Energy, Sustainability and Society

REVIEW **Open Access**

Approaching social acceptance of energy technologies: ten European papers showcasing statistical analyses–a targeted review

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Abstract

Background Addressing global climate challenges necessitates a shift toward sustainable energy systems, with public acceptance of energy technologies playing a vital role in their successful adoption. While extensive research has been conducted on this topic, the lack of a unified framework for integrating various data and approaches from existing studies remains a challenge. This inconsistency makes it difficult to compare findings across different contexts and impedes the development of a comprehensive understanding of the factors influencing acceptance. This review aims to address this challenge by systematically evaluating the statistical methods used in ten large-scale studies on public acceptance of energy technologies in Western Europe published between 2012 and 2023. This Work allows researchers to more effectively compare methodologies and results, offering a transparent and structured approach for analysis, thereby enhancing the overall methodological assessment.

Main text The review of ten large-scale studies identified valuable insights and opportunities for improving the analysis of public acceptance of energy technologies. Traditional methods like regression analysis have provided a solid foundation, highlighting key factors such as perceived benefits, trust, and attitudes. However, the review also revealed potential for growth by integrating more advanced techniques like AI-supported analysis, sentiment analysis, and agent-based modelling. These newer approaches offer the ability to capture complex, non-linear relationships and provide predictive insights. The introduction of statistical pattern graphics significantly enhances the clarity and comparability of methodologies, helping researchers to better understand and improve their approaches, ultimately supporting more accurate and impactful studies.

Conclusions The review emphasizes the need for a unified analytical framework that integrates diverse methods, including both traditional statistical techniques and emerging approaches such as machine learning and sentiment analysis, to enhance the comparability of studies on public acceptance of energy technologies. By consolidating these varied methodologies into a cohesive framework, researchers can generate more consistent, robust insights that account for the complexities of public attitudes across different contexts. This unified approach not only improves the generalizability of findings but also provides stronger empirical evidence to guide policymakers in crafting more informed, effective strategies for promoting sustainable energy transitions at both local and global levels.

Keywords Public acceptance, Energy technologies, Renewable energies, Statistical analysis, Energiewende, Regression models

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Background

The transition to sustainable energy systems is critical to addressing global climate change and achieving long-term ecological and social stability. Public acceptance of renewable energy (RE) technologies plays a vital role in this transition, as societal support is essential for the widespread adoption of clean energy solutions such as solar, wind, and hydrogen technologies. While extensive research has been conducted on public acceptance, the lack of a unified framework to integrate various data and approaches from existing studies limits our understanding of the social and ecological factors driving acceptance. This inconsistency also hinders efforts to generalise findings across different contexts, which is crucial for developing policies that support sustainable energy systems. The recognition that conventional energy sources such as fossil fuels and nuclear power are environmentally unsustainable [1–3] has fuelled a rising interest in RE as a promising alternative [4]. This shift has the potential to reshape the dynamics between energy consumers and producers, along with influencing attitudes toward energy technologies [5–7]. RE-technologies have emerged as solutions to address pressing global challenges, particularly climate change and sustainable development [8–12]. In the face of energy crises and the negative impacts associated with conventional energy sources, the question of how energy is produced and consumed has become of paramount importance. The magnitude of the challenge is reflected by the Sustainable Development Goals (SDGs), a framework established by the United Nations to guide global efforts toward a more sustainable future [13]. One of the 17 SDGs is affordable and clean energy, seeking to boost the adoption of RE sources and enhance energy efficiency. This shift from reliance on fossil fuels to the adoption of RE sources such as solar, wind, hydroelectric, and geothermal power is heavily linked to issues regarding the material basis of energy technologies, where challenges concern resource criticality, availability, recycling, and overall sustainability [14–17].

However, addressing these technical and material challenges alone is not enough to ensure a successful transition. Equally important are the social dimensions of energy adoption, particularly public acceptance. Without broad societal support, even the most sustainable technologies can face significant obstacles. Prominent examples of citizens opposing RE projects highlight that the energy transition cannot be separated from the need to engage and gain acceptance from the public [18–21]. The widespread adoption and integration of RE technologies into existing energy systems relies on the acceptance of these technologies by various stakeholders, including the general public, policymakers, and industry players.

Although there are numerous studies on the acceptance of energy technologies, apart from enhancing existing frameworks to meet contextual complexities and emerging trends in RE adoption [22], the challenge of finding a common analytical framework to integrate data and approaches is yet to be solved [23, 24]. This lack of a unified analytical approach hampers the ability to generalise findings across different studies and to develop a comprehensive understanding of the factors influencing acceptance. This study aims to address this gap by evaluating the statistical methods applied in ten large-scale acceptance studies, thereby identifying common practices and highlighting best approaches to enhance comparability and generalisability across research on public acceptance of energy technologies. First, the methodologies of acceptance research vary greatly [24, 25], which complicates the comparability and generalisability of the results. This heterogeneity of statistical approaches can make it difficult to synthesise or generalise findings. An evaluation of the methods used helps to identify standards and best practices that can improve the consistency and efficiency of future research. Second, there is an urgent need to optimise methodologies in data collection and analysis. By thoroughly examining the methods used in the selected studies, insights can be gained, enabling researchers to plan and conduct future studies more effectively. This optimisation contributes to obtaining more accurate and comprehensive insights into public acceptance of energy technologies.

Main text

Approaches applied for identifying and analyzing relevant studies

This section outlines the process of selecting relevant studies, collecting and filtering the literature, and analyzing public acceptance of energy technologies. As part of this analysis, the method categorizes the statistical approaches into regression-based and non-regression-based methods, enabling structured comparisons. A key novelty is the use of statistical pattern graphics, which visually represent the statistical procedures of each study to improve transparency and comparability. The method outlined ensures clarity, validity and consistency in how the studies were reviewed and analysed. The selection of studies was based on their representation of a broad range of methodological approaches used in public acceptance research of energy technologies. To ensure the inclusion of high-quality and relevant studies, specific criteria were applied. Studies were included if they met the following criteria: (1) they conducted large-scale surveys with a sample size of at least 900 participants; to ensure the inclusion of high-quality and relevant studies, a minimum sample size of 900 participants was used as a sufficient condition for representativity. This threshold was chosen, because larger samples generally increase the likelihood of capturing diverse population characteristics and applying probabilistic sampling methods, which are necessary to achieve true representativity. While we acknowledge that sample size alone is not a necessary condition for representativity, studies with smaller samples were excluded to minimize the risk of methodological biases commonly associated with non-representative sampling, such as convenience or student samples. The selection process prioritized studies that explicitly applied probabilistic sampling techniques, ensuring that the included studies could provide robust and generalizable insights into public acceptance of energy technologies; (2) they focused on public acceptance of energy technologies; (3) they were published between 2012 and 2023; (4) they were conducted within Western Europe, where a significant body of public acceptance research has been concentrated; and (5) they were written in English or German. The exclusion of non-European studies was driven by the need for a consistent socio-political and economic context, which allows for more comparable analyses across studies.

Search process and literature review

Based on the work of Gusenbauer and Haddaway [26], the systematic search capabilities of popular academic search systems were investigated and compared. The process of literature selection for this study involved qualified search systems and specific keywords to effectively narrow down the results. The scope of the literature encompassed scientific publications spanning 2012–2023, to capture the most recent developments in statistical approaches, and aligned with the integration of psychological factors within technology acceptance frameworks [27], as exemplified by Huijts' 2012 Technology Acceptance Framework [28], or the integrated adoption model by Park and Kim [29]. Fourteen search systems were initially considered. Six of these systems were excluded due to inadequate availability of pertinent data; ClinicalTrials.gov, Cochrane Library, OVID, PubMed, TRID, and Virtual Health Library were deemed unsuitable due to their medical focus. The remaining eight search systems, namely ACM Digital Library, BASE, EBSCOhost, EconLit, ProQuest, ScienceDirect, Scopus, and Wiley Online Library, were utilised to conduct the search. The outcomes yielded 23,774 documents in total, ranging from 33 (EBSCOhost) to 8047 (Wiley Online Library) publications, as depicted in Fig. 1. The precise search command used in the academic search systems was: "public acceptance" AND "energy technologies" AND "survey" AND "statistical analysis".

To maintain focus, the top 800 documents from ScienceDirect, 600 from Wiley Online Library, and 500 from ACM Digital Library were shortlisted for further analysis. Using the "advanced search" function in Adobe Acrobat Reader, documents lacking the term "survey" in either the title or abstract were automatically excluded. The focus on surveys primarily served as a filtering mechanism to prioritize studies that explicitly referenced survey-based methods in their abstracts. This approach helped narrow the pool of studies to those likely to align with our research goals to 334. It should be noted that it was not possible to exhaustively check all results obtained due to the high number of documents. In addition, there is a lack of transparency in the sorting algorithms employed by search engines. Consequently, there is a risk of missing essential papers. Nonetheless, employing multiple search systems can help to reduce the chances of overlooking crucial research.

Data extraction and statistical analysis

After filtering for relevance, 73 papers were selected for full-text screening. Of these, 28 were excluded due to a lack of focus on public acceptance or unrelated survey questions, leaving 45 papers for detailed review. Following a rigorous evaluation, the selection criteria emphasised prioritising newer publications, regions resembling Germany in terms of energy infrastructure, and surveys with larger sample sizes. After narrowing down the studies based on these rigorous criteria, a final set of 10 key studies was identified for detailed analysis. These studies were selected for their relevance to the research focus and their adherence to the selection criteria, ensuring a robust foundation for evaluating statistical approaches.

The 10 selected studies were analysed based on two key categories: regression-based and non-regression-based approaches. This categorization reflects both the methodological diversity and the distinct practical applications of these approaches in social acceptance research. This division is not rooted in their ability to infer causality—both categories primarily focus on associations or correlations—but rather in their differing roles and contributions to the research process. Regression-based methods are typically employed when the research aims to explore complex relationships involving multiple predictors and to quantify their relative influence on a dependent outcome. They allow for testing hypotheses while controlling for confounding factors, providing a detailed understanding of the factors influencing public acceptance. Non-regression methods, such as correlation and variance analysis, serve complementary purposes by focusing on direct associations or group differences. These approaches are particularly valuable for exploratory or descriptive analyses, where fewer assumptions are

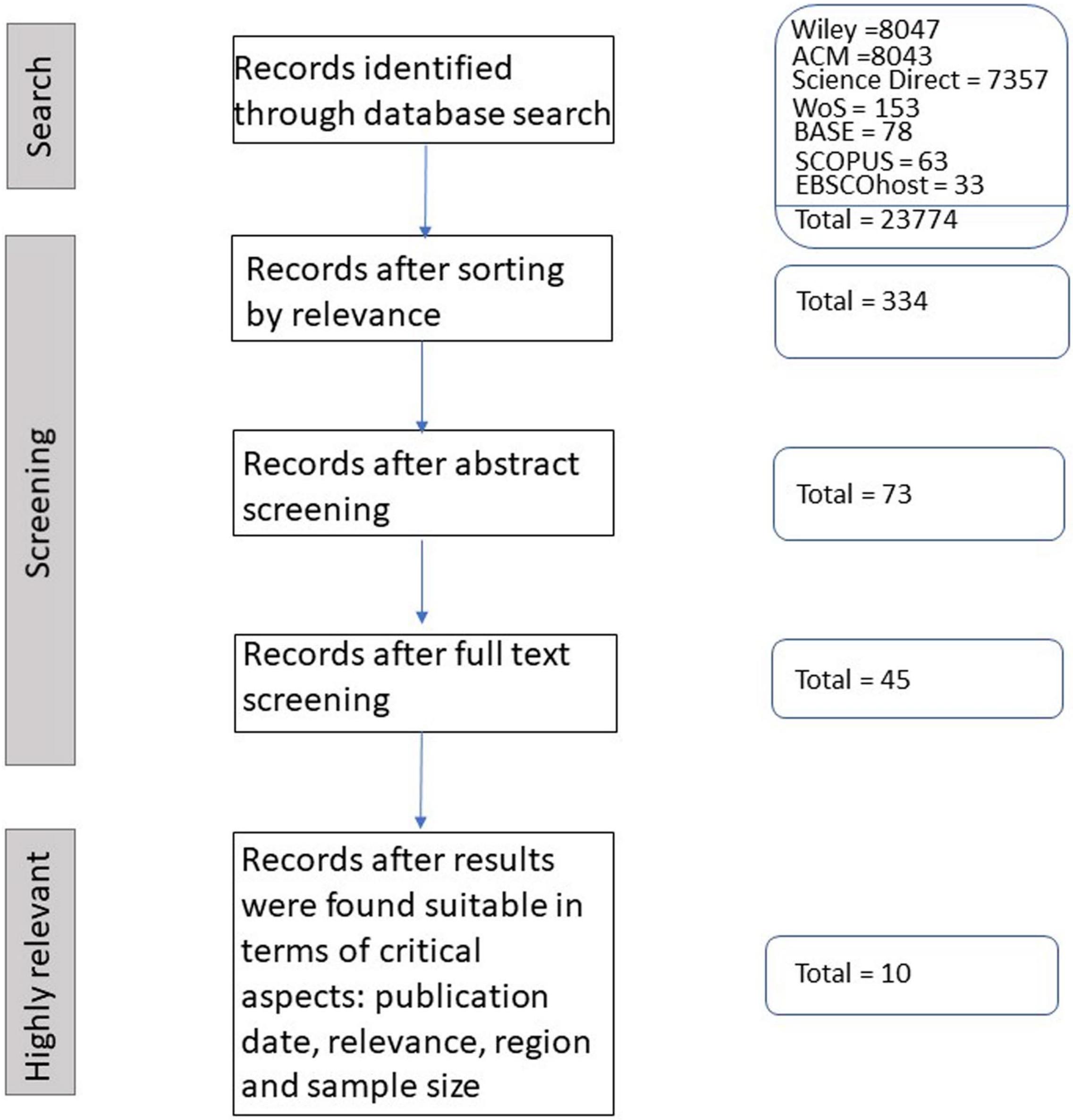

Fig. 1 Outline of the methodology used for the literature selection. Based on Haddaway et al. [30]

required, and they often help to identify patterns or relationships that inform subsequent, more complex analyses. By categorizing the methodologies in this way, this review highlights the complementary strengths of regression-based and non-regression-based methods. This distinction enables a systematic comparison of their roles, helping to assess their respective contributions to understanding the complexities of public acceptance research.

Creation of statistical pattern graphics

A key contribution of this review is the introduction of statistical pattern graphics, which visually represent the entire statistical processes employed in each included study. These graphics were created by mapping the structural flow of statistical procedures, including variable selection, model application, and results interpretation. The creation process involved manually extracting detailed descriptions of the statistical methodologies from each paper and using data visualisation tools to create diagrams that display how statistical techniques were applied. These graphics were developed to allow researchers to easily compare the methodologies across studies, offering a transparent and structured framework for understanding the analytical techniques used in each

Table 1 Comparison of regression-based approaches

	Ambrosio-Albala et al. [31]	Langer et al. [42]	Oltra et al. [33]	Bauwens and Devine-Wright [44]	Seidl and von Wirth (2019)
Type	Multiple Linear Regression	Multinomial Logistic Regression	Multivariate Regression Models	Various regression models and Kruskal–Wallis test	Variance Analysis (ANOVA) and Linear Regression
Objective	Study acceptance of DES technologies	Analyse acceptance levels of wind energy projects, focusing on different acceptance levels	Examine public acceptance of hydrogen fuel cell (HFC) applications across seven European countries	Study attitudes toward renewable energy and wind energy	Examine implementation of the energy transition strategy in Swiss/German/Austrian context
Methodology	Multiple linear regression to examine the influence of demographic and attitudinal variables on acceptance	Multinomial logistic regression to model outcomes with more than two categories	Multivariate regression to assess the influence of demographic and attitudinal variables on acceptance	Multiple regression models (linear regression, multivariate regression) and Kruskal–Wallis test to determine significant differences	Variance analysis (ANOVA) to assess national context and framing conditions, linear regression to investigate factors influencing DES acceptance
Advantages	Easy to interpret, suitable for continuous outcomes	Good for categorical outcomes, no linearity assumption	Handles multiple predictors, both continuous and categorical	Comprehensive, handles multiple variables	Comparative insights, identifies specific factors
Limitations	Assumes linearity, influenced by outliers, not for categorical outcomes	Needs larger samples, complex to interpret, potential bias	Assumes linearity, multicollinearity, complex interpretation, overfitting risk	Complex, overfitting risk, self-selection bias	Cultural biases, assumes linearity, potential oversimplification

study. To avoid exceeding space limitations, only selected statistical patterns have been included in the main text of this paper to illustrate their structure and make the described studies easier to follow. All statistical pattern graphics can be found in the appendix. The statistical pattern graphics not only serve as a comparative tool for human researchers but also offer a valuable starting point for AI-driven analysis. By providing a structured, visual overview of how different statistical methods are applied, these graphics enable AI systems to more efficiently process and analyze the methodological frameworks used in social acceptance studies. Unlike text-based descriptions, which may require complex natural language processing techniques to decode, pattern graphics present a clear and immediate layout of statistical procedures. This clarity makes it easier for AI algorithms to detect patterns across studies, such as recurring methodologies, common variables, and interactions that contribute to public acceptance.

Moreover, AI systems can utilize these graphical representations to assess and enhance statistical methods by identifying areas for improvement, such as detecting potential biases or gaps in data processing. This can help streamline future studies by automating the identification of optimal statistical techniques or suggesting modifications based on previous analyses. As AI continues to develop its capabilities in recognizing patterns and making predictive inferences, these graphics can become essential in refining the methods applied in social acceptance research, potentially leading to more accurate and robust analytical outcomes.

Evaluation of statistical approaches

The analysis is divided into two main categories: regression-based approaches (Table 1) and non-regression-based approaches (Table 2). This division allows for a detailed examination of the strengths, limitations, and application contexts of different statistical techniques used in understanding public acceptance within the energy sector.

A short general introduction regarding how survey data is gathered and processed is necessary: a sample survey collects data from a subset of a population to draw conclusions about the entire population [32]. Items are the elements that make up the survey, for example, the questions, rankings, statements etc. which the respondents react to. The relationship between an item and a variable is such that the item is used as a tool to measure the variable, helping researchers gather data about the variable of interest. Throughout the process of statistical evaluation, variables are constructed from one or more items to attain measurable characteristics. It is up to the researchers which item or items they choose. The most common way of dealing with the data observed in this

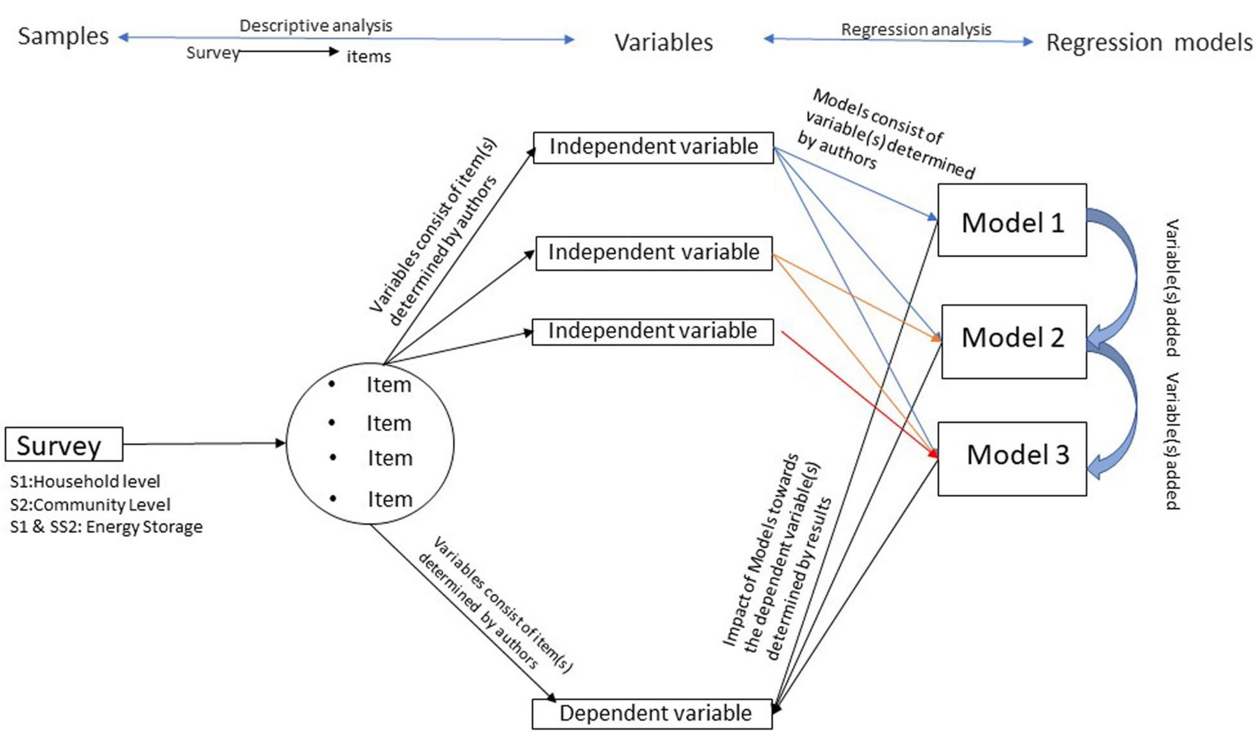

Fig. 2 Structural pattern Ambrosio-Albala et al./authors' depiction

Table 2 Comparison of non-regression-based approaches

	Baur et al. [49]	**Bertsch et al. [50]**	**Langer et al. [42]**	**Ruddat and Sonnberger [52]**	**Schumacher [53]**
Type	Bivariate Correlation	DA, MCDA, MANCOVA	Hypothetical Choice Experiment	DA, Bidding Game, CA, LCA	DA, ANOVA, *T* tests, PCC
Objective	Assess social acceptance of key energy technologies	Public acceptance of RES and grid expansion	Investigate preferred forms of participation in wind energy	Societal perception of energy transition	Public acceptance of renewable energies in Upper Rhine Region
Methodology	Correlation analysis to find relationships between variables	Combined descriptive, MCDA, and MANCOVA methods	Choice experiment with wind energy project attributes	Descriptive, bidding game, correlation, LCA	Descriptive, ANOVA, *T* tests, PCC
Advantages	Highlights key correlations	MCDA effectively identifies the most influential factors, while MANCOVA reveals demographic correlations and interactions	Highlights citizens' preferences for participation types. Identifies key factors for enhancing public engagement	Identification of distinct respondent classes, comprehensive analysis due to combination of descriptive and advanced statistical techniques	Identification of key factors affecting acceptance levels, including regional and experiential differences
Limitations	Cannot infer causation, potential for spurious results	Complexity and self-reported data biases	Hypothetical scenarios may not capture real-world complexities	LCA may oversimplify opinions, sensitive to assumptions	ANOVA and *t* tests assume normal distribution, tests identify differences between groups but do not account for complex interactions between variables

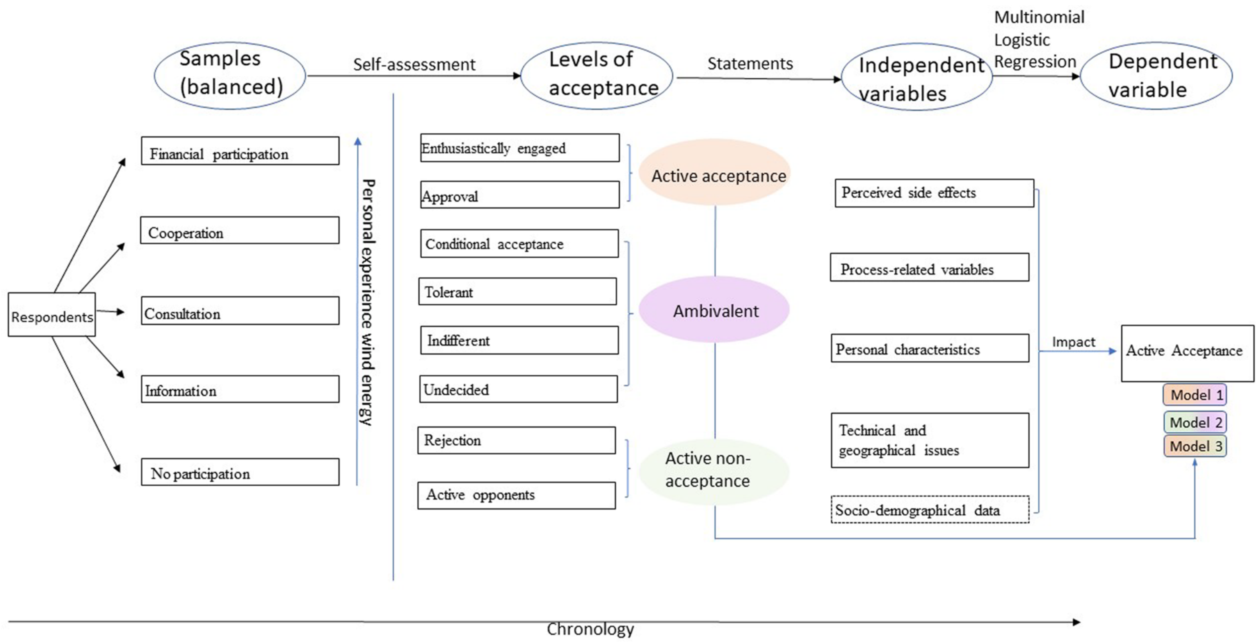

Fig. 3 Structural pattern Langer et al./authors' depiction

review is to conduct a regression analysis, which allows the researchers to discover relationships between one or more independent variables and a dependent variable.

In general, the independent variable or variables make statements about the dependent variable. Since the studies examined in this paper were acceptance studies in the field of energy technologies, the dependent variable was, with few exceptions, the respondents' acceptance of specific energy technologies. It is possible to develop different models within the framework of regression analysis. These models consist of independent variables that are taken together to test their effect on the dependent variable.

However, limitations of regression analysis in capturing complex relationships or causal mechanisms must be acknowledged. Regression models often start with the assumption of linear relationships between variables, which may not hold true for all data sets. While non-linear relationships can be modeled by incorporating transformations or interaction terms, such adjustments require careful consideration and expertise to avoid inaccurate predictions or misleading conclusions. In addition, multicollinearity, where independent variables are highly correlated, can distort results and reduce the model's explanatory power. Multicollinearity primarily affects the standard errors of the coefficients, which can lead to less reliable estimates and inflated variances. While it does not directly reduce the model's explanatory power (e.g., R2 or adjusted R2), it can complicate the interpretation of individual predictors and their contributions to the dependent variable.

Regression-based approach

Ambrosio-Albala, Pepa, Upham, Paul; Bale, Catherine; Taylor, P.G.—exploring acceptance of decentralised energy storage at household and neighbourhood scales: a UK survey (2020).

The paper by Ambrosio-Albala et al. [31] investigated public acceptance of Distributed Energy Storage (DES) technologies at household and community levels in the UK, using a survey of 949 participants. The methodology employed by Ambrosio-Albala et al. involved descriptive and regression analyses on two sub-samples: domestic battery storage and community battery storage. Descriptive statistics such as frequency distributions, percentages, and cross-tabulations were utilised to explore the relationship between socio-demographic variables and acceptance levels. A hierarchical approach was used in the regression analysis to investigate the influence of various variables on acceptance. This approach provided a map of significant regression results for each dependent variable, identifying significant positive and negative predictor variables. This methodological framework is visualized in Fig. 2, which provides a clear depiction of the structural flow of the regression models employed. The authors used various models to analyse the different influences on the acceptance of energy storage technologies. By employing multiple models, they were able to better understand the complexity of acceptance and provide more detailed interpretations of their results.

Model 1 aimed to examine the influence of demographic factors (e.g., gender, age, and education) on the acceptance of energy storage technologies, assuming a linear relationship between demographic factors and acceptance. The limitations included explanatory power, as demographic factors alone may not fully capture the complexities of acceptance. This model provided a baseline understanding of how basic demographic characteristics influence acceptance and highlighted the initial impact of demographics on acceptance, setting the stage for more complex models.

Model 2 assessed the combined effect of demographic factors and perceived benefits, costs, expectations, and effect on acceptance. It assumed that adding these variables would provide a more comprehensive explanation of acceptance than demographics alone. Limitations included potential multicollinearity and overfitting. This model provided a deeper understanding by integrating economic and psychological factors and significantly increased the explanatory power, demonstrating that acceptance is influenced by a broader set of factors beyond demographics.

Model 3 further extended the analysis by including variables representing attitudes, beliefs, values, and emotions, assuming these variables would add nuanced insights into acceptance. Limitations included complexity and potential for reduced interpretability. This model provided a thorough understanding by capturing the full spectrum of factors affecting acceptance and offered the most detailed and comprehensive explanation, showing incremental improvement over Model 2.

While model 1 offered initial insights, its explanatory power was limited, accounting for only a small portion of the variance in acceptance. Model 2 expanded the analysis by incorporating socio-economic factors, significantly enhancing explanatory power. Despite this improvement, the model might still miss out on capturing non-linear interactions and complex causal relationships between variables. Model 3 included attitudinal and emotional variables, offering deeper insights into the factors influencing acceptance. However, the incremental increase in explanatory power was modest, indicating that even with a broader set of variables, regression analysis may struggle to fully capture the complexity of human attitudes and behaviours. This highlights the need for supplementary methods, such as qualitative analyses or advanced statistical techniques, to better understand the multifaceted nature of public acceptance of energy technologies.

Oltra, Christian; Dütschke, Elisabeth; Sala, Roser; Schneider, Uta; Upham Paul—the public acceptance of hydrogen fuel cell applications in Europe (2017).

Another example of this approach is Oltra et al. [33]. The study investigated public acceptance of hydrogen fuel cell (HFC) applications across seven European countries (Belgium, Germany, France, Spain, England and Slovenia) using a multivariate, socio-psychological approach to understand demographic and attitudinal factors influencing acceptance of residential fuel cells and hydrogen fuel cell electric vehicles (HFCEVs). The study revealed low levels of awareness and familiarity with HFC technologies but generally positive attitudes toward their adoption. Bivariate analyses were used to examine differences in attitudes toward HFCs, vehicles, and stationary residential applications, providing a comprehensive understanding of awareness, evaluation, acceptance, and support across these regions. General awareness, including both informed and uninformed awareness related to residential and vehicle applications, was first assessed, followed by evaluations of home HFCs and HFCEVs after providing information on their effects. Various statistical techniques, including multivariate regression models, were employed to analyse survey data. These models examined the influence of the demographic variables (gender, age, education) and attitudinal variables (positive and negative affect, perceived benefits, trust, preference for alternative technologies) on the acceptance of HFC applications.

Model 1 examined the influence of demographic factors (e.g., gender and size of residence) on the acceptance of residential fuel cells, assuming a linear relationship. Weak associations indicated that demographic factors alone may not fully capture the complexities of acceptance.

Model 2 expanded on Model 1 by incorporating attitudinal variables (positive affect, negative affect, perceived benefits/costs, trust, age, preference for gas boilers, size of place of residence). This model aimed for a comprehensive understanding of acceptance, though potential multicollinearity among attitudinal variables was a limitation. It showed that attitudinal factors significantly enhanced explanatory power.

Model 3 examined the influence of demographic factors (e.g., gender and age) on the acceptance of HFCEVs, similar to Model 1. Weak associations persisted, indicating that demographic factors alone may not fully capture acceptance complexities.

Model 4 expanded on Model 3 by incorporating attitudinal variables (positive affect, negative affect, trust, age, preference for conventional cars, perceived benefits/costs), aiming for a comprehensive understanding of acceptance. Potential multicollinearity remained a limitation. This model showed that attitudinal factors significantly enhanced explanatory power.

In line with other publications included in the review, the regression models used in the study provide moderate explanatory power, highlighting the major importance of the aspects of affect [34–36], perceived benefits [37, 38] and costs [37, 39], trust [40, 41], age, and preference for alternative technologies. In contrast, factors such as familiarity, size of place of residence, and educational level also had an effect on acceptance; however, their strength was considerably lower. Although these models illustrated how demographic and attitudinal factors interact to shape public acceptance of HFC technologies, some limitations were acknowledged. The unfamiliarity of respondents with the technology risked collecting unstable attitudes or pseudo-opinions. Neutral and specific information was provided to mitigate this, though processing of the information by participants was uncertain. Measurement invariance and internal validity were addressed by deriving items from previous studies and ensuring careful translation.

Langer, Katharina; Decker Thomas; Roosen, Jutta; Menrad, Klaus—factors influencing citizens' acceptance and non-acceptance of wind energy in Germany (2018).

Many of the studies reviewed followed a similar pattern to Ambrosio-Albala et al. [31] and Oltra et al. [33], although they introduced variations into the regression analysis to align with their research objectives. The study by Langer et al. [42] aimed to evaluate factors influencing acceptance of wind energy projects in Germany, using a comparative regression analysis across three levels of acceptance: active acceptance, ambivalence, and active non-acceptance—Fig. 3 provides a visual representation of the methodological framework employed in their analysis, highlighting the relationships between demographic factors, attitudes, and acceptance levels. The authors conducted a regression analysis by examining the relationship between dependent and independent variables. Specifically, they assessed respondents' prior experience with wind energy projects as this related to their level of acceptance. To evaluate their acceptance, participants were asked to assess their attitudes toward wind energy projects using specific assessment items. The foundation of this self-assessment was the acceptance levels of Hofinger [43], which at a later stage were reduced to the three broad levels. To analyse the three levels of acceptance groups, a multinomial logistic regression was carried out with the aim to predict the respondents' probability of being part of one of these groups. Multiple linear regression was used to identify the significant predictors of acceptance. The analysis included both socio-demographic variables and attitudinal factors, allowing for a comprehensive understanding of the factors driving acceptance. To evaluate the factors influencing acceptance levels, Langer et al. conducted a comparative analysis of two acceptance levels at a time. For instance, they examined variations between individuals who showed ambivalence toward wind energy projects and those who actively supported them (Model 1). In addition, they compared individuals who did not accept wind energy projects with those showing ambivalence (Model 2), and contrasted supporters with non-supporters (Model 3). This methodology allowed for an assessment of respondents' attitudes toward wind energy projects and their corresponding level of acceptance.

Model 1 compared ambivalence with active acceptance, focusing on demographic and experiential variables. While this model provided insights into how basic characteristics differentiate between ambivalent and accepting individuals, its limitations included the potential for unaccounted variables influencing acceptance.

Model 2 compared active non-acceptance with ambivalence, emphasising similar factors to Model 1 but highlighting differences in their influence. This model provided an understanding of what distinguishes non-acceptance from ambivalence, though there was potential overlap with variables in other models.

Model 3 compared active acceptance with active non-acceptance, incorporating a wide range of variables including attitudes and beliefs. This model offered a comprehensive differentiation between acceptance and non-acceptance, yet faced limitations such as increased complexity and potential for overfitting.

Bauwens, Thomas and Devine-Wright, Patrick—positive energies? An empirical study of community energy participation and attitudes to renewable energy (2018).

Bauwens and Devine-Wright [44] conducted a rigorous investigation into the factors influencing attitudes toward renewable energy and wind energy in Belgium. They revealed that involvement in community energy initiatives can effectively mitigate the prevailing indifference or uncertainty toward RE. This effect is deemed crucial to facilitate a swift and socially embraced transition to a low-carbon energy system, which corroborates similar findings in related literature [45, 46]. The study employed a systematic approach, defining independent variables by linking them to survey items. Descriptive analysis identified differences between reference and comparison groups, as well as within cooperative groups. To determine statistically significant differences between samples, the authors performed the Kruskal–Wallis test on attitudes toward RE and wind energy in general. This allowed for a comprehensive comparison of attitudes among members of community energy initiatives. Participants from the cooperatives "EcoPower" and "Beau-Vent" were included for the subsequent comparison of cooperative members' attitudes. Correlation analysis was used to explore the connections between member categories and their attitudes, encompassing general attitudes toward wind energy, the local implementation of wind turbines, and RE as a whole. A multivariate regression analysis provided a more comprehensive view of potential variations in attitudes toward RE. This analytical approach was applied to investigate two dependent variables: general attitudes toward RE and the overall stance on wind energy. The following models were used to identify the influential factors driving attitudes toward locally implemented wind turbines:

Model 1 assessed the impact of energy cooperative membership and pro-environmental identification on acceptance of RE, assuming that membership and identification are significant predictors of acceptance. While this model highlighted the importance of social identity and community involvement, it faced potential self-selection bias.

Model 2 incorporated socio-demographic variables such as gender and education, assuming these factors add explanatory power to the existing model. This broader understanding showed how socio-demographic characteristics interact with community membership to influence acceptance but had limitations like potential multicollinearity and reduced interpretability.

Model 3 included motivations for joining the cooperative as additional variables, assuming these motivations provide deeper insights into acceptance. This model demonstrated the motivational drivers that enhance acceptance of RE, though it increased model complexity.

Model 4 introduced attendance at Annual General Meetings (AGMs) to assess the influence of active participation in shaping acceptance.

Model 5 added variables related to the influence of spatial factors and employment status, assuming these factors provide further explanatory power, but faced challenges like potential overfitting and complexity.

Model 6 applied the same variables as Model 5 specifically to wind energy acceptance, assuming similar factors influence acceptance across different renewable technologies. This model provided targeted insights into wind energy acceptance and validated the broader model within the specific context of wind energy but had potential for reduced generalisability to other technologies.

Seidl, Roman, Wirth von, Timo—social acceptance of distributed energy systems in Swiss, German, and Austrian energy transitions (2019).

The study conducted by Seidl and von Wirth [47] aimed to assess the acceptance of distributed energy systems (DES) in Germany, Switzerland, and Austria, and adopted a structural approach to examine the implementation of the Swiss/German/Austrian energy transition strategy. Building on prior research [48], this study focused on these countries to identify key stakeholders in the energy system transitions. The authors began by assessing the construct of "Responsibility". Participants were asked to rank various actors in terms of their responsibility for implementing the strategy, including national political bodies, energy suppliers, municipalities, small- and medium-sized enterprises (SMEs), households, and land- and property owners. To analyse acceptance levels related to this topic across the three countries ANOVA, a statistical method used to compare the means of three or more groups to determine if there's a significant difference between them, was conducted. It assumes that framing conditions and national context influence acceptance. It contributes by highlighting how national differences and framing conditions impact DES acceptance and was used to identify both commonalities and distinctions. Subsequently another variance analysis was carried out to evaluate the acceptance of DES. This involved the detection of five key item constructs, namely "challenges", "opportunities", "attitude toward innovation", "active acceptance", and "open-ended inquiries", serving as indicators to evaluate the prevailing sentiments regarding DES. The responses to the "open question" item were analysed qualitatively and categorised accordingly. Following this, a linear regression analysis was performed to investigate the influencing factors in DES acceptance by examining their impact on the dependent variable "active acceptance". It assumes linear relationships between variables and acceptance. Limitations include potential cultural biases and the challenge of isolating specific factors, apart from the absence of stepped models and potential for oversimplification. The regression provides a focused analysis of key variables affecting acceptance, which contributes by identifying specific factors that drive active acceptance, providing actionable insights for policy and practice.

This publication stands out for its evaluation of framing effects. In the experiment, respondents were randomly assigned one of four short descriptions (vignettes) emphasising global, national, local relevance, or a control condition. The hypothesis suggested that respondents presented with a local vignette, which highlighted DES for municipal energy independence, would show higher acceptance rates than those given a global vignette focused on reducing CO_2 emissions. The dependent variable was active acceptance, with the vignettes as independent variables. An ANOVA was conducted to examine the relationships between these groups and their impact on the dependent variable across three samples.

Non-regression-based approach

While the studies discussed so far predominantly utilized various forms of regression analysis to explore public acceptance of energy technologies, other research adopted divergent approaches to address the complexities of this issue. Table 2 provides a detailed comparison of these non-regression-based methods, highlighting their objectives, methodologies, advantages, and limitations.

Baur, Dorothee; Emmerich, Philip; Baumann, Manuel; Weil, Marcel—assessing the social acceptance of key technologies for the German energy transition (2022).

Baur et al. [49] compared local and general acceptance in reference to stationary battery storage, biofuel production plants and hydrogen refuelling stations in Germany. Therefore, they used a bivariate correlation analysis. In contrast to the regression analysis, bivariate correlation analysis aims to measure the strength and direction of the relationship between two variables without establishing a cause-and-effect relationship. The correlation coefficient measures the linear relationship between the variables and ranges from −1 to 1. This analytical approach allowed the authors to identify any connections pertaining to both general and local acceptance (see Fig. 4). Throughout this process, all possible variable combinations were scrutinised to uncover links related to both types of acceptance. However, the primary focus remained investigating the correlation between local and general acceptance while considering other variables, with the aim of detecting any disparities or variations between these two acceptance forms. The challenge in employing this approach lies in its inability to determine causality, only indicating the presence of a relationship between variables. It can sometimes reveal relationships that lack significance, as it does not account for other influencing factors. The approach assumes that relationships between variables are straightforward and linear, which may not always hold true. Since this method does not provide information on the direction or strength of more complex interactions between multiple factors, it opens the opportunity for more advanced methods to offer clearer insights. Machine Learning Algorithms, using techniques such as random forests for example could be used to identify complex, non-linear relationships between acceptance and the variables under study, such as environmental awareness or exposure to media campaigns. In this regard machine learning models can provide predictive insights and highlight key drivers that were missed by simpler correlation approaches. Or agent-based modeling could simulate how individual acceptance behaviors interact at a community level, revealing how local opposition or support for energy projects evolves over time. For example, it could model how the diffusion of information about the benefits of biofuel plants influences general acceptance in neighboring regions.

Bertsch, Valentin; Hall, Margeret; Weinhardt, Christof; Fichtner, Wolf—public acceptance and preferences related to renewable energy and grid expansion policy: empirical insights for Germany (2016).

Bertsch et al. [50] conducted a study focused on public acceptance of renewable energy sources (RES) and the necessary expansion of transmission grids in Germany. The research aimed to understand the factors influencing acceptance at both local and national levels.

The authors used a combination of methods, including general descriptive analysis, multi-criteria decision analysis (MCDA), and multivariate analysis of covariance (MANCOVA) to analyse the survey results. Figure 5 provides a detailed visualization of their methodological framework, illustrating the integration of these statistical techniques and the relationships between key variables examined in their analysis. The text was structured around five specific research questions (Q1–5). Q1, examined overall support for the energy transition and agreement with RE policies by exploring participants' willingness to make lifestyle changes to reduce their ecological footprint and their preferences for a potential future energy mix. In Q2, participants indicated a minimal distance for distinct energy technologies to be accepted in their neighbourhood. These distance statements were brought together with the mix preferences from Q1, hinting at relations between certain distances from energy sources and accepted energy mixes, as well as noticeable differences between local and national acceptance. Q3 utilised SWING-weighting to reveal the impact of drivers on the respondents in reference to the acceptance of energy technologies. Respondents evaluated the impact of possible drivers on a 7-point scale in reference to their subjectively perceived impact of energy and infrastructural technologies. In a second step the respondents stated the subjective importance of these drivers individually on a 5-point scale to eventually identify the drivers with the highest influence. Q4 examined technology rejection by the respondents, thereby building upon Q2 and Q3, which focused on local acceptance and drivers for accepting energy technology. To understand to what extent the rejection of energy technologies was explicable, the authors referred to the rejection of technologies in Q2. This rejection occurred when participants expressed their unwillingness to accept a specific technology in their neighbourhood, irrespective of its distance, and also provided negative ratings for at least one driver in Q3. The authors investigated whether participants who rejected at least one technology also perceived negative impacts of these technologies based on different drivers. As a result, "non-explicable" energy technologies were defined as those that were rejected despite receiving solely positive or neutral impact assessments for all drivers. The importance of policy objectives, covered in Q5, was examined by the pairwise comparison judgment known from the analytical hierarchy process (AHP). The resulting weight distributions showed whether the

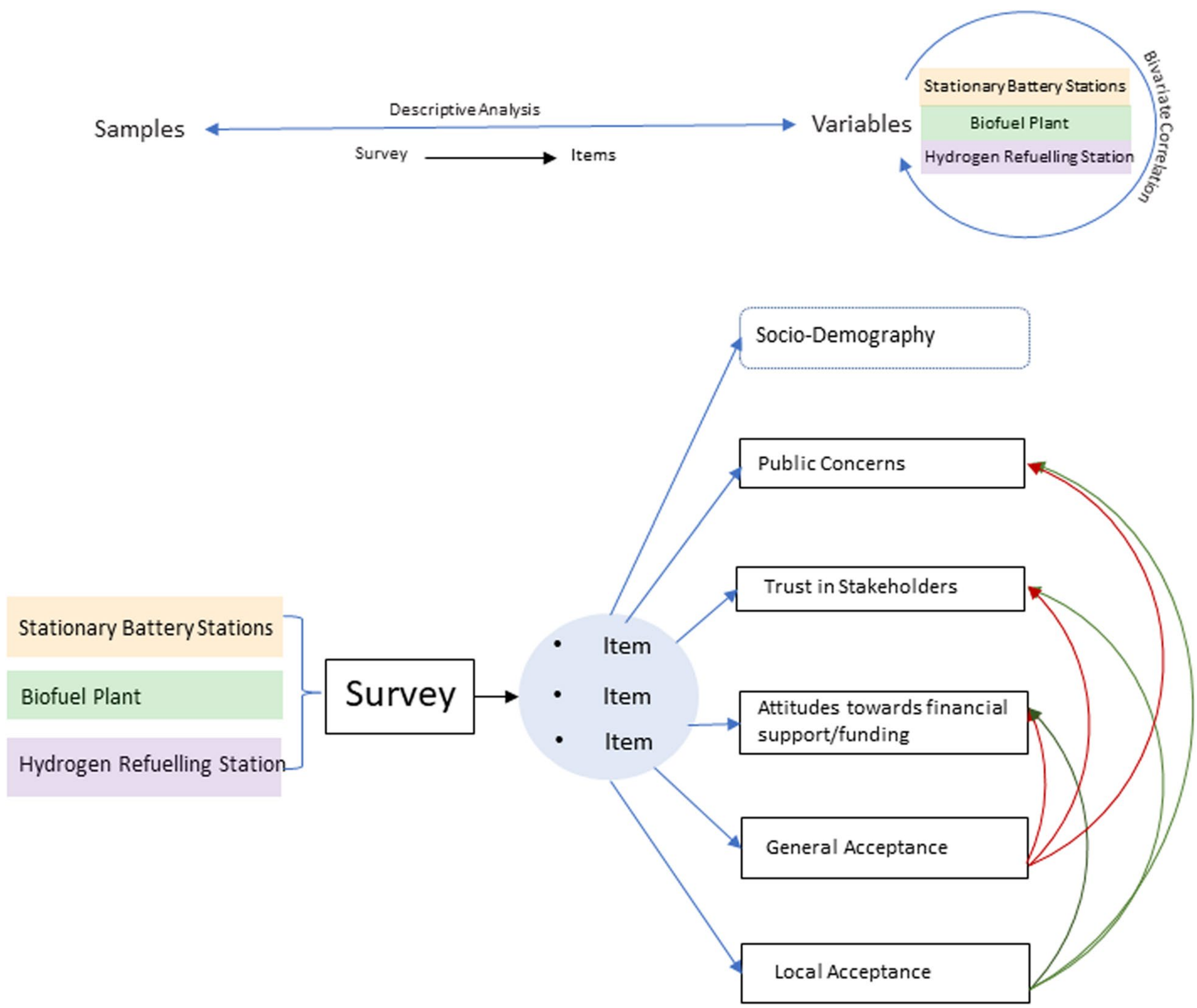

Fig. 4 Structural pattern Baur et al./authors' depiction

objects were evenly distributed or skewed, giving information on how they ranked from the respondents' perspectives. Q6 examined the connection between research questions 1–5 and investigated socio-demographic links within the data. A MANCOVA was undertaken to find correlations among the variables, and in this way Bertsch et al. analysed the relationships between socio-demographic information, power generation mixes, and preference statements for energy policy objectives by examining significant differences between group means. Although Bertsch et al. condensed the immense amount of data so that it could be interpreted and presented in a clear and understandable manner, the challenge from a statistical point of view with an approach like this is that the complexity of using multiple methods makes it hard to ensure consistency and accuracy across all analyses. Self-reported data might introduce biases, as people may not always be truthful or accurate in their responses. The diverse methods used can make it challenging to combine the findings into a single, clear conclusion. In addition, handling and analysing large amounts of data can be time-consuming and increase the chance of errors. The complexity of MANCOVA also requires a larger sample size for accurate results and can be difficult to interpret without advanced statistical knowledge.

Langer, Katharina; Decker, Thomas; Menrad, Klaus—public participation in wind energy projects located in Germany: which form of participation is the key to acceptance? (2017).

Langer et al.'s second included work [51] investigated the importance of social aspects in the implementation of wind energy projects, emphasising that Germany's energy transition can only succeed by considering local citizens' needs and expectations. This study specifically

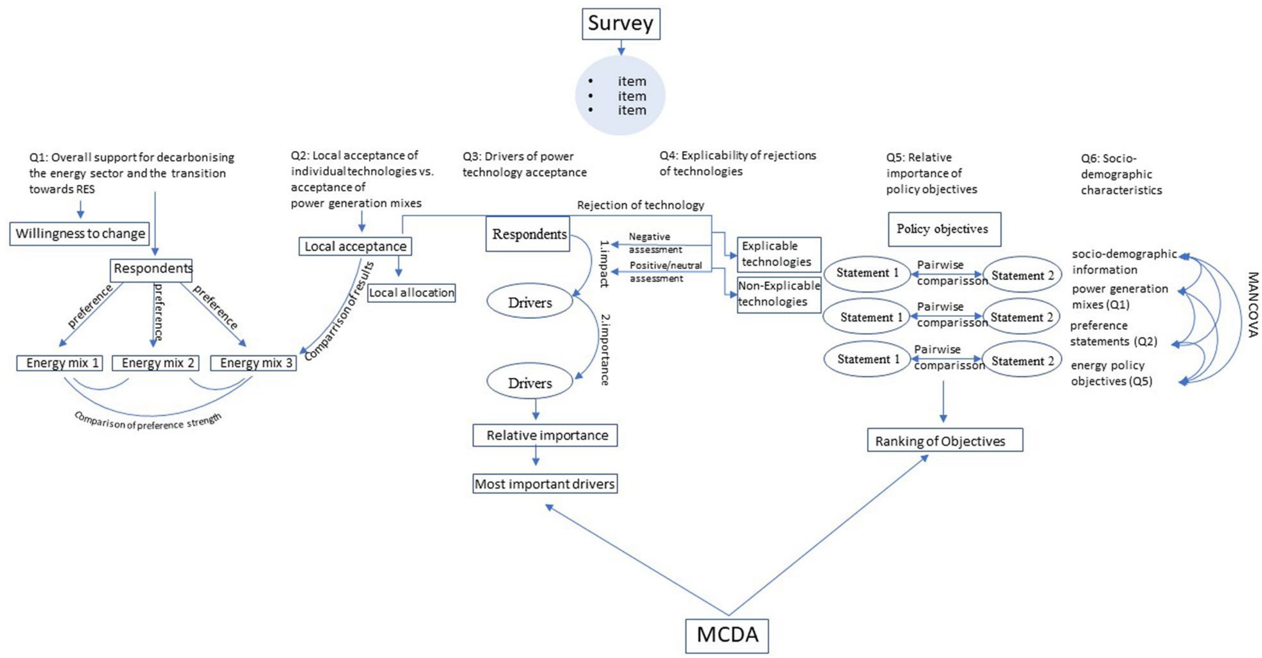

Fig. 5 Structural pattern Bertsch et al./authors' depiction

explored which forms of participation are preferred by citizens in relation to wind energy projects. Participatory options range from no participation to various levels, including alibi participation, information, consultation, cooperation, and financial participation.

The authors conducted an evaluation of attitudes, choices, and preferences by employing a conjoint analysis, a methodology employed to assess consumer or user needs in the initial stages of product or service development. In this approach, utility values for specific product attributes are determined based on consumer preferences. Choice-based conjoint analysis (CBCA) was used to draw conclusions from the respondents' decisions about different hypothetical wind energy projects. To accurately discern respondents' preferences, the survey's answer options needed to encompass alternative choices. The inclusion of alternatives allowed for the extraction of preferences through the act of choosing. By preferring a certain energy project, implicit trade-offs between the related attributes of a project have automatically been made by the participants. In analysing the findings of this choice experiment, Langer et al. utilized hierarchical Bayes estimation to determine part-worths. This method involves gathering repeated choices from each respondent to model their preferences accurately and effectively and thus compare preferences both across and within respondents. The aim is to find the optimal weight for the model pooled across respondents and the model within respondents, generating a high probability that the part-worths represent the respondents' choices. To further improve parameter estimates and narrow down predictions, covariates were added to the conjoint analysis to put in exogenous information not available within the choice-tasks. Analysing the impacts of the covariates within the hierarchical Bayes model, a multivariate regression model was utilised to reveal the relation between the covariates and the part-worths.

Challenges with this approach include that the hypothetical scenarios might not fully capture the complexities of real-life situations. People's responses to imagined situations can differ significantly from their actions in reality, as actual decisions often involve more emotional and contextual factors that are hard to replicate in a survey. Respondents might provide socially desirable answers, overstating their willingness to participate or support certain projects. The reliance on self-reported data can introduce bias, as participants may not always accurately predict their future behaviour. Moreover, the specific attributes chosen for the experiment may not encompass all relevant factors, potentially omitting key aspects that influence acceptance.

Ruddat, Michael; Sonnberger, Marco—the public perception of the energy transition: results of a nationwide representative survey in Germany (2016).

Ruddat and Sonnberger's paper [52] investigated public acceptance of Germany's energy transition, focusing on social aspects such as behavioural changes, acceptance of infrastructure costs, and environmental impacts.

It examines attitudes toward various RE technologies and the importance of energy efficiency.

The authors divided their results into seven categories. To analyse five of the categories, “attitude toward the energy switch”, “trust in institutions”, “previous experience with energy production plants”, “acceptance of energy production plants”, and “participation”, data were examined via descriptive analysis, using percentages to describe the distribution of the respondents’ answers to the survey questions.

Regarding the sixth category, “willingness to pay”, the authors employed several analytical methods. Initially, a descriptive analysis was carried out to show distributions of answer options. For respondents who confirmed their willingness to pay extra for their energy to contribute to the success of the energy switch, a follow-up method was applied. In this “bidding game”, participants gradually specified how much extra money they were willing to pay per year. Each time a respondent agreed a suggested amount, the next bid was offered. If the bid was declined, no further bids were presented. The bids were structured in 50€ steps, and after a maximum bid of 150€, respondents could state a suggested amount.

Based on the results of the general willingness-to-pay item, a correlation analysis was conducted to evaluate the relationships between willingness to pay and different variables for wind power, solar power, and general attitude toward the energy switch. To specify the results of the bidding game, a correspondence analysis (CA) was carried out. This method enabled the examination of significant distributions for different groups within the bidding game results. Since the results were depicted in a coordinate system, distances between the different groups or categories could be located. The three main groups identified by the bidding game as low, medium, and high willingness to pay, were displayed in the same coordinate system as previously determined groups, based on the survey items. This additional information allowed for narrowing down the proximity between the main groups and the determined groups, and thus their relation was better understood. Pursuing the aim to identify distinct groups in their acceptance of energy technologies within the energy transition, Ruddat and Sonnberger employed a latent class analysis (LCA) to examine the various response patterns of the participants. For each individual, the probability of belonging to a particular class was established based on their response patterns. Since the exact number of possible classes was unknown, the researchers determined the number of classes using literature and model-based quality criteria, such as fit indices. To inform the LCA, five survey questions regarding the acceptance of energy technologies were selected. Based on the response patterns, four classes were identified: “NIMBYs”, “Supporters”, “Undecided”, and “Critics”. The LCA results revealed that the “NIMBY” class was by far the smallest, while the sizes of the other three classes were relatively similar but with some variation.

To further examine these classes, another CA was performed. However, due to the small number of individuals in the “NIMBY” class and the lack of relevance in features, this class was excluded from further analysis. The selection of variables followed the procedure described in the previous CA, but focused on the main groups: “Supporters”, “Critics”, and “Undecided”. The results showed the proximity of each variable in relation to these three groups, providing insights into their relationships, which ultimately enhanced the understanding of group dynamics.

In terms of limitations, the descriptive analysis provides only a snapshot without exploring causal relationships. The bidding game may lead to hypothetical bias, as respondents might overstate their willingness to pay in a survey compared to real-life situations. LCA can oversimplify the diversity of opinions by fitting individuals into predefined classes, potentially masking nuanced attitudes. The selection of variables and assumptions made in LCA heavily influence the accuracy and meaningfulness of the resulting classes. In addition, potential biases could arise from the subjective nature of survey responses and the complex interpretation of statistical results.

Schumacher, Kira.—public acceptance of renewable energies: an empirical investigation across countries and technologies (2019).

Schumacher’s paper [53] explored the challenges and opportunities of the energy transition from centralised to decentralised renewable energy systems, highlighting the importance of public acceptance. It emphasised that despite general support, local projects often face opposition due to perceived injustices, and stressed the need for more comparative research to guide policymakers and project developers. Schumacher’s publication consists of several case studies, with the first being the focus for inclusion in this review. She conducted an empirical investigation into public acceptance of renewable energies across the Upper Rhine Region, covering Germany, Switzerland, and France. The study was structured around 13 hypotheses, each examined through specific survey items.

To begin with, Schumacher assessed general acceptance levels for renewable energies (H1) by analysing socio-demographic responses to a question about preferred future energy technologies. H2 examined the public’s willingness to support or oppose RE plants in their neighbourhood, using a Likert-scale and subsequent categorisation based on Schweizer-Ries et al. [54]. The results were verified through a one-way ANOVA to test for regional differences.

H3 compared general public acceptance with local acceptance, assuming the former would be higher. The comparison involved using specific survey items representing socio-political and community dimensions of acceptance. A *t* test was applied to measure the significance and practical value of the differences between these groups.

H4 explored the impact of proximity on public acceptance of RE plants by analysing respondents' preferences for the minimum distance of such plants from their homes, similar to Bertsch et al. The responses were examined by region and technology through percentage distributions.

For H5, Schumacher investigated whether previous experience with RE projects influenced acceptance. This hypothesis was tested through a *t* test comparing respondents who were aware of nearby RE plants with those who were not, examining both regional and technological differences.

The section examining H6 to H12, which focused on factors driving the acceptance of bioenergy plants through multiple linear regression, is excluded here, since regression analyses have already been reviewed above.

H13 looked at the link between public acceptance of renewable energies, community energy, and energy autonomy. Schumacher defined community energy as local participation in RE projects, and energy autonomy as self-sufficiency and integrated community energy systems. The analysis included measuring participation levels and preferences for energy autonomy using Pearson Correlation Coefficient (PCC) to explore the relationships between these variables.

The reliance on ANOVA and *t* tests assumes normal distribution and homogeneity of variances, which may not hold true for all subsets of the data, potentially affecting the validity of the results. In addition, these tests identify differences between groups but do not account for complex interactions between variables. The correlation analysis used for H13, while useful for identifying relationships, does not establish causation, limiting the ability to draw definitive conclusions about the influence of community energy and energy autonomy on public acceptance.

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Conclusions

In this section, a critical analysis of the scope of studies reviewed is provided, examining the methodologies employed and the inherent limitations in the research. It highlights the reliance on online surveys, discussing potential biases introduced by sample composition, and reflects on the strengths and weaknesses of various statistical approaches. In addition, the discussion offers guidance for future research, emphasizing the need for integrating diverse methods to address the complexity of public acceptance in energy technologies. Finally, it outlines the broader implications of these findings for enhancing the accuracy and applicability of future research.

Scope of studies

To begin with, one key peculiarity arises in connection with the structure of the questionnaires used in the included studies: the reliance on online surveys. In all ten papers reviewed, sample composition heavily relied on online surveys, raising an important point regarding the potential bias introduced by varying access to the internet among different population groups. A significant debate surrounds the scientific validity of online surveys due to the selection bias inherent in web surveys, which do not employ random sampling and often rely on convenience samples rather than probability samples [55]. Prior research has highlighted disparities in internet accessibility linked to factors such as gender, race, education, and economic status [56–58]. Notably, a strong association exists between internet usage and younger age groups [59, 60], particularly individuals aged 18–40, who tend to be overrepresented. This phenomenon likely stems from their greater familiarity with online platforms and higher internet usage. Conversely, individuals aged 60 and older are frequently underrepresented due to lower internet adoption rates within this demographic.

Furthermore, educational differences are evident between the general population and the sampled participants. The sample tends to be overrepresented by individuals with higher education levels, while those with lower levels of education are often underrepresented. This discrepancy may be influenced by internet access disparities, as individuals with higher education are more likely to have internet connectivity and be engaged in online activities [61]. Though corresponding socio-demographic correlations should be handled with caution, as variables can be mutually dependent, the potential for selection bias is not improbable. Hence, utilizing online surveys might lead to selection bias, creating an uneven probability of participation and skewing the representation of characteristics such as age, education, and gender [62]. This often results in the overrepresentation of certain groups, namely literate individuals with internet access and a particular interest in the topic [63], potentially leading to a less diverse target population and skewed findings [63, 64]. The fact that all of the papers included in the review relied solely on online surveys, without employing alternative quantitative methods, highlights a broader trend in recent research toward digital data collection [65].

Statistical approaches

Certain commonalities emerged during the examination of the statistical approaches. Correlation analysis, for example, was employed in some of the included studies to explore relationships between variables, providing insights into the interconnections and associations among various factors influencing acceptance. Other studies aimed to assess the impact of specific drivers such as socio-demographic variables or beliefs on acceptance levels, using sophisticated analytic methods to understand the underlying dynamics. Despite this, not all of the publications found socio-demographic factors to be similarly important; some considered factors such as age or education to be important drivers toward acceptance, whereas others did not follow this interpretation. Furthermore, regression analysis was a prominent approach utilised across multiple studies. In the following, the characteristics of the regression models and analyses employed in each study are compared:

Linear versus non-linear models: Ambrosio-Albala et al. used linear regression, which assumes linear relationships. Langer et al. and Oltra et al. used logistic and multivariate regression, which do not necessarily assume linearity and can handle more complex categorical outcomes.

Categorical versus continuous outcomes: Langer et al. focused on categorical outcomes with multinomial logistic regression, while Ambrosio-Albala et al. and Oltra et al. analysed continuous outcomes using linear and multivariate regression models.

Sample Size and Complexity: Langer et al.'s multinomial logistic regression requires larger sample sizes and is more complex than the multiple linear regression used by Ambrosio-Albala et al. Oltra et al.'s multivariate approach adds another layer of complexity by handling multiple predictors simultaneously.

National context and framing: Seidl et al. uniquely incorporated variance analysis to account for national contexts and framing conditions, which is different from the other studies focused on regression models.

Methodological flexibility: Bauwens and Devine–Wright's approach of using various regression models and the Kruskal–Wallis test provides flexibility in handling different types of data and relationships, but also introduces complexity and potential biases.

The regression-based methodologies predominantly focus on identifying and quantifying relationships between variables through linear, logistic, and multivariate regression models. In the following, non-regression approaches are explored. Some of these papers also use regression analysis, but not as the primary method, rather as an add-on to other techniques. The following section compares non-regression methodologies such as bivariate correlation analysis, MCDA, variance analysis, and choice experiments.

Bivariate versus multivariate analysis: Baur et al. used bivariate correlation analysis, which focuses on the relationship between two variables. While this method is simpler than multivariate analysis, it does not account for the simultaneous influence of multiple factors. In contrast, Bertsch et al. used a combination of general descriptive analysis, MCDA, and MANCOVA, which allows for the examination of multiple variables and their interactions.

Choice experiments versus correlation analysis: Langer et al. (2) employed a hypothetical choice experiment, which simulates decision-making by asking respondents to choose between different options described by multiple attributes. This approach provides practical insights into preferences but can be more complex to design and analyse. Baur et al.'s correlation analysis is straightforward and easy to interpret but lacks the depth provided by choice experiments.

Descriptive analysis versus advanced techniques: Bertsch et al. and Seidl et al. included descriptive analysis to provide basic insights into the data. Bertsch et al. then extended their analysis with MCDA to identify the impact of various drivers on acceptance, and MANCOVA to examine correlations among multiple variables. Seidl et al. utilised ANOVA to compare acceptance levels across different national contexts and framing conditions, followed by linear regression to identify specific influencing factors.

Contextual factors: Seidl et al. uniquely incorporated national contexts and framing conditions in their analysis, offering a robust understanding of how these factors influence acceptance. Bertsch et al. also considered socio-demographic variables and policy preferences, providing a broad context for their findings. Baur et al. and Langer et al. (2) focused more narrowly on specific relationships and preferences without extensive contextual analysis.

Analytical depth and complexity: Baur et al.'s bivariate correlation analysis was straightforward but lacked depth. Langer et al. (2)'s choice experiment provided practical insights but was simpler compared to Bertsch et al.'s and Seidl et al.'s methods. Bertsch et al.'s use of MCDA and MANCOVA offered a detailed, multi-faceted understanding but required careful interpretation and was complex. Seidl et al.'s combination of ANOVA and linear regression was robust but assumed linear relationships and faced potential oversimplification.

Guidance for future research

In the field of social acceptance research, selecting the appropriate regression method depends on the nature of the data and the specific research questions addressed. Below is guidance on which regression method to use based on different data types and research needs:

Linear regression

Best suited when:

- The dependent variable is continuous
- Exploring relationships that are expected to be linear and straightforward.
- You have smaller data sets, where complex models might not be justified.

Advantages:

- Linear regression models are easy to implement and interpret.
- Provides clear insights into the relationship between independent variables (e.g., demographic factors) and the dependent variable (acceptance levels).

Limitations:

- Assumes that the relationship between variables is linear, which may not always hold true.
- Can be heavily influenced by outliers and multicollinearity.

Example use case:

- Investigating the influence of demographic factors (age, income, education) on the level of acceptance of a new renewable energy technology within a community.

Logistic regression (multinomial and binary)

Best suited when:

- The dependent variable is categorical, such as different levels of acceptance (e.g., support, indifference, and opposition) or binary outcomes (e.g., accept or not accept).
- The relationships between variables are not linear.

Advantages:

- Can handle binary or multiple categories as outcomes.
- Does not assume a linear relationship between the dependent and independent variables.

Limitations:

- Requires larger sample sizes to provide accurate estimates.
- More complex to interpret compared to linear regression.

Example use case:

- Evaluating factors influencing different levels of acceptance (support, ambivalence, opposition) toward wind energy projects in local communities.

Multivariate regression

Best suited when:

- Examining the combined effects of multiple predictors, both continuous and categorical.
- Exploring complex interactions between multiple variables.

Advantages:

- Provides a detailed understanding by incorporating multiple predictors and their interactions.
- Can handle both continuous and categorical variables as predictors.

Limitations:

- Assumes linear relationships between predictors and the outcome.
- Can suffer from issues related to multicollinearity.

Example use case:

- Analysing how demographic variables (age, gender), attitudinal variables (perceived benefits, trust), and contextual factors (local policy support) influence the acceptance of HFC technologies across different European countries.

Mixed-methods approach

Best suited when:

- Research involves a combination of quantitative and qualitative data.
- You need to understand not just the statistical relationships but also the context and deeper insights behind acceptance.

Advantages:

- Combines the strengths of quantitative precision and qualitative depth.
- Provides a more holistic understanding of social acceptance.

Limitations:

- More complex to design and implement.
- Requires more resources in terms of time and expertise.

Example use case:

- Combining regression analysis of survey data with in-depth interviews to understand public acceptance of a new energy policy, examining both statistical trends and the underlying reasons for acceptance or opposition.

Limitations of the study

As the various facets of this study are examined, a question arises: can the results be applied more broadly? From a methodological standpoint, it is important to recognise that inherent limitations are encountered when attempting to encompass the entire research domain within a single investigation. Specifically, this review starts by highlighting the restrictions tied to the criteria used in searching for relevant publications in this area. These limitations include factors like publication dates, geographical focus, and the size of the samples. Hence the review is not suitable to trace the overall development in the field of social acceptance in the energy sector. Consequently, the conclusions drawn from this investigation do not fully represent the diversity of the research domain, but only those included within the scope.

Specifically, publications falling outside the temporal boundary of 2012–2023 were excluded from the selection process. In addition, a stringent criterion for sample size, demanding a minimum threshold of 900 survey respondents, was imposed. Each of these criteria, while essential for maintaining research rigour, inevitably imposes limitations by narrowing the scope of inquiry. Consequently, an extensive limitation arises, which necessitates the exclusion of numerous research questions and hypotheses that may offer valuable insights. These questions and hypotheses remain beyond the purview of the present investigation due to these defined boundaries.

The study's scope is geographically limited to Western Europe, which introduces constraints on the generalisability of the findings. The exclusion of non-European studies was intended to maintain a focused and comparable analysis within a consistent socio-political and economic context. However, this limitation restricts the applicability of the results to regions outside Western Europe, where different social, cultural, and regulatory environments might influence public acceptance of energy technologies. Consequently, the insights derived from the statistical methods examined may not fully capture the diversity of approaches and challenges present in other global contexts. Future research should consider including studies from a broader range of geographical areas, where energy-technology-based issues are rather neglected, such as Africa [66], South East Asia [67] or South America, which would be of interest to provide a more comprehensive understanding of the statistical methods used in public acceptance research worldwide.

Implications

Researchers should critically evaluate and test the assumptions underlying their chosen methodologies. For regression models, this includes checking for linearity, normality, and homoscedasticity. For non-regression methods, researchers should ensure that the selected techniques appropriately capture the complexity of public attitudes and behaviours. This is especially relevant given that one of the key findings of this review is that future research should consider integrating both regression and non-regression methods to leverage the strengths and mitigate the weaknesses of each approach. For instance, combining linear regression with MCDA as displayed by Bertsch et al. can provide both detailed statistical insights and a broader evaluation of factors influencing acceptance. Incorporating advanced statistical techniques such as structural equation modelling (SEM) and machine learning algorithms can also help in capturing complex, non-linear relationships and interactions between variables, which can enhance the predictive power and accuracy of models used to assess public acceptance. Mitigating biases is crucial to the integrity of these advanced methodologies. Efforts should be made to minimise biases, such as hypothetical bias in choice experiments and self-selection bias in survey samples. Incorporating a mix of qualitative and quantitative data can help validate findings and provide a more nuanced understanding of public acceptance. This combination of methodologies ensures that the insights gained are robust and reflective of actual public attitudes.

Representative sampling is another important consideration. Future studies should aim for more representative samples that capture a diverse range of socio-demographic backgrounds. This approach will improve the generalisability of the findings, providing a more accurate reflection of public attitudes and ensuring that the results are applicable to a broader population. However, it must also be noted that there is no clear consensus in the research field, as some findings suggest that factors like age, education, or prior knowledge have only very weak effects on acceptance [68], while others such as Bertsch et al. [50] and Langer et al. [51] indicate the opposite.

Given the variations in acceptance observed across different regions and contexts, context-specific research is essential. Future research should place a greater emphasis on understanding the local cultural, economic, and social factors that influence public acceptance. Comparative studies across different countries and regions (see Schumacher or Oltra et al.) can highlight these contextual differences and inform more tailored policy interventions. By understanding the unique factors that drive acceptance in different contexts, researchers and policymakers can develop more effective strategies to promote the adoption of renewable energy technologies.

Synthesis and future directions

This targeted review of public acceptance of energy technologies in Western Europe has revealed significant insights into the methodologies and statistical approaches employed in existing research. By analysing the statistical methods used in ten large-scale acceptance studies, the review highlights both the strengths and limitations of various approaches, including regression and non-regression techniques. The findings underscore the complexity of social acceptance research, influenced by a multitude of demographic, attitudinal, and contextual factors.

One core message is that apart from Seidl et al., the focus of the studies analysed in this paper has been on quantitative methods. To enhance future research, a mixed-methods approach combining quantitative and qualitative data is recommended. This integration can mitigate biases and validate findings, leading to a more nuanced and robust understanding of public acceptance. Qualitative findings can strengthen the arguments based on quantitative data, and they can also lead to the generation of quantitative results, thereby increasing readability and comprehension.

Another key message is the need for a unified analytical framework that integrates diverse methodologies to enhance the comparability and generalisability of results. Moreover, the dynamic nature of technology and society, coupled with the increasing availability of big data, suggests that incorporating new analytic methods, such as AI-supported analysis, sentiment analysis, geospatial analysis, agent-based modelling (ABM), or network analysis could significantly enhance future research.

In incorporating specific guidance on the selection and application of statistical methods this paper has provided actionable insights and practical recommendations based on the review's findings, ensuring that the lessons learned are clearly communicated and can be applied. It addresses the diverse needs of researchers working with different types of data and research questions, helping them choose the most appropriate methodologies to design and implement future studies in a way that maximises the validity and reliability of their findings. This makes particular sense, because there is the need for a unified analytical framework that integrates diverse methodologies to enhance the comparability and generalisability of results. Moreover, the dynamic nature of technology and society, coupled with the increasing availability of big data, suggests that incorporating new analytic methods, such as AI-supported analysis, Sentiment Analysis, Geospatial Analysis, ABM or Network Analysis could significantly enhance future research. Regression analysis, widely utilised across multiple studies, provides valuable insights into the relationships between demographic, attitudinal, and contextual variables and acceptance levels. However, the assumptions of linearity and potential biases such as multicollinearity underscore the need for careful application and interpretation. Incorporating more advanced techniques like SEM and machine learning algorithms can enhance the analysis by capturing complex, non-linear interactions. Non-regression methods, including bivariate correlation analysis, MCDA, and choice experiments, offer additional perspectives by focusing on specific relationships and decision-making processes.

In terms of exploring the acceptance of energy technologies, AI and machine learning techniques offer innovative perspectives by enabling the analysis of large and complex data sets that are difficult to capture with traditional survey methods. Sentiment analysis, for example, leverages data from social media platforms and other online sources to evaluate public opinion qualitatively and quantitatively [69]. By analyzing real-time data on public attitudes toward energy technologies, sentiment analysis offers timely and dynamic insights that can help researchers and policymakers gauge and respond to shifts in public sentiment more effectively than retrospective survey data [70]. This real-time nature is critical for energy policy planning, where rapidly evolving public opinions can have a substantial impact on the success or failure of new technology implementations. Traditional surveys, often limited by static and retrospective data collection, cannot offer this level of immediacy and flexibility.

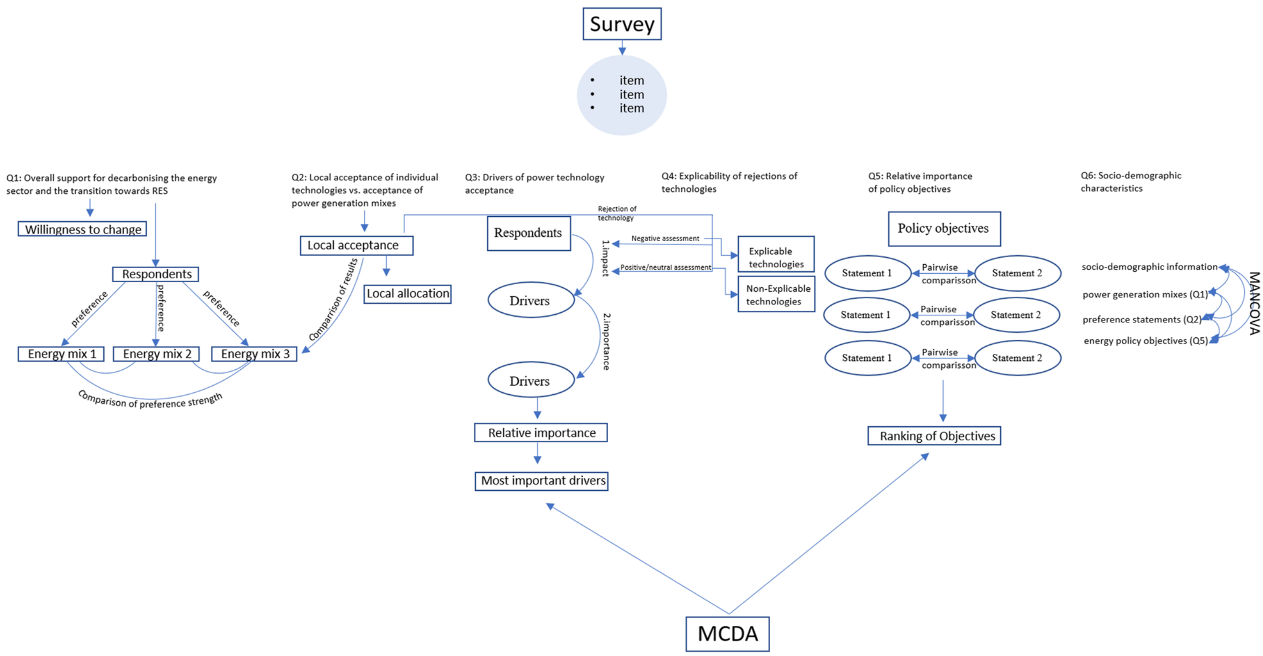
In addition, the application of machine learning techniques within AI allows for the detection of patterns and trends within large data sets that might otherwise go unnoticed. Traditional methods like regression or ANOVA often assume linear relationships and may fail to capture the non-linear and complex interactions within social acceptance processes. In contrast, AI's ability to model and detect such patterns, including latent relationships between variables such as demographics, socioeconomic factors, and public attitudes, provides richer insights. Furthermore, AI's predictive capabilities offer forecasts of future public opinion trends, enabling more proactive planning by policymakers. The continuous and dynamic nature of AI-driven approaches offers significant advantages in comparison with static survey methods, which often provide snapshots rather than ongoing trends. This allows for better adaptation to the changing dynamics of public opinion, offering a more nuanced understanding of the factors influencing acceptance over time. Incorporating geospatial analysis adds an important spatial dimension to the study of energy technology acceptance. By mapping the deployment of energy technologies and analyzing their relationship to demographic and socio-economic factors, researchers can identify geographical patterns in public acceptance and resistance. This spatial approach sheds light on how proximity to energy infrastructure, environmental conditions, and community characteristics influence attitudes. For example, geospatial analysis can highlight localized resistance to certain technologies, such as wind turbines, due to concerns about visual or environmental impacts, thereby offering valuable insights for site planning and policy formulation. This not only enhances the understanding of regional differences in acceptance but also supports more strategic decisions in the deployment of energy projects.

Agent-based modeling (ABM) provides a further layer of sophistication by simulating social dynamics and individual behaviors in response to technological innovations. ABM is especially relevant for understanding the complex, non-linear relationships that often characterize public acceptance of energy technologies. Unlike traditional statistical models, which may struggle to capture the nuanced interactions between individuals, communities, and technologies, ABM allows researchers to explore how these interactions evolve over time. For instance, ABM can simulate how positive or negative opinions about a technology spread within a community and how these evolving opinions influence the overall acceptance of the technology. This capacity to model collective behavior and the diffusion of attitudes makes ABM a powerful tool for studying social acceptance in a way that traditional methods cannot. As highlighted in [71], ABM offers unique insights into the interactions between actors in energy and sustainability systems, capturing the dynamic effects that emerge from individual decisions and social influences. By modeling real-world complexities, ABM provides a way to forecast and simulate scenarios that can guide policy interventions more effectively. Moreover, the theoretical foundation of ABM, as discussed in [72], demonstrates its utility in addressing empirical challenges in social science research, particularly in the context of energy transitions. By modeling complex systems of public acceptance, ABM can reveal the emergent behaviors that result from individual and collective decision-making processes. This makes it an invaluable tool for policymakers who need to understand the long-term impacts of public acceptance on energy transitions and technology adoption. Traditional methods may miss these emergent phenomena, as they typically focus on static variables and relationships without capturing the dynamic, interconnected nature of social systems.

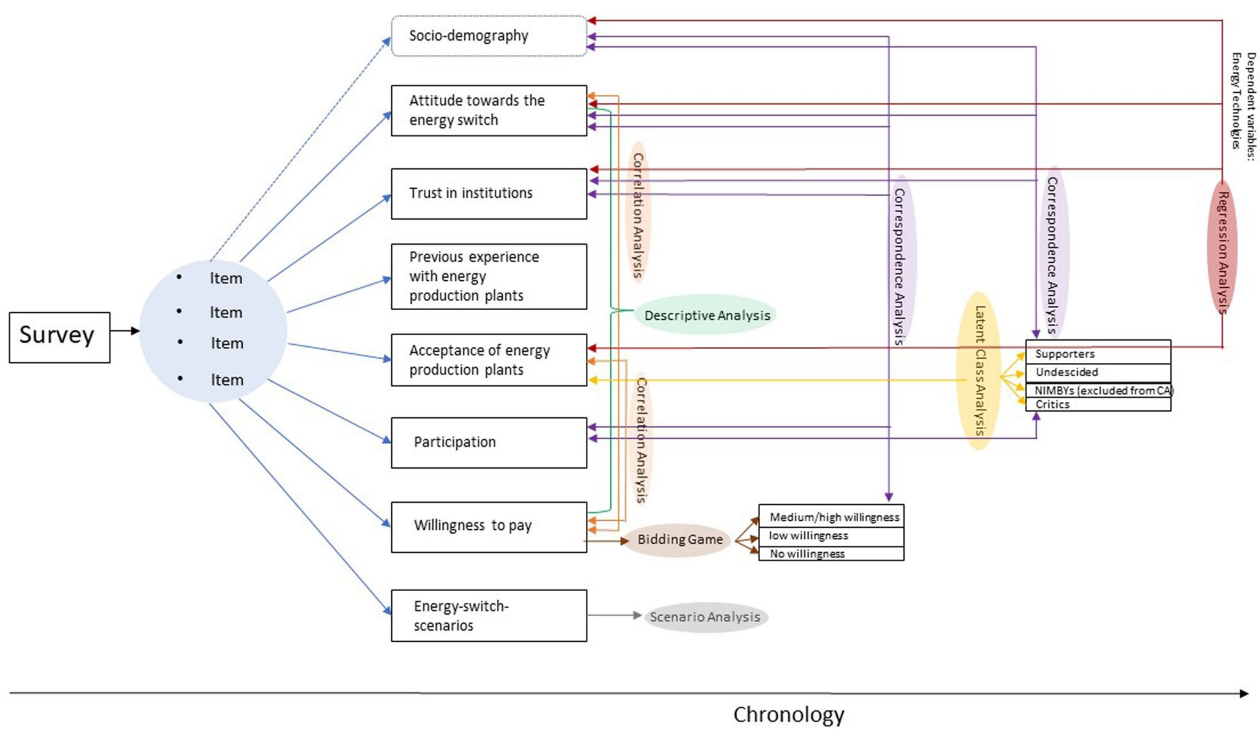
In conclusion, alternative methods such as ABM and sentiment analysis are not merely supplementary tools to traditional statistical approaches; they provide essential avenues for exploring the dynamic and often complex social processes that influence the acceptance of new energy technologies. ABM's ability to simulate collective behavior and model complex systems, combined with AI and sentiment analysis's capacity to process large, real-time data sets, offers more comprehensive and accurate insights than traditional methods alone. These approaches facilitate more targeted policy planning by offering a deeper understanding of public attitudes and how they evolve over time. By integrating these alternative methods into future research, scholars and policymakers can make more informed decisions that better reflect the complex realities of public acceptance in energy transitions.

Appendix

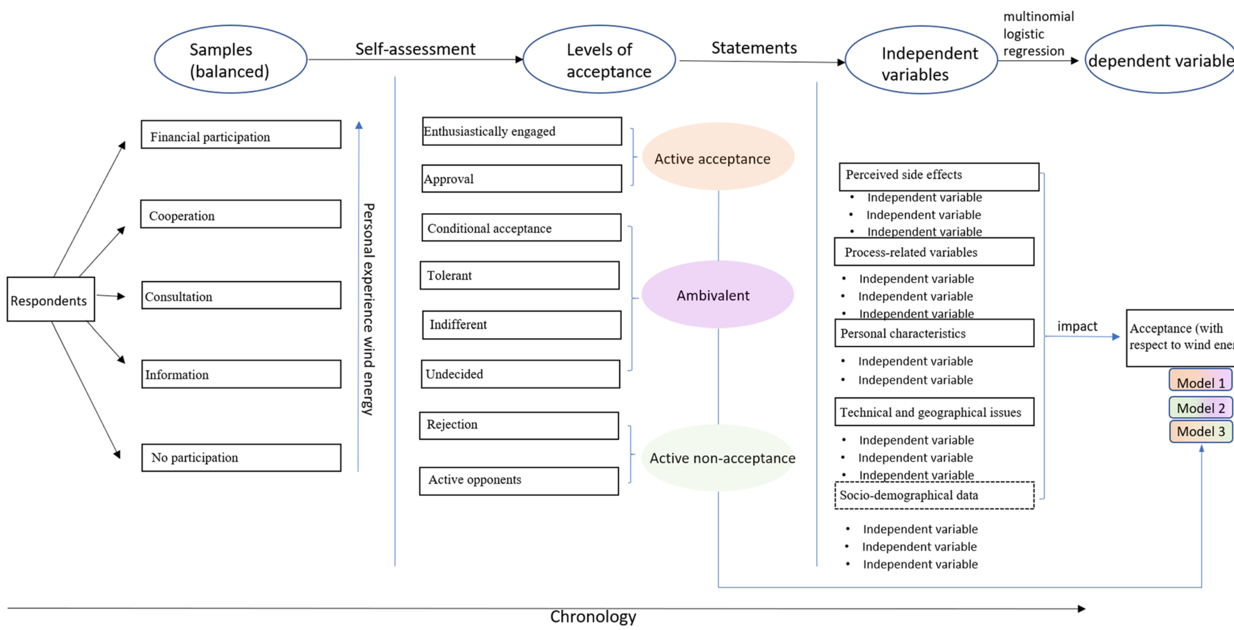
Pattern maps (by date of publication).



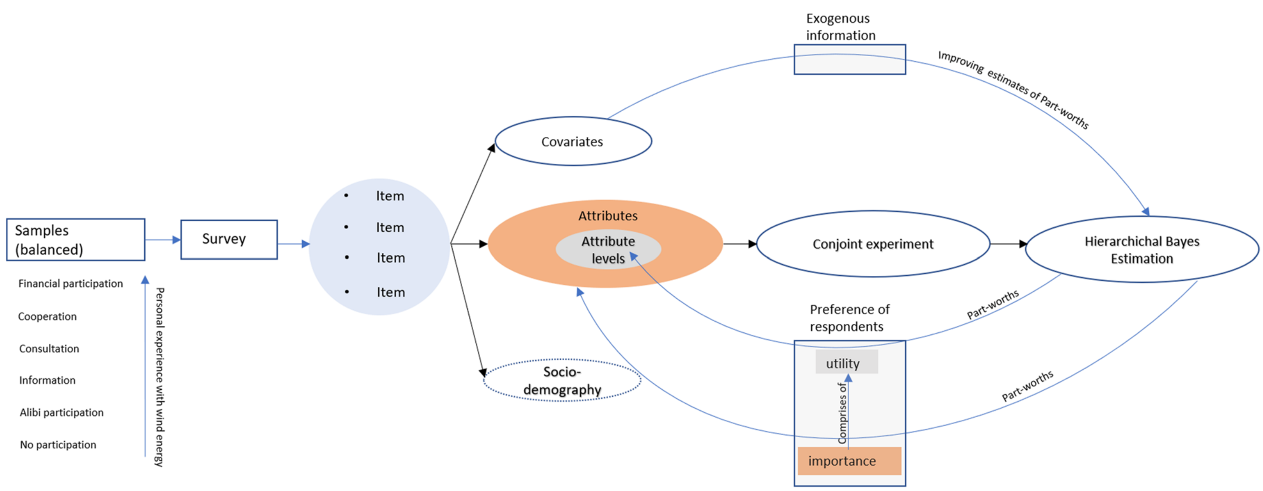
Bertsch, V.: Hall, M.; Weinhardt, C.; Fichtner, W.: Public acceptance and preferences related to renewable energy and grid expansion policy: Empirical insights for Germany (2016)



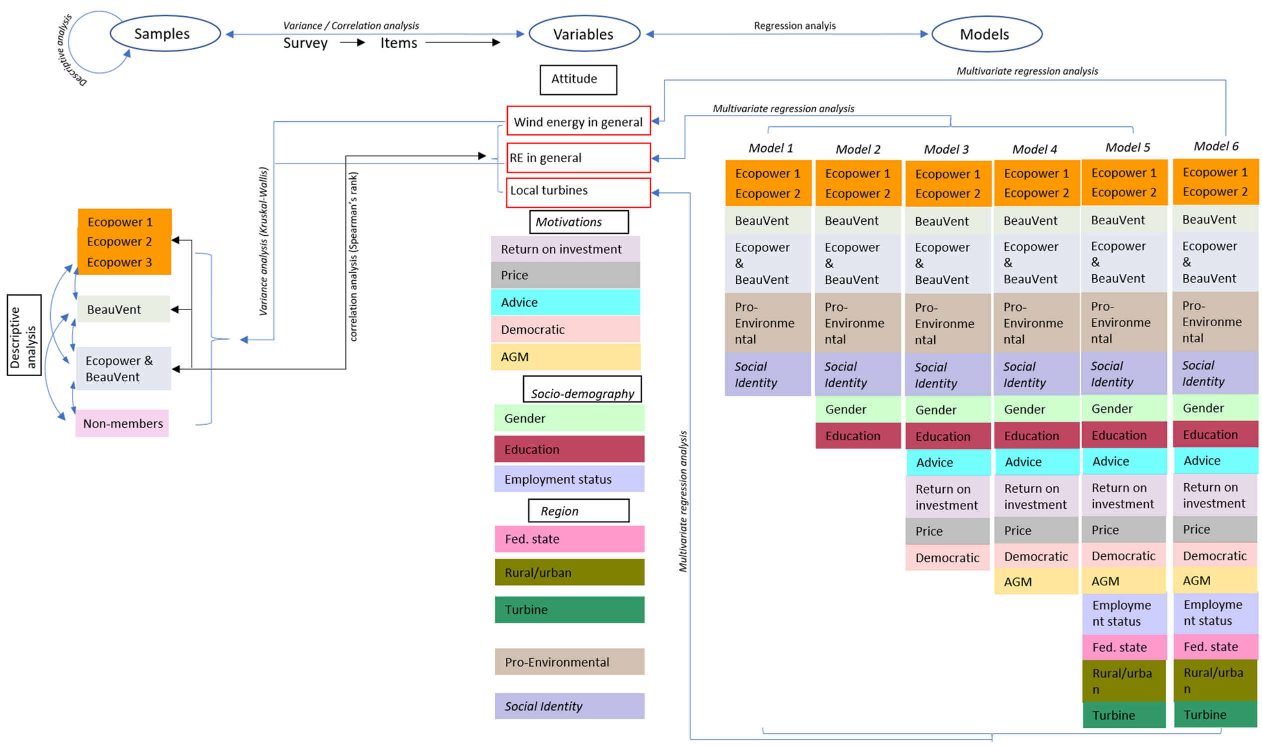
Ruddat. Michael; Sonnberger, Marco. The Public Perception of the Energy Transition: Results of a Nationwide Representative Survey in Germany (2016)



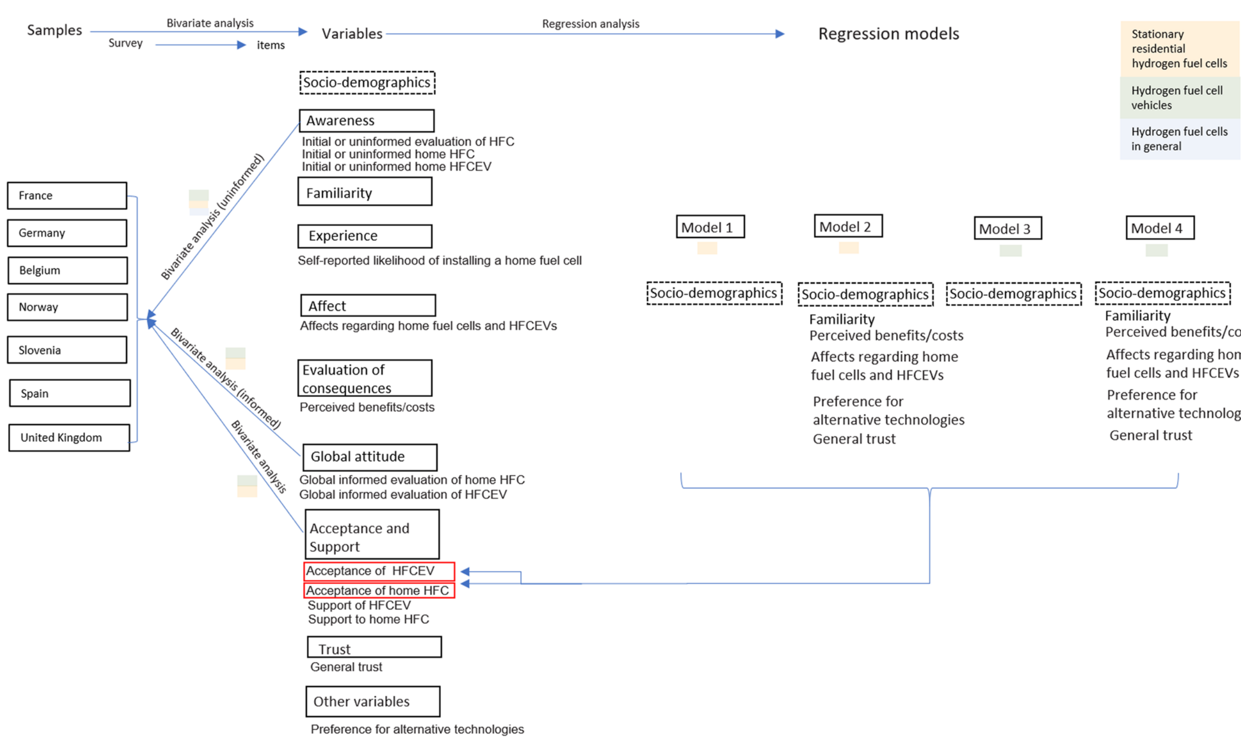
Langer, Katharina; Decker, Thomas; Roosen, Jutta; Menrad, Klaus—Factors influencing citizens' acceptance and non-acceptance of wind energy in Germany (2017)



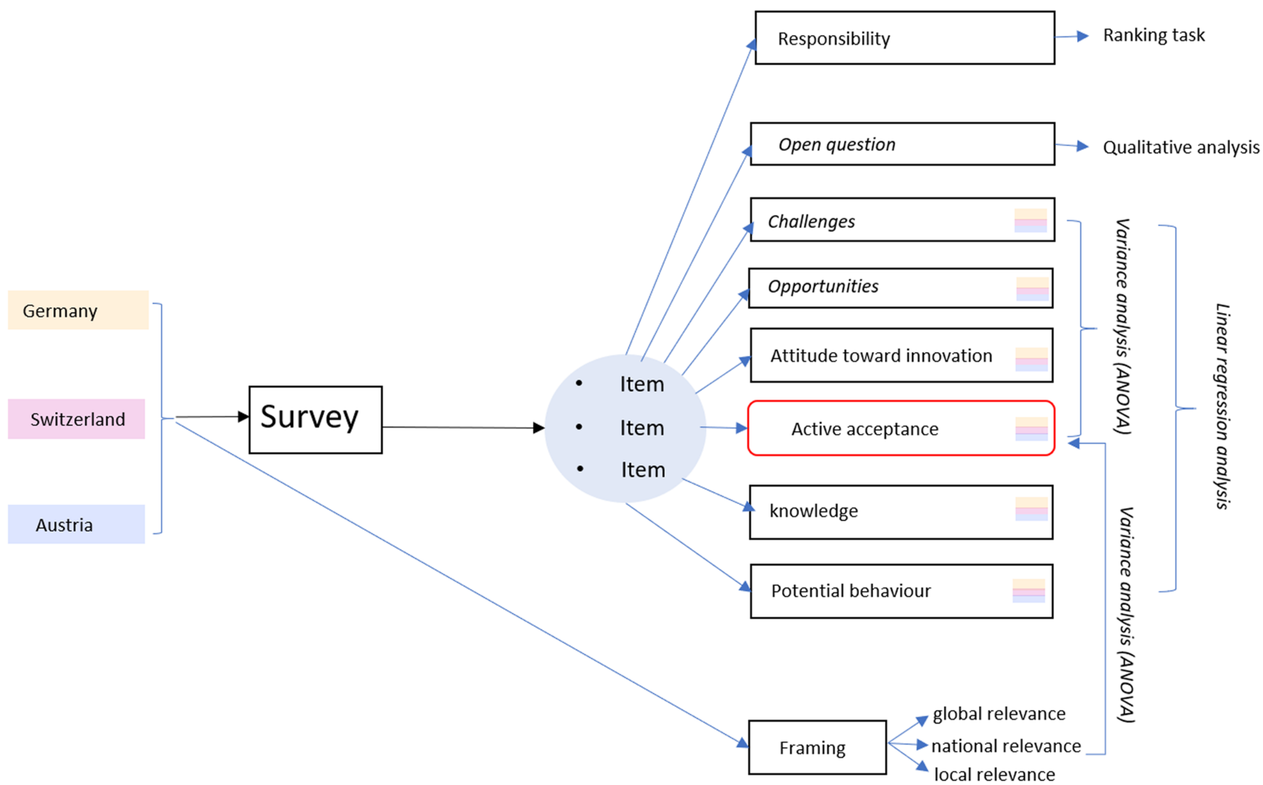
Langer, Katharina; Decker, Thomas; Roosen, Jutta; Menrad, Klaus—Public participation in wind energy projects located in Germany: Which form of participation is the key to acceptance? (2017)



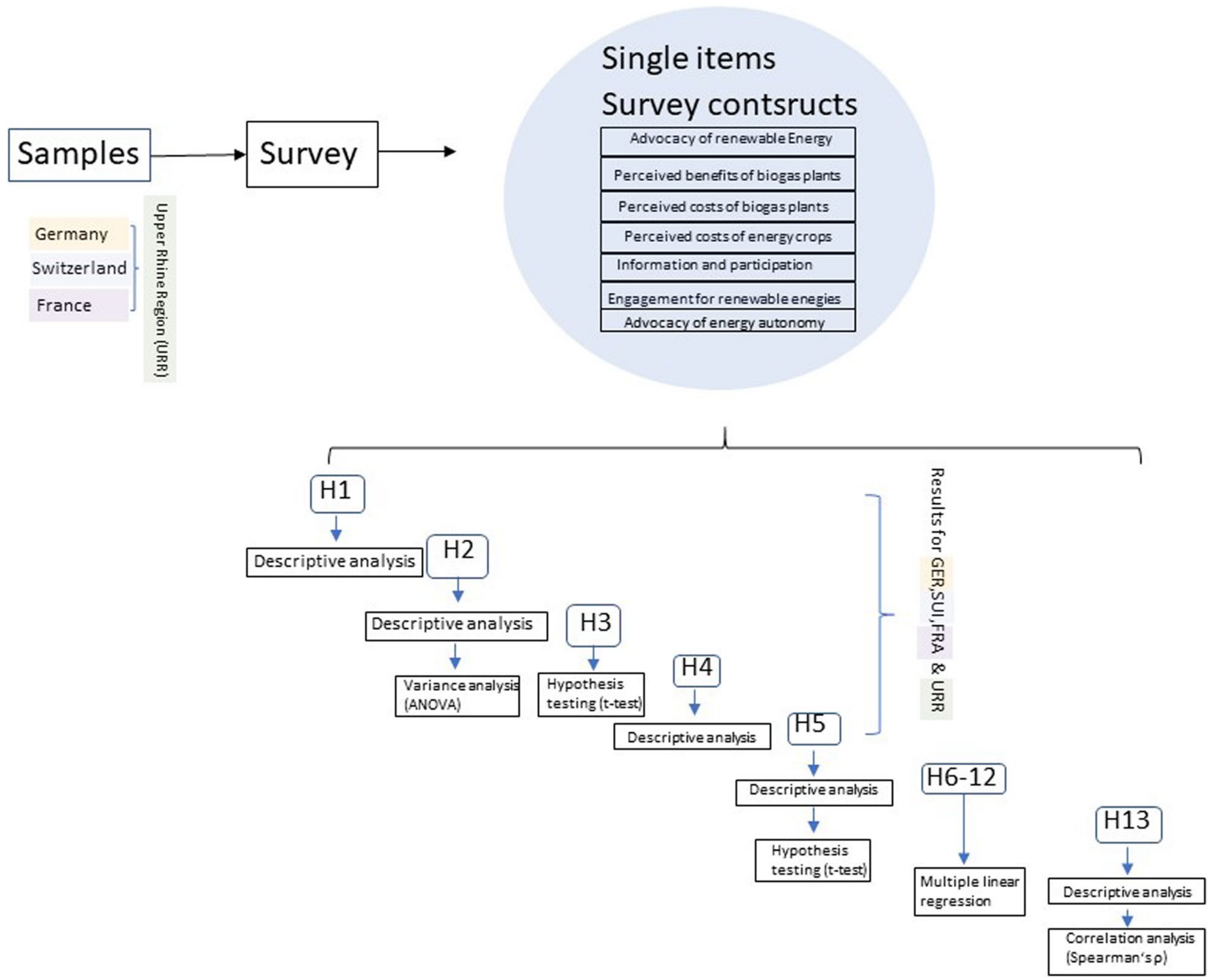
P. Devine-Wright, T. Bauwens—Positive energies? An empirical study of community energy participation and attitudes to renewable energy (2018)



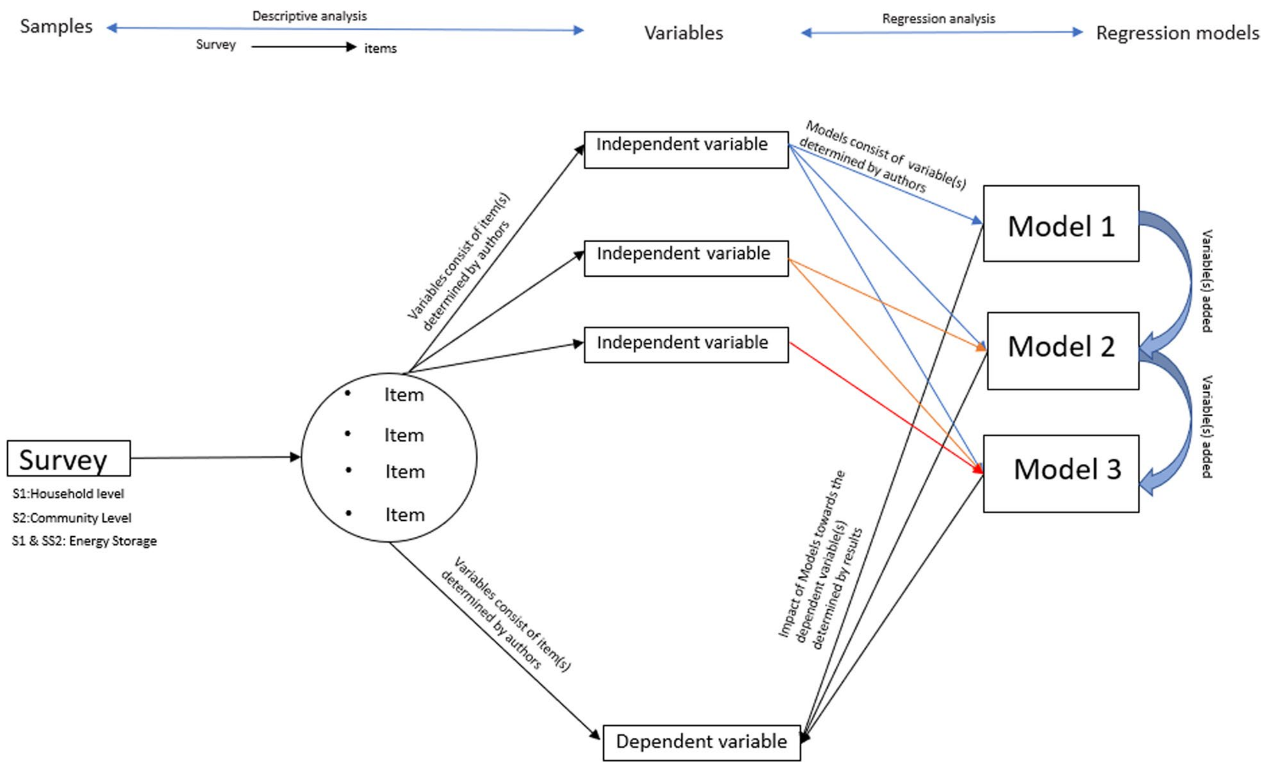
Oltra, Christian and Sala, Roser and Lores, Monica and Upham, Paul and Dütschke, Elisabeth and Schneider, Uta and Wiemann, P.—The public acceptance of hydrogen fuel cell applications in Europe (2018)



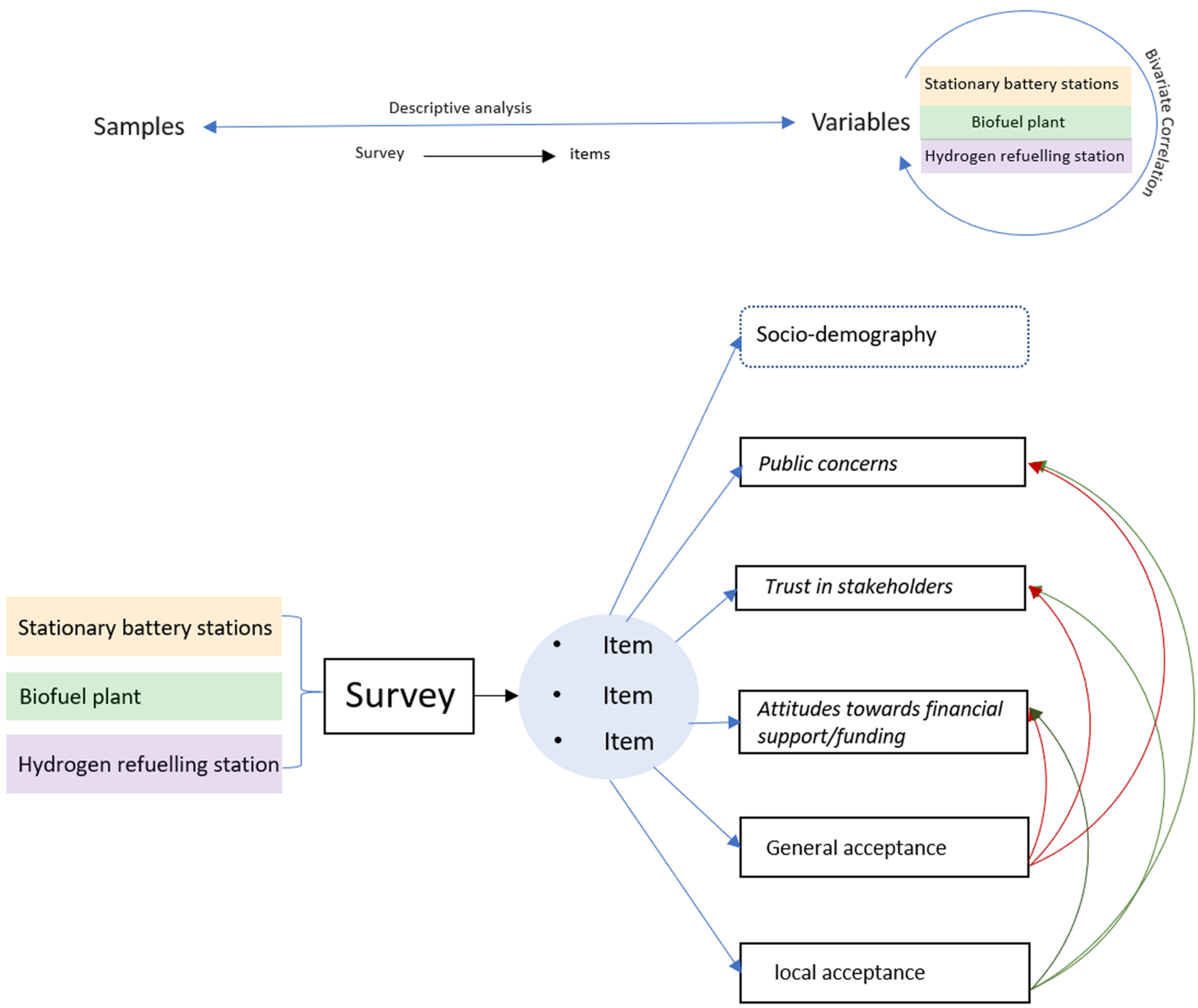
Seidl, R. and von Wirth, T. and Krutli, P.—Social Acceptance of Distributed Energy Systems in Swiss, German, and Austrian Energy Transitions (2019)



Schumacher, Kira.—Public acceptance of renewable energies – an empirical investigation across countries and technologies (2019)



Ambrosio-Albala, P. and Upham, P. and Bale, C. S. E. and Taylor, P. G.: Exploring Acceptance of Decentralised Energy Storage at Household and Neighbourhood Scales: A UK Survey (2020)



Baur, D.; Emmerich, P., Baumann, M.; Weil, M.- Assessing the social acceptance of key technologies for the German energy transition (2022)

Abbreviations

AI	Artificial intelligence
ABM	Agent-based modelling
ANOVA	Analysis of variance
CA	Correspondence analysis
DES	Distributed energy systems
HFC	Hydrogen fuel cell
HFCEV	Hydrogen fuel cell electric vehicle
LCA	Latent class analysis
MCDA	Multi-criteria decision analysis
MANCOVA	Multivariate analysis of covariance
PCC	Pearson correlation coefficient
RE	Renewable energy
RES	Renewable energy sources
SDGs	Sustainable development goals
SEM	Structural equation modelling

Acknowledgements

Proof-reading of english native speaker
Julie Cook Academic Editing and Proofreading Services.

Author contributions
PS: worked the concept, wrote the manuscript text, created the figures and graphs MB: helped with the concept, reviewed the text MW: helped with the concept, reviewed the text.

Funding
Open Access funding enabled and organized by Projekt DEAL. The work was realised with financial support by the German Research Foundation (DFG) under Project ID 390874152 (POLiS Cluster of Excellence, EXC 2154).

Availability of data and materials
No datasets were generated or analysed during the current study.

Declarations

Competing interests
The authors declare no competing interests.

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Received: 19 April 2024 Accepted: 13 February 2025
Published online: 11 March 2025

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