity to understand acceptance levels and the related factors affecting acceptance.

The approach adopted in this study implies more techno-economic context than a purely social science-based view with causal acceptance models. This study agrees with [8] in AI-based methods being complementary rather than replacing traditional, accepted causal models from social sciences. The learning model by ChatGPT may influence the data used to train the algorithm, whereas this study provides added value by confirming the potential to be used as fast indicative directions for managerial decisions, specifically in the solar power context. The novelty lies in comparing opinion mining and ChatGPT to

Table 8
Examples of local sentiments linked to European solar projects.

[a] Sentiment Country – Project	2015	2016	2017	2018	2019	2020	2021
Malta - Mġarr Photovoltaic Farm	–	–	–	–	–	Positive (63)	Neutral (52)
Spain - Gemasolar Thermosolar Plant	Neutral Positive** (75)	Neutral Mixed to Positive** (65)	Positive Mixed to Positive** (60)	Neutral Mixed to Positive** (60)	Positive Mixed** (50)	Neutral Mixed** (50)	Positive Mixed** (50)
United Kingdom - Llanwern Solar farm	–	Positive (55)	– Mixed to Positive** (60)	Negative Mixed to Positive** (65)	– Mixed to Positive** (70)	Positive Mixed to Positive** (75)	Positive Mixed to Positive** (80)
United Kingdom - Shotwick solar farm	Negative Neutral** (40)	– Neutral** (50)	– Neutral** (45)	Negative Neutral** (50)	– Neutral** (50)	Positive Neutral** (50)	– Neutral** (50)
United Kingdom - Cleve Hill Solar Park	–	–	–	Negative Mixed to Negative** (30)	Mixed Mixed to Negative** (35)	Neutral Mixed to Negative** (40)	Neutral to Positive Mixed to Positive** (60)
United Kingdom – Amlwch	–	– Mixed to Negative** (40)	– Mixed** (50)	Mixed Mixed** (50)	Neutral Mixed** (50)	Positive Mixed** (50)	Positive Mixed** (50)

[a] How is the media sentiment for "project", in Country or specific location? Please indicate by year. **How is the media sentiment for "project", in Country or specific location? Please indicate by year. Use a scale of 0–100.

analyse the acceptance and sentiment of solar energy and applying the CA-GALT method to support pointing to data points requiring further attention. The findings provide some support for the hypothesis of the chain from acceptance to market deployment, in relation to acceptance, reputation, and sentiment. This is even if the chain of reasoning is not fully clarified, and some aspects require further focus.

The manifold studies relating to the general acceptance of technologies, for example [9,10,16,17], can benefit from the potential of effective means to understand acceptance levels. This underlines the potential benefits of understanding the impact on decision-making. These types of studies can benefit of fast indicative directions to support further analysis, managerial decisions, and indications of needs in countermeasures to influence acceptance at different levels. This also applies to previous studies in the energy technology field applying opinion mining, for example, [19,21,22]. Understanding acceptance and related factors, and chains of reasonings is important as the attitudes and opinions count in energy technology development and investments [32], for which contribution is provided by clarifying the chain from acceptance to market deployment.

The regional focus on Europe was chosen in this study to focus the research to interesting geographical areas. Europe was chosen due to larger regional differences between countries, and the ease of identification compared to for example states in USA. The differences in country level have guided the analysis and provide additional value. The comparative approach, nevertheless, does not require to point out regional details from every country to reach conclusions. The same logic applies, should the regional focus be repeated for another region. The analysis can identify countries with occasional lower sentiment, in this case indicating lower product reputation. The local focus is influenced by project-related data availability. Solar power-related local focus could benefit of consideration according to a stage model along stages of "no interest", "under consideration", and "installation" to study determinants that influence transition between stages [49]. This might provide additional value to understanding factors affecting local acceptance. The acceptance at a global level relates to technological diffusion [38], regional acceptance ties together advanced technological infrastructure and tendency to progress [42], and local acceptance relates to perceived usefulness as a factor in determining the acceptance [47].

Managerial implications involve understanding how the different methods, opinion mining, ChatGPT, and CA-GALT can be combined to screen essential details from a large dataset to gain reliable enough analytics to indicatively support decision-making. This screened dataset is possible to be classified further manually to gain specific details on which different actions can be based. It is possible to identify aspects that point out to, for example challenges in deployment in the implementation phase to support managerial decision-making. For example, challenges in solar panel installation by a single company can be obtainable. Managers implementing solar power-based technologies can benefit of the rapid indication by potentially less resources being needed on solar power acceptance related issues. The solar power acceptance is at such level that, from the product management perspective, a quite colossal failure would be needed, before the reputation would be affected. This might require a scandal, before influencing the reputation and acceptance.

The practical implication for industry might generally concern faster stakeholder analysis to support technology deployment, and possibilities to identify action items related to product development and marketing. At a country level, this type of analysis can be used to support policy development by incorporating indicative stakeholder views from large audiences into the decision-making. Research organisations can benefit from the newly introduced approach to scientific debate, involving the applicability of AI-based methods compared to traditional causal sociological models. Also, how these approaches can be combined to support the deployment of renewable technologies. New standards for AI-based research would be beneficial to be created to support methodological development. The advantages of AI-based methods involve the comparison possibility of larger and smaller data entities. In general, climate change as a multidisciplinary challenge requires the cooperation of different scientific disciplines, while data science emerges increasingly as a contributor for the future.

6. Conclusion

The key findings of this study involve indicating how different methods, involving AI, quantitative, and big data-based analysis can be combined to screen essential details from big data, reliably enough to indicatively support decision-making. The novelty lies in applying opinion mining, ChatGPT and CA-GALT methods to analyse the acceptance and sentiment of solar energy. The novelty involves the application of ChatGPT to study the general acceptance of solar power technology. Different, related aspects, "solar power", "solar panel", and "solar PV" are focused on. Analysing media sentiment (positive, negative, neutral) has been one way to approach understanding acceptance levels. The sentiment and acceptance are related as the media sentiment can influence the acceptance. Understanding of acceptance-related chains of reasoning is enhanced. It is found that solar power is well accepted at global, regional, and local levels, however, the analysis can identify countries with occasional lower sentiment, indicating lower product reputation. The potential for providing a fast indication of both media sentiment and the level of acceptance via ChatGPT is indicated, whilst opinion mining can better acknowledge trends. Energy technology development, market deployment considerations, and related communication efforts can benefit from a fast indication of acceptance and sentiment. The findings further validate previous opinion mining-based results, while the theoretical side related to analysing global contexts seems to be evolving. In comparison to more traditional acceptance studies, AI-based methods seem to provide input to acceptance issues rapidly with limited reliability, while utilising large global datasets. This input can be used as an indication.

The limitations relate to the technical performance of AI, in this case, the ChatGPT. The access to data has some limitations, and the applied code is a methodological black box. The results are generally indicative without causality. Similarly, opinion mining results are based on black-box software with 80 % accuracy in sentiment classification at most, with further error possibilities related to search words. Opinion mining has limitations in understanding sarcasm or irony in the text. The logic of reasoning is further validated by AI but may still be debatable among different fields of science and academics due to differences in research tradition. Currently, the limited experience in ChatGPT use for opinion mining and assessing acceptance may also pose some limitations. Further studies, aside from addressing the limitations, can include validating the stairs of acceptance concept via individual technology studies. Further investigation is required on the use of AI technology in acceptance studies, including comparison to existing methods. The chains of reasonings relating to technology acceptance also require further study. Stairs of acceptance concept requires further research by additional data analyses to further validate the concept. The logic and numerical quantification for defining stair width and height are still needed. Testing ChatGPT plugins or advanced data analytics options also necessitates further study. Asking ChatGPT for reasons for responses might also provide an interesting angle.

CRediT authorship contribution statement

Kalle Nuortimo: Conceptualization, Methodology, stairs of acceptance, Opinion mining. **Janne Harkonen:** Conceptualization, Writing - original draft, chat GPT analyses. **Kristijan Breznik:** GA-GALT analyses.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used [ChatGPT] to [Investigate different public acceptance levels]. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication, as far as it is possible.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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Fig. 2 has been reproduced from Ref. [37] under the Creative Commons Attribution License.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rser.2024.114296.

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